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Preliminary Results from Stentrode BCI First-in-Human Trial

Nicholas L. Opie[1-3,*], Peter E. Yoo[3] Gil S. Rind[1-3], Stephen M. Ronayne[1-3], Christin Bird[4], Bruce Campbell[4], Andrew Morokoff[4], Peter Mitchell[4], Thomas J. Oxley[1-3].

[1]Vascular Bionics Laboratory, Department of Medicine, University of Melbourne, VIC, AUS. [2]Florey Institute for Neuroscience and Mental Health, The University of Melbourne, VIC, AUS. [3]Synchron Inc. CA, USA. [4]Royal Melbourne Hospital, VIC, AUS.

Introduction:
We have developed a novel, minimally-invasive brain-computer-interface that mitigates the risk of open brain surgery. Our device, the Stentrode is implanted via contrast angiography through blood vessels and is designed to self-expand to conform to the vascular curvature when deployed.

Materials, Methods and Results:
Our seminal participant was implanted with a Stentrode BCI in the superior sagittal sinus overlaying the motor cortex in August 2019. The Stentrode was connected to a wireless telemetry unit implanted in the pectoral region, which together with the brainOS software was able to acquire, transmit and interpret his neural signals. Data acquisition began 7 weeks after implantation to ensure proper wound healing. Within 5 weeks after the initial data acquisition, the participant was using the system to control communication software and to write emails to friends, family and the local council. In combination with eye-tracking, he was able to type at a speed of 14 Correct Characters Per Minute (CCPM) with an error rate of 9% (68 errors across 748 trials).

Discussion:
By removing the requirement of risky open-brain surgery, the Stentrode provides a safer alternative to invasive BCI's, while still maintaining the high-quality signals acquired from beneath the skull. A three month clinical follow-up showed no signs of thrombosis, infection or occlusion, which, when coupled with the preliminary efficacy results presents a viable alternative to invasive BCI systems.

Significance:
In our world first, we have demonstrated the clinical feasibility of an endovascular brain-computer interface, showing that the Stentrode can acquire, transmit and interpret neural signals enabling home-control of communication software in a participant with upper limb paralysis caused from motor neuron disease.

Grasp concept encoding through different sensory modalities in human posterior parietal cortex

S. Wandelt [1], S. Kellis[1,2], L. Bashford[1], B. Lee[2], C. Liu [1,2], R. A. Andersen[1]

[1]Tianqiao and Chrissy Chen Brain-machine Interface Center at Caltech; [2]USC Neurorestoration Center, Keck School of Medicine of USC, Los Angeles, CA, USA

*1200 E California Blvd, M/C 216-76, Pasadena, CA 91125. E-mail: sarahwan@caltech.edu

Introduction: Grasping and manipulation of objects are important aspects of human independence and represent critical losses in paralysis due to spinal cord injury (SCI). Intracortical recordings from posterior parietal cortex (PPC), in a single tetraplegic human have previously been shown to exhibit planning and execution activity during motor imagery of different grasp shapes using visual cues (image of grasp). However, PPC is also involved in other tasks, such as visual word recognition and phonological processing[1]. These different sensory and behavioral paradigms could potentially modulate preparatory activity and how grasps are represented during motor imagery. To understand how cue modalities affect motor imagery in PPC, we tested visual, auditory and written cues in a grasp motor imagery task and evaluated how grasp-related information was represented in the cue, delay, and action phases of this task.

Material, Methods and Results: Trials began with a short inter-trial interval, followed by a cue to one of five grasps: Lateral, Medium Wrap, Palmar Pinch, Sphere3Finger and Writing Tripod. The cue was either visual (i.e. image of hand grasping object), auditory (i.e. spoken grasp names), or written (i.e. grasp name in written text). Then, after a brief delay, the subject imagined performing the cued grasp. One block of each cue modality was recorded on each session day. For each of the seven recorded session days, cross-modality grasp classification was performed to quantify similarity in information content between cue modalities. Cross-modality classification consisted of training a LDA classifier on data from one cue modality and testing it on all cue modalities. Decoding performance was evaluated using eight-fold cross-validation. Features were calculated by performing PCA and keeping the first N PC's that accounted for 90% of the explained variance. Results for individual session days were combined and 95% confidence intervals (CI) of the mean were computed.

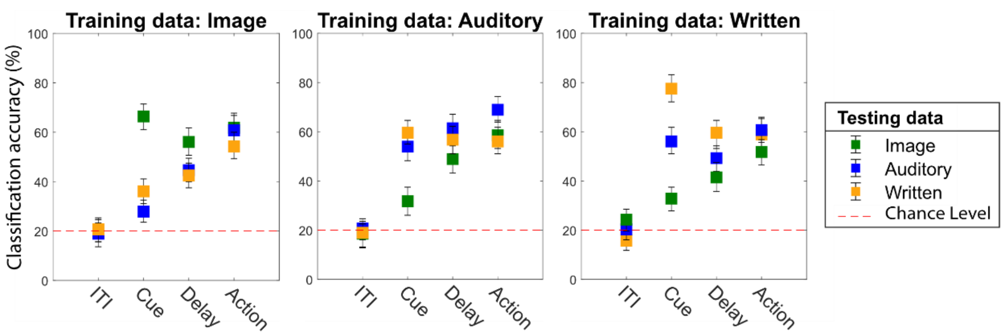

Figure 1: Cross – modality classification accuracy for each trial phase. Training data was collected from the modality indicated in the title, while the color indicates the testing modality. Error bars represent 95% confidence intervals.

Training the classifier on any cue modality results in higher-than-chance classification for the other modalities during cue phase, indicating a shared neural structure in sensory modality processing. The highest classification accuracy is obtained during written cue processing. Classification accuracy in the action phase was not significantly different across any modality, consistent with a transition of sensory cues to movement plans and imagined movements.

Discussion: These results indicate that regardless of the modality used for cueing, the underlying meaning of the grasp concept remains the same, which is reflected by the classification model for one cue modality generalizing to others, completely during the action phase, and partly during the cue phase. The high generalization of models trained on auditory modality to written modality during cue phase and vice versa may indicate the presence of language processing in this phase, transitioning to motor imagery planning and execution in later phases as with the visual modality. The results suggest that PPC performs visual, auditory and written cue integration, as well as motor planning activity, while performing a grasp motor imagery task.

Significance: Understanding how brain regions in the human grasp network integrate sensory information, and how these can potentially affect grasp preparatory and motor imagery decoding abilities, is important for the design of high performance brain computer interfaces for reaching and grasping.

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Functional connectivity predicts MI-based BCI learning

M.-C. Corsi[1,2*], M. Chavez[3], D. Schwartz[4], N. George[2,4], L. Hugueville[4], Ari E. Kahn[5], S. Dupont[2], D.S. Bassett[5-8], F. De Vico Fallani[1,2]

[1]Inria Paris, Aramis project-team, F-75013, Paris, France; [2]Institut du Cerveau et de la Moelle Epinière, ICM, Inserm, U 1127, CNRS, UMR 7225, Sorbonne Université, F-75013, Paris, France; [3]CNRS, UMR 7225, F-75013, Paris, France; [4]Institut du Cerveau et de la Moelle Epinière, ICM, Inserm U 1127, CNRS UMR 7225, Sorbonne Université, Ecole Normale Supérieure, ENS, Centre MEG-EEG, F-75013, Paris, France; [5]Department of Bioengineering, School of Engineering and Applied Science, University of Pennsylvania, Philadelphia, PA 19104, USA; [6]Department of Neurology, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA 19104, USA; [7]Department of Physics and Astronomy, College of Arts and Sciences, University of Pennsylvania, Philadelphia, PA 19104, USA; [8]Department of Electrical and Systems Engineering, School of Engineering and Applied Science, University of Pennsylvania, Philadelphia, PA 19104, USA

*E-mail: marie.constance.corsi@gmail.com

Introduction: Despite its clinical application, voluntarily modulating brain activity appears to be a learned skill that affects the usability of brain-computer interfaces (BCIs) and neurofeedback systems. Indeed, it is often associated with a strong inter-subject variability and with the difficulty for a substantive portion of the population to self-regulate their brain activity [1]. To address these issues, several approaches based on the search for better neural decoders, but also for psychological and/or neurophysiological factors [2] have been considered. If studies revealed the involvement of a larger brain network, beyond the BCI-targeted areas [3], the evolution of the functional connectivity over BCI sessions has poorly been studied. We hypothesized that the training would be accompanied with a decrease of functional integration in areas related to learning process, and that the associated properties would provide information to predict the learning rate.

Material, Methods & Results: Twenty naive healthy subjects performed a BCI training consisting of 4 sessions over 2 weeks in which electroencephalographic signals were recorded. The task consisted in controlling the vertical position of a moving cursor through the α and/or β modulation to reach a target displayed on a screen. To hit the up-target, the subjects imagined a right-hand grasping and to hit the down-target, they remained at rest. After removing physiological artifacts and performing the source reconstruction, we conducted the connectivity analysis by computing the imaginary coherence between each pair of ROIs [4]. To study the regional connectivity, we computed the relative node strength N by summing the values of the associated row of the connectivity matrix.

Over the sessions, we found a progressive decrease of task-related connectivity in both α and β ranges across sessions involving mainly fronto and parieto-occipital interactions (Figure 1). At the regional level, connectivity changes revealed a significant across-session declines spatially distributed involving bilaterally visual areas and associative regions. Better BCI performance was associated with the decrease of relative node strength in areas involved in visual attention task (occipital pole), in both mental rotation and working memory (orbital part of the inferior frontal gyrus), in decision making and memory consolidation (fronto-marginal gyrus). We observed a significant and positive correlation between the regional connectivity and the learning rate ($p < 0.035$), meaning that the potential to improve performance is higher when the functional disconnection of these regions has not yet started. Notably in the α_2 band, significant predictions were obtained in areas involved during motor imagery and working memory (e.g. precuneus).

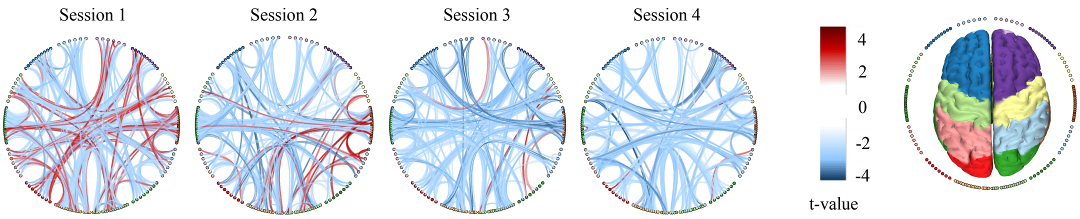

Figure 1. Task-related connectome obtained with source reconstructed signals in the β_1 band. The nodes correspond to the regions of interest from the Destrieux atlas and the links represent the statistical values resulting from a paired t-test performed between the motor-imagery and rest conditions ($p < 0.05$).

Discussion & Significance: In this study, we identified functional connectivity changes during BCI training. They were characterized by a progressive functional disconnection over sessions. These network features appeared to be significant predictors of BCI learning rate. If conducting studies on longer BCI training to assess the evolution of these patterns is necessary, our results could pave the way to an individualized BCI training based on the study of the properties of the functional brain network organization.

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Prediction of tonic pain using support vector machines with phase-based connectivity features

Y. Han[1], E. Valentini[2], S. Halder[1*]

[1]*School of Computer Science and Electronic Engineering, University of Essex, Colchester, United Kingdom;*
[2]*Department of Psychology, University of Essex, Colchester, United Kingdom*

*Wivenhoe Park, Colchester, Essex, CO4 3SQ, United Kingdom. E-mail: s.halder@essex.ac.uk

Introduction: Alpha oscillations have been proposed as a biomarker for tonic pain. In the current study, the classification features were extracted from electroencephalogram (EEG) data as phase-based connectivity in the alpha band. Then the selected features were applied for the prediction of tonic pain using probability scores obtained from a support vector machine (SVM) classifier.

Material, Methods and Results: 36 healthy participants (14 males, average age 25.4 years) took part in the experiment, 7 participants were excluded because of missing data. The pain and neutral conditions were induced by immersing the participant's left hand in a tank containing hot water ('H', temperature = 44.46°C±0.49°C) or warm water ('W', temperature = 38.48°C±0.53°C), an unpleasant auditory stimulus ('S', 90.21dB±10.94dB) was set as a control condition, and resting-state data were recorded with eyes open ('O') [1]. EEG was recorded with 62 electrodes. The sampling rate was down-sampled to 500 Hz from 1000 Hz. The data were segmented into 10 seconds epochs for the SVM classification.

Inter-site phase clustering (ISPC), a phase-based connectivity measure, was extracted from EEG data and used for training a classifier to differentiate four conditions [2].In the training step, 22 ISPC features with SVM feature weights above 0.5, were selected by neighbourhood component analysis from 6 binary classifiers. These features were then applied in the multi-class classification. We obtained an accuracy of 71.67% (SD 3.29%) for pairwise classification while the performance of the four-class merged classifier was 44.86% (SD 12.66%). Furthermore, the probability of each observation's class was measured by using the confidence scores of the classifier. The probability score of one sample was its score's ratio of the sum of this sample's all positive confidence scores. All negative confidence scores were set to 0. In each condition, the probability score was highest for prediction of the true condition (see Fig. 1).

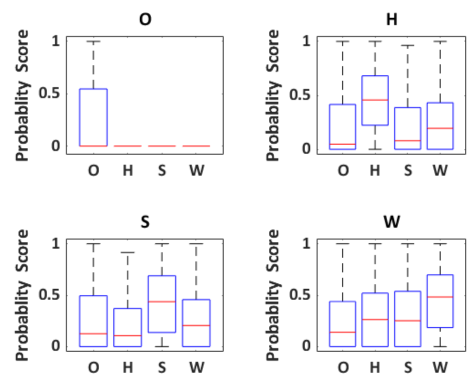

Figure 1. *The probability scores' distributions of all conditions' predictions. The red line in each box represents the median probability score the corresponding condition. The letter above each plot indicates the true condition.*

Discussion & Significance: Although the accuracy of multi-class classification dropped compared with binary classification, the probability scores suggest the prediction of tonic pain may be possible using EEG only. In the future, the scoring model will be improved by optimizing the classifiers, finding more reasonable thresholds in prediction of specific conditions and adapting the approach to online prediction of tonic pain.

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A BCI for automatically assessing color vision

James J. S. Norton[1,2]*, Grace F. DiRisio[3], Jonathan S. Carp[1,2], Jonathan R. Wolpaw[1,2]

[1]*National Center for Adaptive Neurotechnologies, Wadsworth Center, New York State Department of Health, Albany, NY, USA;* [2]*Stratton VA Medical Center, Albany, NY, USA;* [3]*Colgate University, Hamilton, NY, USA*

E-mail: jamesjsnorton@gmail.com

Introduction: Present methods for assessing color vision require the person's active participation; thus, they may fail in children or in those with disorders of cognition. To solve this problem, we are investigating BCI-based methods for assessing color vision that use steady-state visual evoked potentials (SSVEPs; [1]) to identify metamers—light sources with different spectral distributions that appear to be the same color (Fig. 1a, [2]). We hypothesize that a stimulus that alternates between two light sources that are metamers will elicit an SSVEP of minimal size. If true, then it should be possible to identify colors that an individual perceives as metamers using SSVEPs. Because metamers provide a means to assess color vision, this would enable the development of an automatic BCI-based alternative to standard time-consuming, behaviorally-based approaches to color vision assessment (e.g., the anomaloscope).

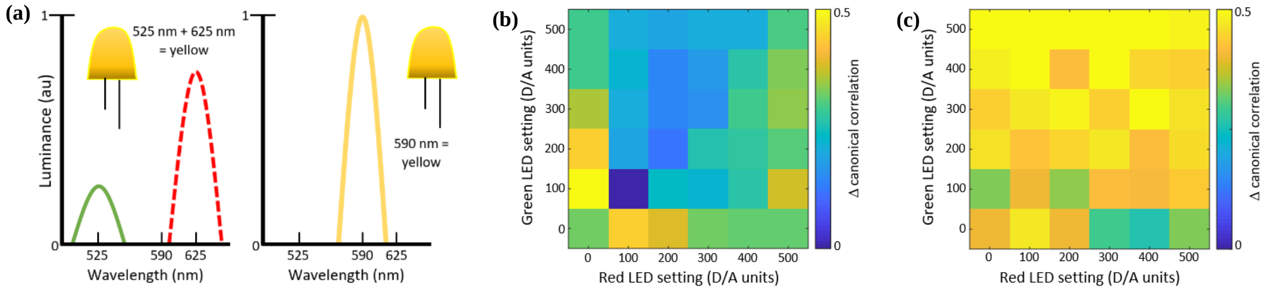

Figure 1: (a) (left) Dichromatic (525 nm and 625 nm) and (right) monochromatic (590 nm) light sources that appear to be the same color (i.e., are metamers). Average increase in SSVEP size during grid search for (c) the average of 7 people without a CVD and (d) a person with a CVD.

Material, Methods, and Results: Our experiments compared behaviorally-identified metamers with SSVEP-identified metamers and examined whether people with and without color vision deficits (CVDs) could be differentiated using SSVEPs. Using a custom digitally-controlled stimulator to produce a pair of metameric light sources (Fig. 1a), we asked participants to behaviorally-identify metamers by adjusting a dichromatic light source until it was the same color as a monochromatic source of a set luminance (600 D/A units). To identify metamers using SSVEPs, we recorded EEG from 16 electrodes. SSVEPs were elicited by alternating between the dichromatic and monochromatic sources at 10 Hz and measured with canonical correlation analysis. Metamers were defined as the settings (in D/A units) of the dichromatic source that minimized (using a grid search) the size of the SSVEPs for a monochromatic source setting of 600 D/A units. Metamers identified using SSVEPs (56±4 green and 154±22 red) were not significantly different (paired t-test, n=7, p=0.61 and p=0.18 respectively) from behaviorally-identified metamers (54±6 green and 149±16 red). Based on a second grid search, there were clear differences in the SSVEPs elicited from people without CVDs from three individuals with a CVD (Figs. 1b and 1c).

Discussion: SSVEPs can be used to identify metamers and differentiate people with and without CVDs. SSVEP-identified metamers were defined as the settings of the stimulator that elicited an SSVEP of minimal size. Thus, it should be possible to formulate the SSVEP-based identification of metamers as an optimization problem and solve it using a closed-loop BCI. This is a potential direction of future work.

Significance: A BCI-based system that can automatically assess a person's color vision without requiring their active participation has numerous clinical, research, and industrial applications.

Acknowledgements: Thanks to Z. Yu, T. M. Vaughan, A. Borum, A. Akhtar, T. Bretl, E. Johnson, and P. S. Carney for their comments and the funding provided by the NIH (P41EB018783) and VA (I01BX002550).

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Influence of corticomotor reorganization on BCI performance in children with hemiparetic cerebral palsy

E. Zewdie[*1,2], Z. Jadavji[1,2], HC. Kuo[1] and A. Kirton[1,2]

[1]*University of Calgary, Canada;* [2]*Alberta Children's Hospital, Calgary, Canada*

*Corresponding Author. Email: ephrem.zewdie@ucalgary.ca

Introduction: Children with hemiparetic cerebral palsy (CP) caused by perinatal stroke undergo developmental corticomotor reorganization to compensate for structural damage[1]. We have shown that these children are able to use motor imagery-based Brain Computer Interface (BCI). However, how brain structural and functional organization affects their BCI performance is unknown. Motor imagery based BCI can be used to control functional electrical stimulation (FES) for rehabilitation[2]. Classification accuracy is essential for the interpretation of the motor imagery to drive the rewarding feedback[3]. This accuracy is likely affected by factors such as which EEG channels are used and the organization of the underlying cortex. We hypothesized that corticomotor reorganization will influence the classification accuracy and BCI performance in children with hemiparetic CP.

Material, Methods and Results: Ten children aged 6-18 years with MRI-confirmed perinatal stroke and hemiparetic CP were included. Robotic Transcranial Magnetic Stimulation (TMS) (Axilium, France) was used to produce motor maps from hand muscles. The same children participated in a BCI-FES pilot trial which uses motor imagery based BCI to trigger FES (recoveriX, g.tec, Austria). Children had affected hand motor maps from either contralateral (unilateral, n=5) or both the lesioned and non-lesioned hemisphere (bilateral, n=5). Bilateral responses was associated with higher percentage of maximum accuracy of motor imagery BCI paradigm compared to unilateral only (p=0.056). Six of the ten children had ipsilateral responses from TMS of the non-lesioned side, resulting in mirror-movements. Presence of ipsilateral responses did not affect BCI performance (p=0.762). Qualitative lesion size did not appear to affect BCI performance.

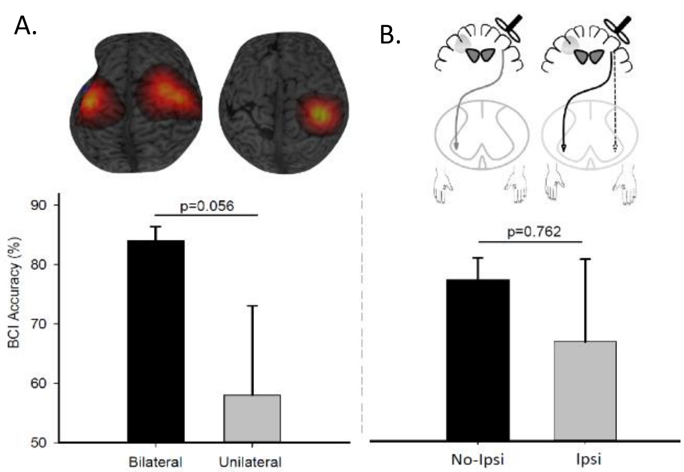

Figure 1*: Percentage Motor Imagery BCI Accuracy.* A) Comparison of children with bilateral motor maps with those with unilateral maps. B) Comparison of children with ipsilateral response with no-ipsilateral response.

Discussion: Cortical motor network structure may influence BCI performance.
Significance: Motor maps may be used to predict BCI performance and can be used to generate individualized BCI approaches and personalized rehabilitation in cerebral palsy.

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Supervised decoding of motor performance from EEG signals in Parkinson's disease patients undergoing DBS

Sebastián Castaño-Candamil[1*], Tobias Piroth[2], Peter Reinacher[2], Bastian Sajonz[2], Volker A. Coenen[2], Michael Tangermann[1]

[1]*University of Freiburg, Freiburg, Germany;* [2]*University Medical Center, Freiburg, Germany*

Zentrum für Neurowissenschaften, Albertstr. 23, Freiburg, Germany. E-mail: sebastian.castano@blbt.uni-freiburg.de

Introduction: Identification of neural surrogates of motor performance (termed *neural markers*) in Parkinson's disease is fundamental for developing adaptive deep brain stimulation (DBS) systems. These systems seek online adaptation of stimulation parameters as a function of neural markers, for improving treatment's efficacy. In our contribution, we introduce a novel framework for supervised data-driven extraction of neural markers from EEG signals, that are modulated by DBS therapy and, thus, suitable for closed-loop adaptive DBS systems.

Material, Methods and Results: Our approach is based on two building blocks: 1) A motor task, termed the *CopyDraw test* [1], that delivers a clinically relevant motor-score label *z*, capturing DBS-induced changes of motor performance; and 2) a supervised machine learning model that seeks to decode *z* from concurrently recorded EEG signals. Seven Parkinson's disease patients undergoing DBS therapy, participated in 16 sessions, under varying DBS conditions. In 13 out of the 16 sessions analyzed, we were able to identify neural markers of motor performance, extracted using the supervised source-power comodulation (SPoC) algorithm [2]. In 11 of them, they achieved a significantly better decoding accuracy compared to state-of-the-art neural markers.

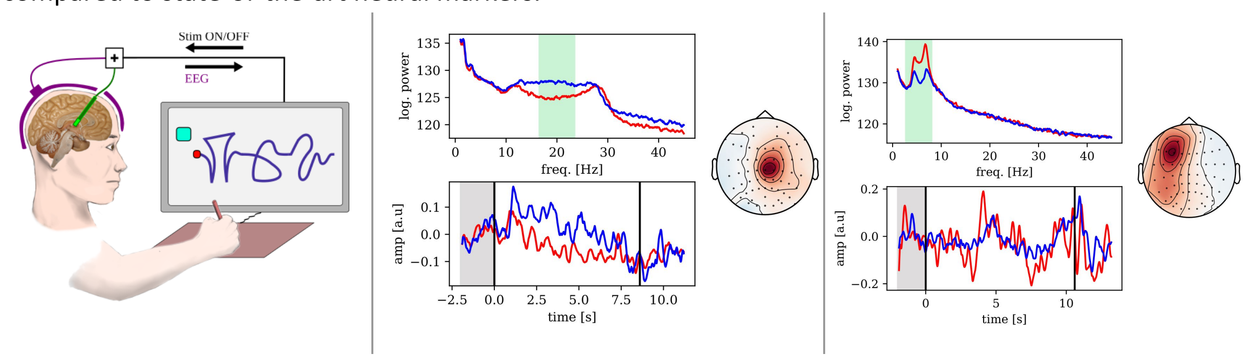

Figure 1. ***Left:*** *Experimental setup with CopyDraw test.* ***Middle:*** *Component informative of motor performance, of motor origin.* ***Right:*** *Component informative of motor performance, of cognitive origin. In middle and right subfigures, top and bottom subpanels show frequency spectrum and event related dynamics of extracted components, where red and blue lines indicate features extracted during DBS on and off, respectively. Right subpanel shows the corresponding spatial pattern. Green shades indicate frequency origin of the pattern.*

Discussion: The major findings of our contribution can be summarized as follows: 1) PD-relevant motor performance can be decoded from the power of neural sources using supervised machine learning methods; 2) the extracted sources also provide information about the undergoing DBS condition, which can be interpreted as controllability; 3) extracted sources can be interpreted not only as motor processes, but also possess characteristics of cognitive phenomena.

Significance: Our contribution is the first supervised data-driven approach for the identification of neural markers in PD. Given the high individuality of PD symptomatology, the results presented are a fundamental step towards DBS therapy individualization by closed-loop strategies.

Acknowledgments: DFG (EXC1086, bwHPC, andINST 39/963-1 FUGG), BMBF (16SV8012).

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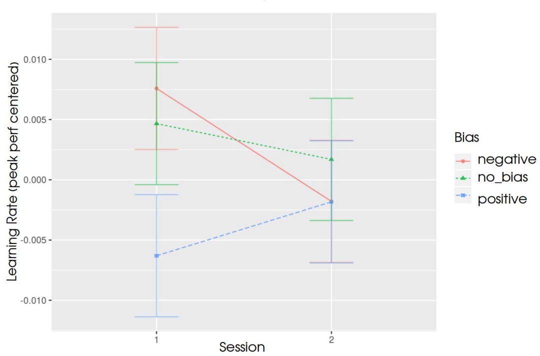
Biased feedback influences learning in Motor Imagery BCI training

Jelena Mladenović[1,3], Jérémy Frey[2], Smeety Pramij[1], Jérémie Mattout[3] & Fabien Lotte[1]

[1] Potioc, Inria / LaBRI (CNRS / Bordeaux INP / Univ Bordeaux),France; [2] Ullo La Rochelle, France; [3] Cophy, CRNL Inserm U1028 Lyon, France

Introduction: Many user trainings were proposed to assist the user in accomplishing the Motor Imagery (MI) BCI task, e.g. the use of positive (biased) feedback (an optimistic representation of one's labeled brain activity) has shown to increase performance [1] or learning [2]. On the contrary, in [3] negative feedback increased user learning within one session. In order to better understand the benefits of biased feedback on performance and learning during the BCI training, we consider user states such as workload and the flow state. While workload could account for the amount of effort users put into the task, flow is a state of optimal cognitive control, immersion, and pleasure which has shown to benefit performance in various fields [4].

Material, Methods and Results: 30 participants (12 women, mean age: 28.56 years, SD: 6.96) were split between 3 groups: 1. no_bias, 2. positive bias and 3. negative bias, where the SVM classifier output between [0,1] was biased in real-time using a cumulative beta distribution function. Participants engaged in 2 sessions, each consisting of a calibration (2 runs) and testing (6 runs). A run contained 20 trials per class and lasted ~5 mins. Users played the Tux Racer game using left-right hand MI. After each run, workload and flow states were assessed with NASA-TLX [5] and EduFlow [6] questionnaires. Online performance is the peak performance of the classifier. Learning rate is the slope of the linear regression of online performance over runs within a session. We found a significant interaction: group×session in learning rate (2-way ANOVA, $p<0.01$), Fig 1.A; but there was no difference in performance between groups. We found correlations ($p<0.05$, corrected with FDR) between state of flow and both performance (Pearson's $r=0.30$) and learning rate ($r=-0.20$); no correlation between workload and performance but a correlation with learning rate ($r=0.13$). Finally, we found a significant difference between groups, $p<0.05$ for the cognitive control, 1st dimension of EduFlow score, Fig 1.B.



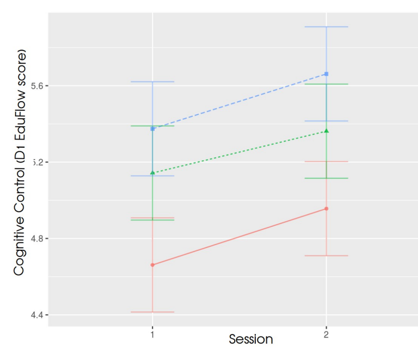


Fig 1.A. (left) ANOVA of learning rate,. B. (right) ANOVA of EduFlow score (cognitive control), between sessions for each group.

Discussion: We obtain similar results as with negative feedback [3], here negative *biased* feedback increases learning short term, while in the 2nd session learning severely decreases, possibly due to user demotivation.

Significance: Biased feedback influences directly user learning, and user sense of control. Interestingly, flow state correlates positively with performance (same as in [7]) but negatively with learning.

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Decoding of error-related potentials for characterizing individual subjective preferences

F. Iwane[1,2*], S. Wei[1], I. Iturrate[1], I. Batzianoulis[1], R. Chavarriaga[1], A. Billard[1] and J. del R Millán[1,2]

[1]*Ecole Polytechique Fédérale de Lausanne, Lausanne, Switzerland;*
[2]*The University of Texas at Austin, TX, USA*

*2501 Speedway, Austin, TX 78712, USA. E-mail: fumiaki.iwane@epfl.ch

Introduction: One typical application of BMIs is to provide additional information to agents based on users' cognitive brain response. In this regard, a promising approach is the exploitation of neuronal correlates of error monitoring [1, 2]. This evoked brain response is generated upon perception of an erroneous action performed by an external agent, which is typically characterized by deflections in EEG signals. In previous studies, the objective criteria for assessing actions remained the same for all users. Thus, it still remains to be understood whether ErrPs are generated while users evaluate actions based on individual subjective criteria, and if these neuronal correlates can be exploited to perform individually personalized human agent interactions in the BMI scenario.

Material, Methods and Results: 17 subjects, between 24±2 year-old participated in the study. During the experiment, EEG signals were recorded while subjects were controlling the end-effector of a 7-degree-of-freedom robotic arm (KUKA LWR 4). The user directed the robot to move either left or right by using a joystick, while the robot autonomously tried to avoid an obstacle placed in the middle of the trajectory. They were instructed to release the joystick when they observe the undesired robot trajectories, e.g. the robot was getting too close to the obstacle. Upon the release of the joystick, the robot increased its height to avoid the obstacle.

By using the single-trial posterior probability obtained from the classification analysis, we produced individual preference maps based only on EEG signals, which were compared to the individual behavioral preference maps (Fig. 1b). The statistical analysis found the significant statistical difference between intrasubject and averaged intersubject correlation coefficients (Wilcoxon's signed rank test, $p < 0.01$), shown in Fig. 1c.

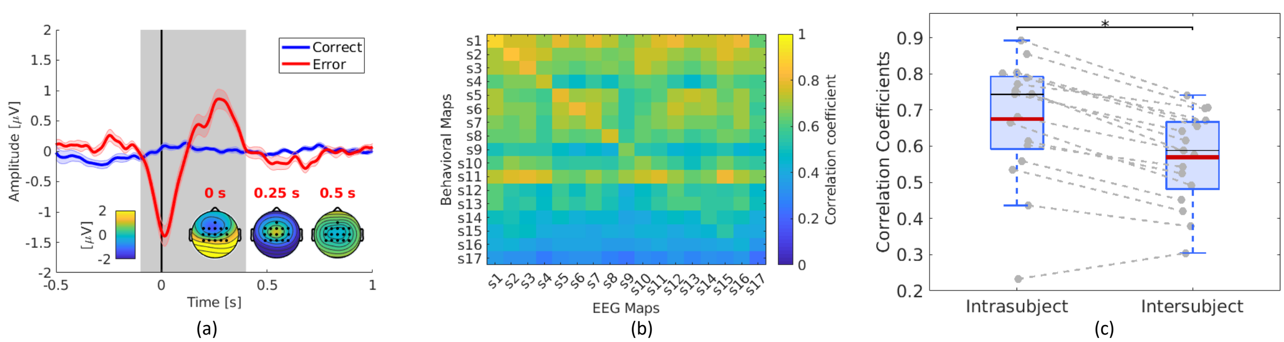

Figure 1. *(a) Grand-averaged Error-related Potentials. (b) Correlation coefficients between Behavioral and EEG Maps. (c) Statistical Test.*

Discussion: The present study demonstrated that ErrPs encoded the individual subjective preferences on the robot trajectories.

Significance: The presence of ErrPs during subjective evaluation paves a new road for personalized brain machine interaction.

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Low frequency EEG-based movement decoding for the continuous online control of a robotic arm

Valeria Mondini[1], Reinmar J. Kobler[1], Víctor Martínez-Cagigal[2], Andreea I. Sburlea[1], Gernot R. Müller-Putz[1*]

[1]Institute of Neural Engineering, Graz University of Technology, Graz, Austria; [2]Biomedical Engineering Group, Universidad de Valladolid, Valladolid, Spain

*Email: gernot.mueller@tugraz.at

Introduction: Continuous decoding of voluntary movement would be desirable for closed-loop and natural control of neuroprostheses. Recent studies have shown the possibility to infer hand positions and velocities from the low-frequency (LF) electroencephalographic (EEG) activity [1], [2]. So far, this has only been performed offline. Here, we present for the first time two studies showing online control of a robotic arm by means of continuously decoded movements from LF-EEG.

Material, Methods and Results: Fifteen healthy participants took part in the two studies. The paradigm implemented a pursuit tracking task, where participants had to track a moving target on a screen with a robotic arm. The participants' two-dimensional right-hand movement, EEG, and electrooculographic signals were simultaneously recorded. In the first part of each experiment, participants performed some calibration runs with the robot fully controlled by their right-hand/arm movement. After the EEG decoding model was fitted to predict the right-hand movements, the robotic arm control was gradually switched from real to EEG-based decoded movements, first with 33%, then 66%, up to the final condition of 100% EEG control.

The EEG processing pipeline included filtering (0.18-1.5Hz), eye artefact [3] and pops/drifts [4] attenuation, partial least squares (PLS) regression, and Kalman filtering. In the first study (10 participants), a linear Kalman filter estimated positions, velocities and accelerations. Grand average correlations between real and decoded trajectories were r_{kal}=[0.30, 0.32, 0.29, 0.26] (for 0, 33, 66 and 100% EEG control). Correlations with only PLS were also computed. Although all correlations were significantly (α=.05) higher than both chance (r_{chance}=[0.13, 0.12, 0.11, 0.11]) and PLS (r_{PLS}=[0.25, 0.26, 0.22, 0.20]), we found an amplitude mismatch between real and decoded trajectories (amplitude ratio 0.4). In a second study (5 participants), we used a nonlinear square-root unscented Kalman filter to integrate positions, velocities, and speed. Grand average correlations were r_{kal}=[0.43, 0.34, 0.27, 0.23] and r_{PLS}=[0.35, 0.26, 0.22, 0.16]. The amplitude ratio between real and decoded movements was 1.07. Source projection of the decoder patterns highlighted parieto-occipital activation for the velocities (both studies), primary motor cortex for the speed (study 2).

Discussion: Both Kalman approaches permitted to successfully integrate the information in the decoding models, as documented by the significant increase between r_{PLS} and r_{kal}. The integration of speed in study 2 additionally adjusted the amplitude of decoded trajectories, suggesting an informative role. Parieto-occipital and motor cortex activations are in line with the task type (visuomotor) and offline studies [2].

Significance: Continuous low frequency EEG-based movement decoding for the online control of a robotic arm was achieved. Two (linear and nonlinear) Kalman approaches to integrate decoding information were introduced. The role of speed for trajectory decoding was further elucidated.

Acknowledgements: This work has been supported by the ERC Consolidator Grant 681231 "Feel Your Reach". V. Martínez-Cagigal was in receipt of a PIF-UVa grant from University of Valladolid.

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Five years of Utrecht NeuroProsthesis: The value of a BCI implant in late-stage ALS

A. Schippers[1], S. Leinders[1], E.G.M. Pels[1] , Z.V. Freudenburg[1] , M.P. Branco[1] , F.D. Guerreiro Fernandes[1], E.J. Aarnoutse[1], M.J. Vansteensel[1], N.F. Ramsey[1]

1 UMC Utrecht Brain Center, Department of Neurology and Neurosurgery, University Medical Center, Utrecht, the Netherlands

E-mail: a.schippers-5@umcutrecht.nl

Introduction: In the Utrecht NeuroProsthesis (UNP) project, we test the feasibility of home use of a fully implanted BCI system as a new method of communication for people with locked-in syndrome. More than five years have passed since the first implantation of the UNP system in an individual with late-stage ALS (in October 2015, described in detail in [1]), and during these years the participant has been able to use the system reliably and independently to communicate with the outside world. Here we present an evaluation of the added value of the UNP system to this patient during these years.

Material, Methods and Results: Technical specs of the UNP system have been described earlier [1 and 2]. Even though there have been small changes in impedance and high frequency band power over time, the system can be used accurately and has provided stable BCI control for a period of more than 5 years, allowing her to communicate and to call her caregiver whenever she needs attention. Indeed, signal processing settings that are required for independent home use have not changed between September 2016 and April 2019, and after that there have only been slight changes in the high frequency signal settings. Initially, independent home use of the system was mainly outside of the house and on average only for a couple of hours per month. However, as of spring 2018, home use increased, ranging from an average of 37.7 hours per month between April and September 2018, to 148 hours of home use in April 2019 [2]. Nowadays, the UNP is used during the entire day as her sole assistive technology. The increase in home-use coincided with the loss of eye movement control and thus the inability to use an eye tracker (the preferred assistive technology prior to the UNP), which demonstrates the value of the UNP in situations where other assistive technologies prove to be inadequate. The user even states (43 months after the implantation) “without the UNP I would be without words” [2], highlighting the importance of the system for her. Satisfaction with the system has increased in the course of time: a high satisfaction was already reported after several weeks of use, but this increased even further over the following years.

November 2020 marked the beginning of the sixth year of study participation of this participant. We aim to continue to improve the system to match her needs and wishes, with the goal to assist her and our other users in their communication with the outside world.

Significance: This overview illustrates the added benefit of our fully implanted system for people with severe motor impairment and shows that when disease progression eliminates the use of more typical assistive technologies, a fully implanted ECoG-based system may be increasingly valuable.

Acknowledgements: We thank the participants and all people involved behind the scenes for their tireless efforts and valuable insights.

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Independent Home Use of a Portable Intracortical BCI

Jeffrey Weiss[1], Grace Brueggman[2], Brian Dekleva[1,3], Nikhil Verma[1], Michael Boninger[1-4], Jennifer Collinger[1-4*]

Depts. of [1]Physical Medicine and Rehabilitation and [2]Bioengineering, University of Pittsburgh; [3]Center for the Neural Basis of Cognition; [4]Dept. of Veterans Affairs, Pittsburgh, PA, USA

[*]3520 Fifth Ave, Suite 300, Pittsburgh, PA, USA, 15213. E-mail: collinger@pitt.edu

Introduction: While EEG and ECoG based BCI systems have moved towards take-home trials [1-3], intracortical BCI (iBCI) has been limited to use under experimenter supervision. We recently demonstrated a portable iBCI to enable computer access [4]. We have further developed the system to facilitate independent use and have initiated a take-home trial of the device.

Material, Methods and Results: We improved the software for our previously described portable iBCI [4] to facilitate independent use by simplifying the user interface and automating common procedures. The system was evaluated by a participant with a C5/C6 spinal cord injury who was already enrolled in an iBCI clinical trial (NCT 01894802) and had been implanted with four Utah arrays in sensorimotor cortex. We trained the participant's caregivers to connect headstages and setup the device. The participant was able to independently calibrate a 3DoF decoder to control a virtual mouse or up to 6 virtual keypresses to interact with the tablet PC. The participant logged his home iBCI usage, including duration and ease of use for each activity, and reported issues to the study team via instant messaging or during regular study visits. The participant completed a Patient Experience Measure (PEM) survey after the first 24 hours of use and again after a week of use. Whenever possible, the study team rapidly responded to user feedback and pushed software updates to the system using git.

During the first week, the subject primarily used the iBCI to play computer games and draw. After 24 hours of use the subject reported in the PEM that he enjoyed and looked forward to using the device. He reported that the device was easy to setup and had a user-friendly interface, but also reported that he would be more inclined to use the device if it were easier to use. The subject's opinions were generally consistent after a week of use but he reported occasional frustration with the system, including decoder, user interface, and hardware issues. We attempted to alleviate user frustration with software updates based on the subject's feedback. The subject had residual arm function and regularly used a laptop and tablet. He reported that he could not use the iBCI to accomplish tasks faster or more accurately than without the device, nor could he independently perform tasks that were impossible without the device.

Discussion: While the participant in this study did not gain any functionality with the iBCI, he enjoyed using the system at home without restrictions imposed by lab experiments. Additionally, iBCI learning could potentially be tracked more thoroughly during extended home use than in occasional lab sessions, and neural data can be collected across a range of conditions that may not be captured in a laboratory environment.

Significance: We have demonstrated that an iBCI can be used independently at a user's home without experimenter supervision.

Acknowledgements: This work was supported by DARPA (N66001-16-C-4051) and NIH (UH3NS107714 and U01NS108922). Any findings or conclusions expressed in this material are those of the authors and do not necessarily reflect the views of DARPA, SSC Pacific, or NIH.

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Incremental upgrade of closed-loop ECoG-based BCI with increasing number of degrees of freedom for exoskeleton control by a tetraplegic subject

A. Moly[1*], M. Mainsant[1], T. Costecalde[1], G. Charvet[1], S. Chabardes[2], A.L. Benabid[1], T. Aksenova[1]

[1]Univ. Grenoble Alpes, CEA, LETI, Clinatec, F-38000 Grenoble, France ; [2]Centre Hospitalier Universitaire Grenoble Alpes, 38700, La Tronche, France

[*]Correspondence and requests for materials should be addressed to A.M (email: alexandre.moly@cea.fr)

Introduction: Brain computer interface (BCI) generally includes two stages: decoder training (calibration), and execution. Calibration stage duration depends up on the quality of the recorded signals, model complexity and the number of parameters to be fitted. For large numbers of degrees of freedom (DOF) the calibration time is getting larger which may be an important drawback for practical BCI (patient's fatigue increasing and concentration reducing …). Generally, for a given experimental paradigm, all the model parameters for all DOF are simultaneously identified/trained during online or offline procedure. Most of the time, for a new paradigm, a decoder is calibrated from zero even though some DOF have already been trained in other experimental paradigms. Nevertheless, BCI is reported as a co-adaptive system of decoder/patient training. Patients learn to use BCI incrementally, from simple control e.g. brain switch to high dimensional control of complex effectors [1]. We developed an online mixture of expert decoder able to incrementally increase the number of DOF using previously created model to follow patients' improvements without retraining the model from zero.

Materials, Methods and Results: An adaptive ECoG-driven BCI platform has been developed for the "BCI and Tetraplegia" clinical research protocol at Clinatec [1]. A tetraplegic patient underwent bilateral implantation of two (64 electrodes) wireless WIMAGINE® implants developed at Clinatec. Since, he trained to control in real time increasingly complex effectors such as an exoskeleton. To succeed, a mixture of experts (ME) decoder able to incrementally upgrade DOF control was developed. ME supposes that (multiple) active and idle states are associated with specific movements or actions that can be independently shaped by regression models called "experts". The selection of an expert or their mixing is completed by a "gate" model [2]. Each expert is associated to a subset of DOF which may be independently trained. Experts may be considered as independent "sub-model blocks" which can be added or removed from the entire models for the new paradigm. Experts keep all sufficient statistics to integrate previous experiments to a new paradigm without loss of information. Clinatec's BCI experimental strategy was to train the patient, and the model integrated increasingly complicated task, by incrementally adding new DOF to enhance paradigm control. The patient was able to control numerous DOF one by one with high accuracy, such as walking, left and right hand 3D trajectory control, as well as rotation of both wrists and mix them up to reach 8 DOF control[1].

Discussion: Adaptive modeling allow incrementally adding DOF to existing models to avoid starting from scratch a new model each time that the control paradigm evolves. With the increasing model complexity related to the control of more complex effectors, this strategy allows saving training time, and gather more data for model robustness.

Acknowledgement: CLINATEC is a Laboratory of CEA-Grenoble statutory links with the University Hospital of Grenoble (CHUGA) and with University Grenoble Alpes (UGA). This study was funded by CEA and the French Ministry of Health (Grant PHRC-15-15-0124), Institut Carnot, Fonds de Dotation Clinatec. Fondation Philanthropique Edmond J Safra is a major funding institution Clinatec.

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Decoding Virtual Velocity from Hippocampal Theta and High-Gamma Activity

Jeremy Saal[1]*, Pieter Kubben[1], Albert Colon[2], Hans van Dijk[2], Roy Krijn[2], Dean Krusienski[3], Christian Herff[1]

[1]*Maastricht University, Maastricht, Netherlands;* [2]*Epilepsy Center Kempenhaeghe, Heeze, Netherlands;* [3]*Virginia Commonwealth University, Richmond, Virginia, USA*

*Universiteitssingel 50, 6299ER, Maastricht, Netherlands. E-mail: j.saal@maastrichtuniversity.nl

Introduction: Decoding cognitive processes, such as navigational planning, may provide utility in brain-computer interface (BCI) control of wheelchairs, robotic arms, and computer cursors. Human intracranial EEG research implicates the hippocampus as playing a role in spatial navigation; however, the hippocampus has not been investigated in the context of BCI. There has been success decoding navigational features, including location [1] and planned trajectory [2] from rat hippocampus activity, but decoding navigational features from human hippocampal recordings has received little attention. Moving forward, a comprehensive evaluation of which navigational features can be decoded from the hippocampus is necessary. As a first step towards this goal, we aim to evaluate the extent to which virtual velocity can be decoded from intracranial electroencephalography recordings of the hippocampus in humans.

Materials & Methods: Three patients with intractable epilepsy were implanted with 16-33 bilateral hippocampal depth electrodes based on clinical need. The patients performed a keyboard-controlled virtual-navigation task in which they had to drop off and pick up packages to three distinct zones (Fig. 1A). Task and neural data were synchronized through LabStreamingLayer [3]. Theta (4-7 Hz) and high-gamma (52-99 Hz) were extracted using one-second windows with a half-second overlap.

Results: A Shrinkage Linear Discriminant Analysis (LDA) was used to classify the top and bottom 10% of virtual velocity from the theta and high-gamma activity. Receiver operating characteristic (ROC) curves and the resulting area under the curve (AUC) were used to evaluate classifier accuracy. We found above chance level performance of the classifier for all participants tested, with AUC's ranging from 0.75 to 0.78 (Fig 1B).

Discussion: We show, for the first time to our knowledge, that invasively recorded hippocampus activity can be used to classify virtual velocity.

Significance: This is the first step towards exploring the feasibility of a hippocampus based BCI.

(A)

(B)

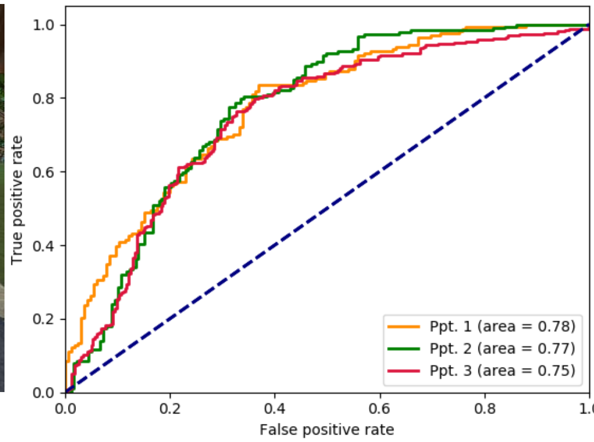

Figure 1: (A) Image of the virtual environment. (C) Receiver operating characteristic (ROC) curve for slow vs. fast.

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Continuous Decoding of Executed and Imagined Grasping Using sEEG Electrodes

M.C. Ottenhoff*[1], **L. Wagner[2]**, **A. Colon[2]**, **S. Tousseyn[2]**, **P. Kubben[1]**, and **C. Herff[1]**

[1] *Maastricht University, Maastricht, Netherlands*

[2] *Epilepsy Center Kempenhaeghe, Kempenhaeghe, Netherlands*

*Universiteitssingel 50, 6229ER Maastricht, Netherlands. E-mail: m.ottenhoff@maastrichtuniversity.nl

Introduction: Naturalistic prosthetic control could restore some independence to paralyzed patients. A brain-computer interface (BCI) might achieve this by decoding the users movement intention continuously with low-latency. High performing decoders have been presented decoding from the subthalamic nucleus [1], but not from other subcortical structures. Decoding from deeper structures is promising, as it has access to high frequency oscillations from a wide variety of brain areas, but is little explored so far [2]. Here, we demonstrate that executed and imagined grasping movement can be continuously decoded from stereotactic EEG electrodes.

Materials, Methods and Results: Eight patients (mean age 39.5 ± 15.8, 4 male, 4 female) with medication-resistant epilepsy participated in this study, while being under pre-surgical assessment to identify epileptogenic zones. All participants provided written informed consent (METC 2018-0451). Participants were asked to continuously open and close their left or right hand for 3s, followed by a 3s rest. A total of 30 trials for each side (in randomized order) was collected for both actual and imagined movement. The Beta [12-30 Hz] and High Gamma [55-90 Hz] envelope were extracted in 1s windows with 100ms frameshift. A linear discriminant analysis classifier (LDA) was trained on a 3-class problem using 10-fold cross validation and evaluated by the area under the receiver operator curve (AUC). The LDA was able to decode executed grasping movements with an AUC up to 0.82 (0.78 to 0.85) for movement detection and 0.90 (0.87 to 0.93) for laterality. For imagined movement, the performance reached 0.72 (0.66 to 0.75) and 0.60 (0.50 to 0.71), respectively. (Figure 1)

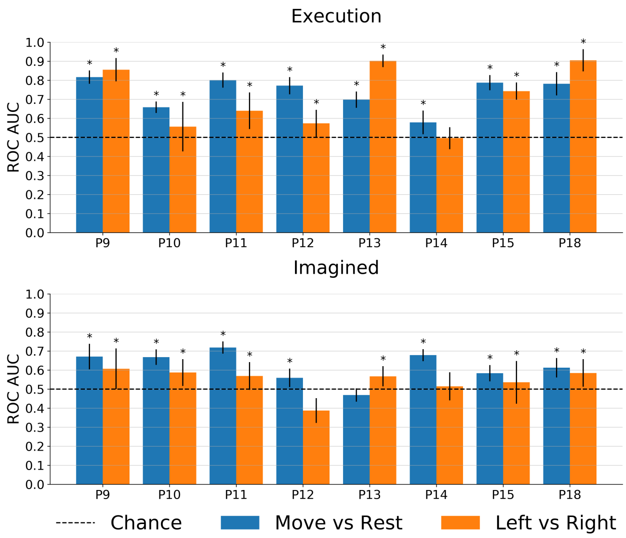

Figure 1: AUC for executed (top) and imagined (bottom) grasping. *: $p < 0.001$. (Monte Carlo simulation)

Discussion: Executed and imagined grasping movements can be decoded continuously using sEEG electrodes, showing high maximum performance. Additionally, laterality was well decodable in executed movements, but poorly in imagined movements. The wide and variable coverage of brain areas in sEEG is likely the cause of high variability and low performance.

Significance: This works presents a new step in the direction of naturalistic control of prosthetics, showing the feasibility of low-latency grasping movement decoding using sEEG electrodes.

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Tracking long-term changes in ECoG BCI control using deep autoencoders

N. Natraj[1,2*], R. Abiri[1,2], S. Seko[1,2*], Y. Graham[1,2], N. Hardy[1,2], E.F. Chang[1], K. Ganguly[1,2]

[1]*University of California-San Francisco, San Francisco, CA,* [2]*San Francisco Veterans Affairs Medical Center, San Francisco, CA.*

*UCSF Mission Bay Campus, 1700 Owens Street, SFO, CA 94110. E-mail: nikhilesh.natraj@ucsf.edu

Introduction: For individuals with paralysis, Brain Computer Interfaces (BCIs) have the potential to restore lost function through the decoding of neural activity to control external assistive devices. Typically, the control signal in BCIs are low-dimensional as they comprise the imagined motor movements of a single end-effector (such as imagined right arm movements). However, recent work in invasive, spike-based intracortical recordings has shown that the whole-body can be represented from a single cortical region such as the "hand-knob area" [1]. This suggests that BCI recordings can allow decoding of much higher-dimensional representations, with the potential to translate to complex control of assistive devices with higher degrees of freedom. In this study, we sought to understand whether high-dimensional BCI control signals can be decoded using mesoscale electrocorticography (ECoG). We first established separable control signals using diverse discrete imagined actions. Then, by leveraging the stability of ECoG [2], we tracked the consolidation of the high-dimensional control signals with practice over many weeks. To this end, we used a deep autoencoder to uncover the latent space that captured the refinement of the high-dimensional control signals with long-term BCI training.

Materials, Methods, and Results: A right-handed subject with severe spastic tetraparesis was implanted with a 128-channel chronic ECoG array over left sensorimotor cortex (Fig. 1A). To initialize the high-dimensional control signal, the subject observed a cursor move on the screen to radial targets in a center-out fashion. The subject was correspondingly instructed to imagine moving different end-effectors of the body and miming words such as "up", "down. In total, we initialized multiple such imagined actions, resulting in a 12D control signal. A multi-layer perceptron was initialized on these imagined data to classify individual imagined actions using the envelope of three neural oscillations: delta band (0.5-4Hz), beta band (12-30Hz) and high-gamma (70-150Hz), all binned at 8Hz. Stable decoding of the high-dimensional control signal was achieved through closed-loop decoder batch updates from online sessions (8 such actions shown in Fig. 1B). How might neural activity evolve to consolidate the control signal from the time of decoder initialization? We focused on a subset of the control signal that was used to map control in each direction of 3D cartesian space. The representation of these commands in common latent neural space was uncovered using a deep autoencoder with sparsity constraints on activation of hidden units. Results revealed the emergence of stable representations of the control signal in latent space from first initialization to proficient online control (Fig. 1C).

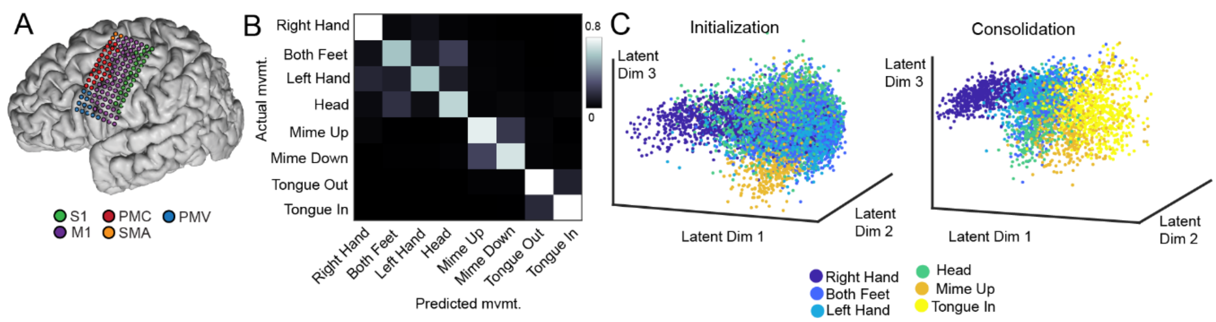

Figure 1: A) ECoG cortical grid for the subject over sensorimotor cortex, color coded by anatomical region. S1 - sensory, M1- motor, PMC – caudal premotor, SMA – suppl. motor area and PMv – ventral premotor. B) Confusion matrix of individual decoded imagined actions. C) Left: Latent state representation of the neural data for 6 of the imagined actions via a deep autoencoder when the decoder was initialized. Right: Latent state representation of the neural data for the same six imagined actions after consolidation of the decoder. Each individual dot in both plots corresponds to an individual time-bin of neural features.

Discussion: We show that high-dimensional control signals can be represented in mesoscale ECoG recordings, without any rigid somatotopy and outside of the hand-knob area of primary motor cortex. Notably, we are able to track changes in the latent space representations; this allowed the user to more easily control the BCI system.

Significance: Our results provide evidence for a reliable, high-dimensional BCI control signal which can be used to control assistive devices with higher degrees of freedom.

Acknowledgements: NIH Grant [1 DP2 HD087955] and support from the Weill Institute for Neuroscience, UCSF.

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Cortico-thalamic Closed-loop Deep Brain Stimulation for an Enhanced Treatment of Essential Tremor

E. Opri[1*], S. Cernera[1], R. Molina[1], M.S. Okun[1], K.D. Foote[1], A. Gunduz[1]

[1] University of Florida, Gainesville, FL, USA
*P.O. Box 116131, Gainesville, FL, USA. E-mail: enrico.opri@ufl.edu

Introduction: Essential tremor (ET) is defined as a rhythmical, involuntary, oscillatory movement of the limbs and is one of the most common movement disorders. Intention tremor occurs mostly in the upper limbs (with slow oscillations between ~4-12 Hz) during the initiation and execution of goal-directed reaching motions, while it is absent at rest. It has currently been suggested that a synchronous pathological oscillation in a network that includes the premotor (PM) and primary motor (M1) cortices, the ventral intermediate nucleus (Vim), and the cerebellum is suppressed through deep brain stimulation (DBS) by jamming the “tremor cells” in the thalamus.

Material, Methods and Results: Three patients affected by ET were chronically implanted with both cortical (M1) and thalamic (VIM) leads, connected to a Medtronic Activa PC+S neurostimulator. Together with inertial and EMG collected data, it was possible to explore biomarkers related to movement intention/execution, and to tremor. The Activa PC+S neurostimulator allows us to use thalamocortical neuromarkers to modulate the stimulation parameters in real time, enabling a truly responsively delivered DBS. Tremor Rating Scale scores and inertial sensors were used to evaluate therapeutic benefit and tremor suppression. The closed-loop system was tested in real-case scenarios, such as reaching for a cup to drink from it. Hence, we show the feasibility and implementation of a closed-loop system using cortical neuromarkers evoked during different behavioral tasks, such as moving a hand or reaching a cup, to enable the control of stimulation activation and deactivation. We show that responsive DBS efficiently suppresses tremor, thanks to modulation of the stimulation amplitude based on the patient state (i.e., rest: no stimulation, movement: stimulation).

Discussion: Our results suggest that a reliable control of responsive DBS is possible with the use of a single or a combination of targeted brain areas. In addition, standard DBS and closed-loop DBS was shown to have similar performances in tremor suppression. Importantly, the closed-loop paradigm was fully embedded in the patient neurostimulator. Hence, this enhanced DBS therapy solution has the potential to decrease the possible patient’s side effects, such as balance and speech impairment, and slow down battery depletion, by being inactive during non-tremor statuses, while delivering an equally effective but more efficient treatment.

Significance: This chronic and fully embedded closed-loop DBS for the treatment of ET, which self-adjusts based on patient-specific motor behavior, provides consistent energy savings maintaining clinical effectiveness equivalent to continuous DBS, while minimizing undesirable side effects related to DBS.

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Implantable Brain Computer Interface Technology: Bringing it Home

S. Leinders Msc [1]*, M. J. Vansteensel PhD [1], M. P. Branco PhD [1], Z. V. Freudenburg PhD [1], E.G.M. Pels Msc [1], B. Van der Vijgh PhD [1], E. J. Aarnoutse PhD [1] & N. F. Ramsey PhD [1]

1 UMC Utrecht Brain Center, Department of Neurology and Neurosurgery, University Medical Center, Utrecht, the Netherlands

* E-mail: s.leinders@umcutrecht.nl

Introduction: In the Utrecht NeuroProsthesis (UNP) project, we test the feasibility of home use of a fully implanted BCI system for communication purposes in people with locked-in syndrome. Initial results were positive [1] and one participant with late-stage ALS uses the BCI on a daily basis to communicate with her family and caretakers [2]. However, some challenges became apparent to us while working with the end-users and during the translational process of bringing the BCI system into everyday life. Here we present an overview of the issues we have encountered during this project. Although we will support most of our story with data, parts of the overview will be qualitative in nature.

Material, Methods and Results: Technical specifications of the UNP system have been described in [1]. Issues we have encountered include uncharacteristic brain signal features in the second participant (locked-in due to brainstem stroke) [3] and subsequent lower BCI performance. Her brain-click was only reliable (± 85% accuracy) at scanning speed settings too slow to pass our formal spelling test (30 correctly spelled characters in 30 minutes) and for practical home use. In addition, we observed unwanted activation of the sensorimotor hand region during actual movement of body parts other than the hand (e.g. eyes for eye tracker use or head movements for communication), during passive movement of the hand/arm, and sensory stimulation of the hand during transport or breathing. Also, due to spontaneous activity during sleep false positive clicks can occur, some of which may negatively affect usability of the system. Other issues which will be discussed include the need for and possibility of using auditory instead of visual cues, the importance of user and caregiver experience and feedback, ease of system setup and maintenance, the difficulty of having a BCI be reliably available to the user 24/7 and the required reliability of different components of a home-use BCI.

Significance: We expect that some of the challenges related to BCI home-use will be generalizable across different BCI systems. By discussing the challenges we have faced during research with users – not all of which we were able to solve yet – we hope to stimulate an open debate about similar issues between different research groups, which may contribute to solving these issues and to the development of practical home use BCI systems.

Acknowledgements: We thank the participants for their hard work and insights.

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Feasibility and Tolerability of BCI Activated FES in Children with Perinatal Stroke

Z. Jadavji, E. Zewdie, Metzler M, A. Kirton
[1]*University of Calgary, Canada;* [2]*Alberta Children's Hospital, Calgary, Canada*

*Corresponding Author. Email: Zeanna.Jadavji@ahs.ca

Introduction: Perinatal stroke (PS) causes most hemiparetic cerebral palsy (CP) and lifelong disability for 10000 Canadian children[1]. Improved models of neuroplasticity and recovery are affording novel opportunities for neurotechnologies to enhance rehabilitation. However, options remain limited for patients with severe hemiparesis. Brain Computer Interface (BCI) technology has gained momentum as a tool for upper extremity rehabilitation in adults with stroke[2]. Recent studies suggest that BCI activated functional electrical stimulation (BCI-FES) of target muscles may enhance upper extremity function in adults with hemiparesis[3]. This approach has not been tested in hemiparetic children with perinatal stroke. We have demonstrated that both typically developing children and those with stroke can operate simple BCI systems with competency comparable to healthy adults[4]. We aimed to complete the first study combining BCI-FES in children with hemiparetic CP to assess the tolerability and feasibility of this approach in a clinical population.

Material, Methods and Results: Thirteen participants (mean age=12.2 years, 31% female) were recruited through the Alberta Perinatal Stroke Project (APSP), a population-based cohort. Inclusion criteria were: (1) MRI-confirmed perinatal stroke, (2) hemiparetic cerebral palsy, (3) age 6-18 years, (4) informed consent/assent. Individuals with neurological comorbidities or unstable epilepsy were excluded. Testing was completed using the g.tec recoveriX system (g.tec, Graz, AU). Participants attended a training session and "rehab" session. Each wore a 16 lead, gel based, EEG cap and had two electrical stimulation electrodes attached to each forearm. Participants were instructed to imagine wrist extension of their left or right hand continuously in random order. Muscle stimulation and visual feedback were provided throughout the training paradigm and only when the correct motor imagery was detected during rehab. Ten participants have completed training and 6 have returned for the day 2 "rehab" session. Children completed an average of 34 and 33 minutes of training and rehab respectively. Mean classification accuracy for training and rehab were 74.2% (SD8.7) and 68.3%, (SD11.3). Average Cohen's kappa scores for training and rehab were 0.35 and 0.46. No serious adverse effects occurred. The most common complaints were mild headache (7/10) and headset discomfort (7/10). Some participants reported mental fatigue (50%) and frustration (50%) affecting their ability to continue with either session. None of the children ranked the experience as unpleasant.

Discussion: Preliminary results suggest that BCI-FES is feasible to for hemiparetic children with PS.

Significance: BCI-FES has the potential to afford a new therapy for young patients with few other options for rehabilitation. Further clinical trials can now be modeled to optimize approaches and test efficacy.

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Can Gamified Brain-Computer Interface Training Paradigms Improve Performance on a P300 Spelling Task?

D. Kelly[1,2,3,4*], E. Kinney-Lang[3,4], S. Murji[4], A. Kirton[1,2,3,4]

[1]Alberta Children's Hospital Research Institute, [2]Hotchkiss Brain Institute, [3]Cumming School of Medicine, [4]University of Calgary, Calgary, Alberta, Canada

*Corresponding Author. E-mail: dion.kelly@ucalgary.ca

Introduction: A major challenge with brain-computer interface (BCI) use is the requirement for subject-specific training, which is often tedious and unengaging for the user, but necessary to improve efficiency. This randomized, single-blind pilot study aimed to address this challenge by increasing engagement and motivation through a gamified training paradigm and evaluating the effects on performance on a visual P300 spelling task.

Material, Methods and Results: Twenty healthy young adults (11 female, mean age 24.5 years) were randomly assigned to two groups: basic P300 training (Group A; Fig. 1a) or gamified training on "Mario Matcher" (Group B; Fig. 1b). First, participants were instructed to spell the word 'LUCAS' by attending to target letters flashing on a 5x10 intendiX P300 Row-Column Speller (g.tec, Graz) at 3 flashes per row/column following a 5 minute calibration period at 15 flashes [1]. They then completed their assigned training paradigm using the same selection concept on a flashing 3x3 matrix, followed by the same spelling task. During the training paradigms, which consisted of three runs with 9 trials each, participants attempted to select a cube of their choice. In the basic training paradigm, the selected cube was briefly highlighted red. In the gamified paradigm, a "Mario" character appeared, and points were rewarded. The sooner "Mario" was revealed, the more subsequent points per character were rewarded. However, if "Bowser" was uncovered, points were retracted, and less subsequent points were rewarded. Compared with Group A, performance (pre/post change in accuracy) on the spelling task was greater in Group B with a large effect size favouring gamified training ($p<0.05$, d=0.830) (Fig. 1c and 1d). Participants in Group B reported enjoying the training task more than the spelling task and perceiving the task as fun, while Group A reported more boredom and fatigue.

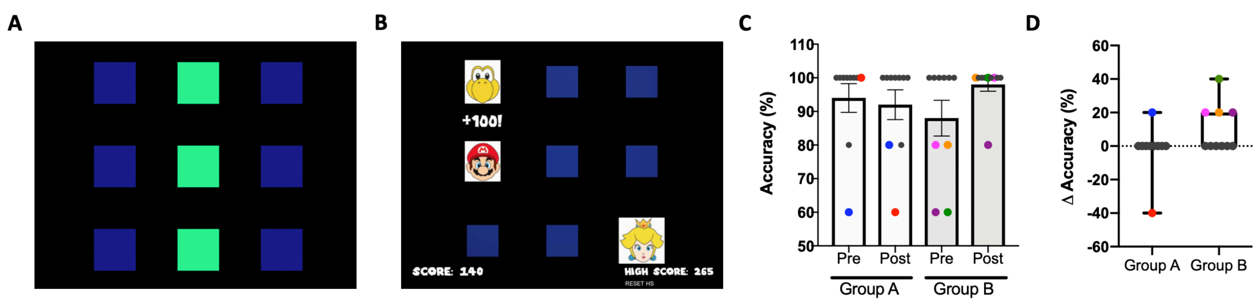

Figure 1. *Basic P300 training paradigm showing a row flash (green) (A). Gamified "Mario Matcher" paradigm showing points rewarded for uncovering "Mario", the user's score (bottom left) and the high score (bottom right) (B). Pre- and post-training accuracy scores (%, correctly selected letters/total letters) for Group A and Group B following a spelling task (C). Changes in pre-/post-training spelling accuracy scores (%) for Group A and Group B (D). Coloured points = individual change in pre/post performance; black points = no change pre/post.*

Discussion: Gamification may increase engagement and motivation during BCI training, potentially improving spelling task performance. These results are consistent with studies demonstrating that motivation modulates P300 amplitude and BCI performance [2,3].

Significance: Information from this study will be used to inform optimized BCI training paradigms for children, who's limited attention and motivation pose pressing challenges for the implementation of BCI.

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Reconstruction of cursor trajectories from intracranial recordings of brain activity in a voice-based cursor control task

Kevin Meng[1*], David B. Grayden[1,2], Mark J. Cook[1,2], Farhad Goodarzy[1,2]
[1]The University of Melbourne, Australia; [2]St Vincent's Hospital Melbourne, Australia

*Dept of Biomedical Engineering, University of Melbourne VIC 3010, Australia. E-mail: ksmeng@student.unimelb.edu.au

Introduction: In recent years, there has been growing interest in decoding speech processes from intracranial recordings of brain activity for the development of brain-computer interfaces using electrocorticography (ECoG) or stereotactic electroencephalography (SEEG) [1,2]. In this study, we aimed to decode speech intentions and reconstruct cursor trajectories during a voice-based cursor control task using SEEG signals.

Material, Methods and Results: Two subjects with intractable epilepsy were each implanted with 13 SEEG depth electrode arrays (DIXI Medical, France), consisting of 5 to 18 contacts per array. The placements of electrodes were solely based on the requirements of clinical evaluation (Fig. 1A). SEEG signals were recorded at 5 kHz using Synamps2 (Compumedics Ltd, Australia). Using a custom application inspired by the Vocal Joystick project [3], subjects were instructed to move a voice-controlled computer cursor in four directions depending on the utterance of selected sustained vowel or nasal sounds (Figs. 1B, 1C). Audio signals were sampled at 16 kHz and synchronized using StimTracker (Cedrus Corporation, USA). Recorded SEEG data were used retrospectively under real-time constraints to generate continuous predictions of utterances to reconstruct cursor trajectories (Fig. 1C). Binary and multi-class version support vector machines were used to perform speech detection and utterance classification, respectively. Neural features consisted of log-transformed normalized power spectral densities for subject-specific recording sites at frequency bands: theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), gamma 1 (30-45 Hz), gamma 2 (55-95 Hz), gamma 3 (105-145 Hz), and gamma 4 (155-195 Hz). SEEG decoding performance was evaluated as classification accuracy of the support vector machines and the mean square error between the original and reconstructed cursor trajectories. The study was approved by the Human Research Ethics Committee of St Vincent's Hospital Melbourne. Both subjects gave written informed consent and participated in the study on a voluntary basis

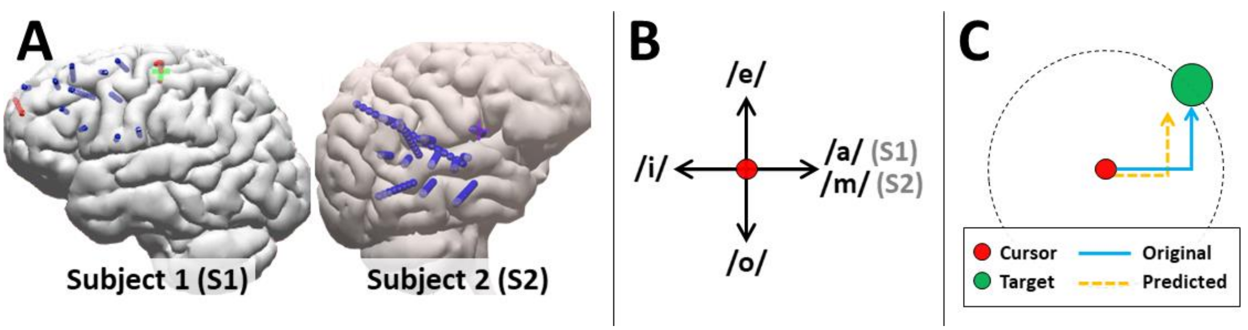

Figure 1. *Overview of the study. (A) Subject 1 (S1) had 168 recording sites in the left frontal lobe; S2 had 147 recording sites in the right temporal lobe. (B) Selected sounds and their associated commands: /i/ left, /a/ or /m/ right, /e/ up, /o/ down. (C) For each trial, the cursor was initially positioned at the center of the screen; the target was positioned at a random peripheral location 120 mm from the center. A custom application recorded microphone input, classified vocal features, and updated the cursor position every 10 ms.*

Discussion: Intentions to produce specific speech sounds in a goal-oriented task could be decoded from intracranial recordings of brain activity in localized areas of both frontal and temporal lobes. Anatomical analyses showed that significant contributions to the classification accuracy arose from deeper structures of the brain that are typically inaccessible with ECoG grids and strips. Future directions include real-time processing of SEEG signals using both overt and imagined speech to control a computer cursor exclusively with speech intentions.

Significance: We proposed a novel framework to study intentions to produce isolated and sustained speech sounds in an engaging task. Successful decoding of intended or imagined speech may be translated into clinically relevant brain-computer interface applications.

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Comparative analysis on frequency and phase coding of SSVEP signals for control of robotic arm using LabVIEW

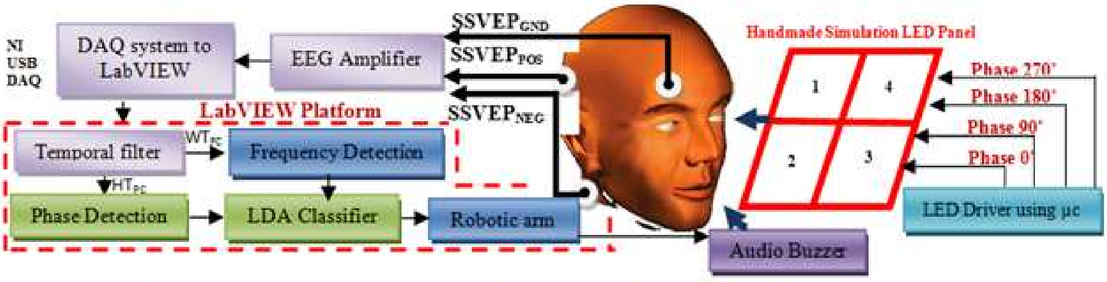
Sandesh R S*[2], Nithya Venkatesan[1], Ananya Ananth Rao[2], Aayushii Goswami[2]
[1]VIT-Chennai-127, [2]RV College of Engineering, Bengaluru- 59, INDIA, *mailsandesh.rs@gmail.com

Introduction:

A BCI is a communication system which enables a person to send commands to an electronic device, only by means of voluntary variations of his brain activity. This work recommends applying transformation techniques to evaluate the performance classification of phase (Hilbert Transform-HT) and frequency coding (Wavelet Transform-WT) of SSVEP signals in LabVIEW.

Material, Methods and Results:

The experimental setup consists of handmade simulation panel with four LED as visual source for phase and frequency coding (Fig.1). The SSVEP signals in both cases are extracted individually using EEG amplifier, and are interfaced to LabVIEW using DAQ system (NI-USB DAQ). The EEG signals are filtered, classified for frequency and phase coded of SSVEP signals, translational commands are then passed for control of 3 DoF robotic arms in LabVIEW [1]. From the Fig.1 (table), it is clear that, there is an increase in accuracy and ITR of phase coded signals as compared to that of frequency coded SSVEP signals.



Experimental results of SSVEP based BCI for robotic arm control, CTI- Command Transfer Interval, ITR- Information Transfer rate

	Phase content N=4 (2 trials) 1-0°, 2-90°,3-180°,4-270°, 25 Hz					Frequency Content N=4 (2 trials) 1-15Hz, 2-18Hz, 3-21Hz,4-24Hz, 0°				
Subject	1	Time in sec	Accuracy	CTI s/cmd	ITR	1	Time in sec	Accuracy	CTI s/cmd	ITR
1	--	27	100%	3.37	35.6	--	29	100%	3.65	33.1
2	3*	31	87.50%	3.87	19.52	2#	34	87.50%	4.25	17.76
3	--	29	100%	3.62	33.15	--	28	100%	3.5	34.28
4	--	30	100%	3.75	32.25	--	32	100%	4	30
5	3#	31	87.50%	3.875	10.87	1*,4#	39	75%	4.875	9.74
6		28	100%	3.5	34.28	3#	35	87.50%	4.375	17.26
7	4#	32	87.50%	4	18.88	2*,3#	38	75%	4.75	10.8
Average		29.7	94.6	3.7	26.4		33.6	89.3	4.2	21.8

Figure 1: SSVEP based BCI system for robotic arm control using LabVIEW, along with experimental results

Discussion:

The experimental results were also compared with results obtained from similar works [2, 3]. The reduction in accuracy is due to, the subjects are not familiar in the SSVEP based BCI experiments or either due to low SNR caused by electrode location.

Significance:

The LabVIEW based SSVEP experimentation enables to create one's own GUI, and can be focused on real time robot arm control in future for patients with severe neurological disabilities.

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Is Classifying Uni- and Bimanual Motor Imagery Feasible as a Three-Class BCI Problem?

C. McGeady[1*], A. Vuckovic[1]

[1]*University of Glasgow, Glasgow, United Kingdom*

*James Watt South Building, University of Glasgow, Glasgow, G12 8QQ. E-mail: c.mcgeady.1@research.gla.ac.uk

Introduction: The past decade has seen growing interest in brain-computer interface (BCI) applications for the motor rehabilitation of stroke patients [1]. For the most part, studies have targeted motor function restoration of the paretic limb, reflecting traditional approaches. There is mounting evidence, however, that improvements in unimanual movements do not translate to improved bimanual coordination [2], limiting recovery as the latter tends to be a better predictor of whether motor improvements are maintained outside the clinic [3]. This pilot study investigates the feasibility of using a BCI to discriminate between unimanual and bimanual motor imagery (MI) in able-bodied people.

Materials and Methods: Sixty-four channel EEG was recorded with g.tec g.USBamp amplifiers from 14 able-bodied participants (aged 25±4, 6 females). Participants sat opposite a computer screen and performed left-hand, right-hand, and bimanual (both hands) MI to a pace set by a cue-based visual paradigm. MI was sustained for 4 seconds and repeated 105 times per class. To implement three-class classification, we used the binary Tikhonov regularized common spatial pattern (CSP) algorithm to build three spatial filters, following a one-versus-rest (OVR) approach. Filters were trained on the middle two seconds of each trial. The first and last four rows of the CSP projection matrices were used to spatially filter training data. Their variances formed a feature matrix to train a classifier, following a one-versus-one coding strategy. To find the most discriminative frequency band for each participant, the process was repeated for 26 bands from 1-30 Hz, at 4 Hz wide, with a 5th order Butterworth filter. We investigated three classifiers: a gaussian support vector machine (SVM), a linear discriminant analysis (LDA), and *k*-nearest neighbour (*k*-NN) classifier. Each classifier was evaluated with respect to its prediction accuracy, estimated by 10x10-fold cross-validation (CV). *Results:* The maximum average CV accuracies returned by the SVM, LDA, and *k*-NN classifiers were 71.6±2.5%, 73.2±2.6%, and 71.3±2.5%, respectively. A paired-sample *t*-test showed that LDA classification was significantly better than SVM and *k*-NN ($p<0.05$). Left-hand discrimination tended to produce the highest true positive rate at 75.0%, followed by the right (73.3%), and bimanual class (70.7%). The left- and right-hand conditions were significantly easier to predict than the bimanual class with the LDA and *k*-NN ($p<0.05$), but not with the SVM ($p>0.05$). Nine participants achieved an average accuracy exceeding 70%, and the top performer achieved a maximum classification accuracy of 81%.

Table 1: Confusion matrices: Left: cross-validation scores of SVM; Middle: LDA; Right: KNN. Bold indicates true positives (%).

	Left	Right	Bimanual
Left	**74.1**	11.1	14.8
Right	10.4	**70.8**	18.8
Bimanual	15.1	15.2	**69.7**

	Left	Right	Bimanual
Left	**75.0**	10.1	14.8
Right	10.4	**73.3**	16.5
Bimanual	17.0	12.3	**70.7**

	Left	Right	Bimanual
Left	**75.8**	9.4	14.8
Right	10.4	**74.6**	14.1
Bimanual	21.1	15.3	**63.6**

Discussion: Results indicate the feasibility of using a BCI to classify bimanual MI. The CV accuracies achieved are inline with other OVR-CSP approaches to multi-class classification of MI reported in the literature [4]. Of the three classifiers explored, LDA performed significantly better than the SVM and *k*-NN classifiers, suggesting LDA should be the focus of future studies. Most participants achieved a classification accuracy of above 70%, implying that, given a screening process, the system could be valuable to stroke patients involved in bimanual motor practice.

Significance: We show a BCI can classify unimanual and bimanual motor imagery in able-bodied participants with practical accuracy, demonstrating that a BCI-based training strategy could be designed to encourage neurologically impaired individuals to participant in bimanual motor practice.

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Observing and executing grasping movements: a similarity analysis among neural and behavioral representations and categorical models

Andreea Ioana Sburlea[1], Nicola Butturini [2] and Gernot Müller-Putz[1]

[1]*Institute of Neural Engineering, Graz University of Technology, Graz, Austria;* [2]*University of Padova, Italy*

E-mail: andreea.sburlea@tugraz.at, gernot.mueller@tugraz.at

Introduction: Electromyographic and kinematic information have been proposed as candidates for the neural representation of hand control. However, it remains unclear how these movement covariates are reflected in electroencephalographic (EEG) activity during different stages of grasping movements, such as hand-preshaping, reaching the final grasping posture and holding.

Material, Methods, Results and Discussion: In an exploratory study [1], we simultaneously acquired EEG, kinematic and electromyographic signals in 31 human subjects while observing 33 different pictures of hand-object interaction and executing the grasps previously observed. Our study aims were three-fold. First, we investigated the relation between EEG and the behavioral covariates associated with the movement execution phase. Using representational similarity analysis, we found that EEG activity reflected different movement covariates in different stages of grasping. During the pre-shaping stage, centro-parietal EEG in the lower beta frequency band reflected the object's shape and size, whereas during the finalization and holding stages, contralateral parietal EEG in the mu frequency band reflected muscle activity. Second, we asked how the EEG patterns of static grasping observation relate with the behavioral covariates of movement execution [2]. We found that the EEG representation of the observation phase in the mu and low beta frequency bands was correlated with the muscle representation during the execution, most strongly in the movement holding phase. This similarity indicates that when visually processing the hand-object interaction, we focus on the final grasping posture. Third, we investigated whether the muscle envelope of different grasping movements can be continuously predicted from low frequency EEG amplitudes using a filtering approach. We achieved higher prediction accuracy for intermediate grasps compared to power or precision grasps.

Significance: These findings contribute to the understanding of the temporal organization of neural grasping patterns, and could inform the design of noninvasive neuroprosthetics and brain-computer interfaces. Moreover, these findings allow us to gain a joint understanding of the relation between movement observation and execution and a mean to facilitate an intuitive control of neuroprostheses in motor impaired individuals.

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Brain-Computer Interface System based on Functional Electrical Stimulation and Avatar Feedback for Lower Extremity Rehabilitation of Chronic Stroke Patients

N. Murovec[1,2*], M. Sebastian-Romagosa[3], W. Cho[1], S. Dangl[1], R. Ortner[3], C. Guger [1,2]
[1]g.tec medical engineering GmbH, Schiedlberg, Austria; [2]Guger Technologies OG, Graz, Austria; [3]g.tec medical engineering Spain S.L., Barcelona, Spain

*Sierningstraße 14, 4521 Schiedlberg, Austria. E-mail: murovec@gtec.at

Introduction: Brain-Computer Interfaces (BCIs) show important rehabilitation effects for patients after stroke. Previous studies have also shown improvements for patients that are in a chronic stage and/or have severe hemiparesis and are particularly challenging for conventional rehabilitation techniques [1, 2, 3].

Material, Methods and Results: For this pilot study nine stroke patients in chronic phase with hemiparesis in the lower extremity were recruited. All of them participated in 25 BCI sessions about 3 times a week. BCI system was based on the Motor Imagery (MI) of the paretic ankle dorsiflexion and healthy wrist dorsiflexion with Functional Electrical Stimulation (FES) and Avatar feedback. Assessments were conducted to assess the changes in motor improvement before, after and during the rehabilitation training. Our primary measures used for the assessment were Range of Motion (ROM) and Timed Up and Go (TUG). Results show significant improvement in passive ROM assessment for ankle from 25.28° (SD = 6.15) before to 34.83° (SD = 8.45) after the rehabilitation training (t-test(8) = -4.647, *P* =.002) and active ROM from 15.73° (SD = 11.69) to 25.18° (SD = 14.82) after rehabilitation training (t-test(8) = -4.060, *P* =.004). Results for TUG assessment for eight patients are not normally distributed (using Shapiro-Wilk test) and shows significant decrease in time from 22.36 seconds (IQR = 15.30 - 66.48) before the rehabilitation training to 19.50 seconds (IQR = 11.00 – 59.50) after the training (Wilcoxon signed rank test *P* =.008). One patient was not able to perform this assessment before the rehabilitation training, but was able to perform it after the with time 92.2 seconds.

Discussion: These outcomes show the feasibility of this BCI approach for chronic stroke patients, and further support the growing consensus that these types of tools might develop into a new paradigm for rehabilitation tool for stroke patients. However, the results are from only nine chronic stroke patients so the authors believe that this approach should be further validated in broader randomized controlled studies involving more patients.

Significance: MI and FES-based non-invasive BCIs are showing improvement for the gait rehabilitation of the patients in the chronic stage after stroke. This could have in impact on the rehabilitation techniques used for these patients, especially when they are severely impaired and their mobility is limited.

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A framework for user training adaptation in Brain-Computer Interfaces based on mental tasks (MT-BCIs)

A. Roc[1,2,*], F. Lotte[1,2]

[1] *Inria, France* [2] *LaBRI (CNRS / Bordeaux INP / Univ. Bordeaux), France*

* E-mail: aline.roc@inria.fr

Introduction: Mental Task (MT-)based BCIs allow for spontaneous and asynchronous interactions with external devices solely through mental tasks such as motor imagery or mental math. Such BCIs require their users to develop the ability to encode mental commands that are as stable, clear and distinct as possible - making them easy to recognize by a computer. Despite their promises and achievements, traditional closed-loop training programs are suboptimal [1] and could be further improved. Some aspects of training programs were studied in depth in light of methods from the fields of educational sciences, ergonomics, or user-centered design [1, 2]. However, the best way to train users is still unknown and some aspects of user training protocols possibly impacting skill acquisition may not have been sufficiently explored yet. Although successful additions of a human perspective in the traditional BCI interaction model were already possible (e.g. [3, 4, 5]), these representations might not sufficiently depict the many aspects that could be improved/adapted in BCI human training protocols. Therefore, we propose a framework identifying and defining the various parameters composing a BCI user training program.

Method, Results: Based on the existing literature [6], we propose a framework describing, at different time scales, the different aspects of BCI user training. As seen in Fig. 1, training is composed of one or more sessions (days) whose order, number or duration can vary. Sessions are themselves composed of runs that can vary as well, etc. In this framework, a training program consists of practicing *exercises,* which refer to *what* MT-BCI users are expected to do and *how* to practice it. Although traditional training usually requires users to practice the same exercise over and over, exercises can vary in many ways across experiments and they can also be adapted within trials, runs or sessions. This representation emphasizes the multiple entry points that allow for training adaptation, for example what skill users should practice (e.g. training for speed or accuracy, etc.), in which spontaneity mode (e.g. cue-based vs. self-decided, synchronous trials vs. self-paced exercise), with which instructions or feedback (e.g. content, modality, timing), or in which environment (i.e. the context in which training takes place).

Discussion: Not only the properties of training aspects should be questioned, but also their presence. For example, there is no indication that the uniform presence of feedback at each step throughout the entire training is the best way to train users. Besides, rather than universally refining training parameters, it may be preferable to adapt the choice of parameters to the user before and/or throughout sessions [5] based e.g. on changes in users' understanding, perceptions, motivation, fatigue, performances, etc.

Significance: Future work should investigate further whether the variation of different training aspects has an influence on behavioral BCI performance, user-related metrics [4] or users' understanding of instructions, self-instructed cognitive strategy, perception of trial-specific quality, willingness to change/redo task, etc. This is a preliminary step on the way to designing new training programs composed of exercise sequences adapted to human learning and/or adaptive according to users' experience or performances.

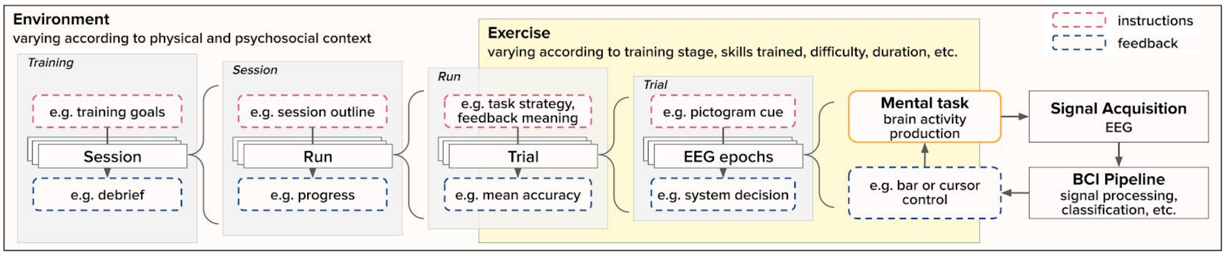

Figure 1. *Representation of MT-BCI training in decreasing order of time scales. Different aspects of the training could be modulated - including their goal, modality, content, duration, variety, frequency, number and/or order.*

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Cursor Task Training Improvement with Tripolar Concentric Electrodes

Walter Besio[1]* Patricia Adegboyega[1], Aiden Keene[1], Merci Ujeneza[1]
[1]Biomedical Engineering, University of Rhode Island, Kingston, RI 02881, USA *besio@uri.edu

Introduction: Brain-computer interfaces (BCIs) allow the translation of brain signals into device control signals. Tripolar concentric ring electrodes (TCREs) for electroencephalography (tEEG) were first reported by Besio [1]. The tEEG has significantly higher spatial resolution and signal to noise ratio (SNR) than EEG [1] [5]. The tEEG was also shown to have significantly less mutual information than EEG [5]. The tEEG has previously been shown to improve BCI accuracy in offline classification [6] and for real-time center-out cursor control compared to EEG [2]. We have also shown that the outer ring of the TCRE produces an equivalent signal to EEG (eEEG) and TCREs can therefore record EEG and tEEG from the same sensor concurrently [4]. The time it takes to train BCI users can be quite lengthy. In this study we compared whether naïve BCI users could become proficient with less runs using either tEEG or EEG.

Materials, Methods, and Results: We evaluated how quickly naïve BCI users could achieve proficiency with conventional EEG or tEEG recorded from TCREs. The study was approved by the URI IRB. We tested 12 healthy BCI naive subjects, randomly assigned, six each, to standard EEG or tEEG, with their goal to, “hit”, sixty percent of the targets in a single “run” of an imagined movement cursor task. The participants head circumference were measured, locations marked, and the scalp was prepared. The TCREs were placed at CP3, C3, C1, Cz, C2, C4, CP4, of the 10-20 International Electrode positions, as well as a conventional disc electrode on each mastoid process as the ground and reference. The skin to electrode impedances were measured for each electrode to ensure they were below 10 kΩ. Each participant completed a short training/ calibration session in the form of a stimulus presentation to obtain data for the individual classifiers. Participants were asked to remain still while doing this, and to imagine motor imagery tasks as arrows pointing left or right appeared on a monitor directly in front of them. Offline analysis using the r^2 feature of BCI2000 was performed to determine the locations and frequencies used for the real-time classifiers [3]. This information was then input to the BCI2000 classifiers table.

Discussion: None of the participants knew which type of electrodes signals they were using; they were blinded to the type. Most of the participants in the eEEG group, five out of six, were not able to reach sixty-percent proficiency, even after 14 runs. Conversely, five of the six participants in the tEEG group reached the sixty-percent proficiency. For the tEEG participant that did not reach sixty percent, they reached fifty-five percent proficiency, which is higher than most of the eEEG participants. The results show that significantly more participants were able to reach ≥sixty-percent proficiency within less runs using tEEG compared to EEG. There was a significant difference in the number of proficient participants (Mann Whitney unpaired test with correction $p = 0.017$). Once a participant reached sixty-percent proficiency they did not perform any further runs.

Significance: The purpose of these experiments was to test whether tEEG signals, obtained from using TCREs, could be used to train naïve participants faster than eEEG signals in imagined movements real-time center-out cursor control. We found that naïve BCI users were able to become proficient faster with tEEG than eEEG. We also found that the participants using tEEG achieved higher maximum percentage of hits. This higher percentage needs to be put into perspective. The participants did not perform any further runs if they achieved at least sixty percent proficiency in any run. It is likely that if the tEEG group would have performed more runs they would have achieved even higher percentages of hits than they did. Whereas, the eEEG participants did not show any increase in percentage of hits with further runs. In fact, the slope of the hit rate percentage went down with more runs with eEEG. During the experiments, we allowed the subjects to attempt to reach sixty percent proficiency in as many runs as it took instead of setting a specific number of runs. In hindsight, setting an exact number of runs to end the task would have strengthened our results. Overall, tEEG users became proficient in less runs, and had higher hit rates than eEEG users.

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Hybird noninvasive brain stimulation modulated the intracortical networks for stroke rehabilitation

Jiahua. xu[1,2], Antal. Andrea[2,3], Andreas Nürnberger[1] , Bernhard A. Sabel[2]

1. Faculty of Computer Science, Otto von Guericke University Magdeburg
2. Institute for Medical Psychology, Medical Faculty, Otto-von-Guericke-University Magdeburg
Email:jiahua.xu@med.ovgu.de

Introduction: Occipital stroke often leads to visual field loss, for which no effective treatment exists. Little is known about the potential of non-invasive low intensity electric stimulation to improve visual functions in patients suffering from a unilateral occipital stroke. Here, protocols of repetitive transorbital alternating current stimulation (rtACS) and transcranial direct current stimulation (tDCS) are studied which are used to induce recovery of vision.

Method: Eight unilateral occipital stroke patients received tDCS/ tACS (ACDC) treatment for two weeks with 10 mins tDCS 1 mA via one electrode placed at either O1 or O2 position above the intact hemisphere with the anode at Fpz. And immediately followed by 20 mins tACS with a maximum of 1.5 mA. the center of the AC stimulation electrode was positioned at Fpz ,The reference electrode was placed on the right upper arm. this research had been approved by the ethic committee of university Magdeburg. Resting-state EEG was recorded at three-time points (before treatment: PRE, after two weeks treatment: POST; follow-up after two months: FU). EEG data were preprocessed and artifacts were removed by the independent component algorithm (ICA). The correlation between global characteristic path length and high-resolution perimetry (HRP) was performed with the Pearson test. Node strength was calculated to investigate the dynamic change of brain networks. Kruskal–Wallis test was performed and p value was corrected by Bonferroni method for post-hoc analysis.

Results: The result shows that ACDC inhibited the node strength of intact parietal ($p<0.05$) and enhanced the node strength of the lesion occipital hemisphere ($p<0.05$)(Figure 1A). A negative correlation($r=-0.80$, $p=0.017$) was observed between the number of white dots of HRP (High-resolution perimetry) and characteristic path length after treatment(Figure 1B), six of eight patients visual field after follow up was enhanced comparing before treatment.

Discussion: after the ACDC treatment, the better visual functionality, the less global characteristic path length, which indicated that the ACDC stimulation reduce the transit path length required for global information transmission. The ACDC stimulation reorganized the Brian network balance between the intact and lesion hemisphere. These results will provide be an alternative clinic therapy further for stroke patients with vision loss

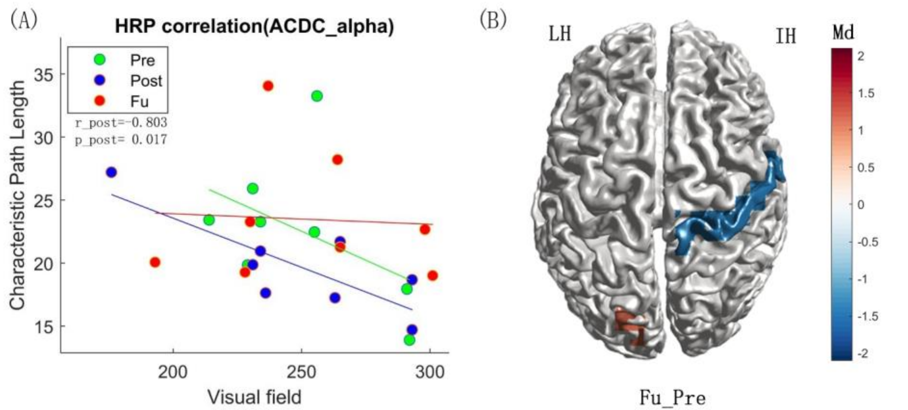

Figure 1 (A) ACDC inhibited the strength of the intact hemisphere and enhanced the lesion hemisphere at Follow-up period. (B)The correlation between normal visual filed and global characteristic path length.

Hybrid brain-computer interface with SSVEP and P300

M. G. Mussi[1*], L. T. Ruiz[1], D. R. Amortegui[1], J. Andersen[1], K. D. Adams[1]

[1]*University of Alberta, Edmonton, Canada*

*8205 114 St NW, Edmonton, Canada. E-mail: mussi@ualberta.ca

Introduction: Children with disabilities may have developmental delays due to challenges associated with physical and communication impairments [1]. Opportunities for play are not always accessible and this not only delays their development, but violates the right to play of every child [2]. Brain-computer interfaces (BCI) could enable children to use their brain signals to control technology for play. People who have disabilities have used these type of systems to perform activities of daily living or to play games [3]–[5]. One BCI paradigm is the steady state visual evoked potential (SSVEP) [6]. With this paradigm, all targets flash with a unique frequency and through the resonance of the pyramidal cells in the cortex it is possible to identify the frequency associated with the desired selection. In a previous study, adults achieved 71% accuracy using this approach in experiments where the flashing targets were embedded in a play environment 2 m from the user's eyes [7]. The low accuracy and the long time necessary to process the SSVEP signal limits the use of this technology in applications with children.

A possible way to increase the accuracy and decrease the processing time could be to use a hybrid-BCI with SSVEP and a second paradigm. The P300 evoked potential is elicited in the brain signal with a latency of 300 ms after a visual, auditory or tactile stimuli. In the P300 paradigm, stimuli are presented in a random order, the participant attends to the desired target stimulus, and each time the attended stimuli is activated, a P300 evoked potential is generated [8]. Such a hybrid combination may enhance accuracy and reduce processing time [9]. The purpose of this study is to use the SSVEP and the P300 paradigms simultaneously as inputs to examine if the accuracy and time can be improved compared to using them independently.

Material, Methods and Results: Validation with adult participants is the first step. Brain signals are acquired through a Cyton board (OpenBCI, New York, US), from the electrodes O1, Oz, O2 , PO8, PO7, POZ and CPZ [10] at 250Hz. The experiment presents three squares on the screen in different positions, flickering at 6, 15 and 30 Hz for SSVEP, and an outline that will appear around the squares, one at a time, in random order for P300. The participant is instructed to gaze at randomly pre-defined squares to select them for 21 trials (7 in each square). P300 and SSVEP signals are collected in real time. The temporal brain signals are down-sampled and filtered before classification. SSVEP samples will be classified through Canonical Correlation Analysis and P300 samples through Linear Discriminant Analysis. The final selection is made through a voting system which considers both classifications.

Discussion: The data is being analyzed and the results will be available at the time of the conference.

Significance: Hybrid BCI can improve system accuracy and improve selection time, which is important for use with children so they do not get frustrated during use.

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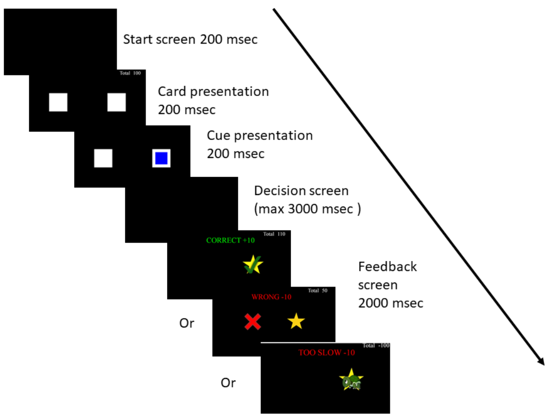
EEG-based brain-computer interface (BCI) for Distress identification for individuals with ASD

Busra T. Susam[1*], Safaa Mohamed [1], Caitlin M. Conner[1], Murat Akcakaya[1], Josh Golt[2], Shannondora Porton[1], Susan W. White [2], Carla A. Mazefsky[1]
[1] University of Pittsburgh, Pittsburgh, PA, USA; [2]University of Alabama, Tuscaloosa, AL, USA
[*]1238 Benedum Hall, 3700 O'Hara St, Pittsburgh, PA, USA 15213 Email: bts38@pitt.edu

1.Introduction: Individuals with autism spectrum disorder (ASD) often have impaired emotion regulation (ER). There is growing interest in complementing psychosocial therapeutic approaches for ER with technology-based tools to improve therapy efficacy. However, the existing technology-based intervention tools for emotional regulation (ER) in adolescents and adults with autism spectrum disorder (ASD) do not usually help the clinical treatment methods generalize to real-life activities[1, 2]. Here, we provide an initial proof of concept for the use of brain activity to support ER studies by using EEG to distinguish between distressed and non-distressed conditions.

2.Material, Methods and Results: In the present study we investigate the effect of distress on the brain activity of individuals with ASD via an EEG-based BCI. 12 individuals with ASD (9 males; age= 12-19 years) participated in EEG data collection under IRB number PRO17070496. We identified patterns of brain activity associated with distress during the Affective Posner task, described in Figure 1. Only data from the game 3 involving deception were utilized. We applied machine learning to recorded EEG data from the Affective Posner Task to classify distressed and non-distressed conditions represented by the LOSE and WIN conditions of the Posner task, respectively.



The Affective Posner Task includes a card game, and participants are motivated by the possibility of winning 50$. The cards are represented as two white squares, and there is a star located under one of the white squares. The aim of this task to find the location of the star. During the game, a blue rectangular appears on one of the white squares as a cue with the correct location of the star with 75% probability. After blue rectangular cue, players decide the location of a star, then a feedback (Correct, Wrong and Too Slow) is represented to players based on their answers. Based on this paradigm, three different games were developed. Game 1 is developed to learn the player's speed with the only feedback of Correct or Wrong on the screen. Game 2 displays all feedbacks on screen after the average speed of a player learned in Game 1. If the players take longer time to decide the location of the star than their average speed, 'Too Slow' feedback is presented on screen. Game 3 has a deception component such that 'Too Slow' feedback is provided after 60% of the correct responses while EEG is collected.

Figure 1. The Affective Posner Task Paradigm

After pre-processing, 3 seconds of EEG data time-locked to the feedback (wrong, correct or too slow) for each trial were extracted. A total of 15 temporal and spectral features were calculated from the extracted EEG to be used in the classification between WIN and LOSE conditions. Radial Basis Function Support Vector Machine (RBF SVM) was used as the classifier. Feature selection was applied to optimize the classification performance. Five-fold cross validation was used to avoid overfitting. Average accuracy of 83.83% $\pm$ 8.41 were observed with specificity of 74.20% ±9.311; sensitivity of 83.34% ±8.97. The most important EEG features for distinguishing distress conditions were the total power of EEG in the frontal cortex, especially in F3, F4 and Fz channels (according to 10-20 international system), and the mean of EEG signal calculated over these 3 channels.

3.Discussion: Our results demonstrate that EEG-based BCI based on the Affective Posner Task paradigm , and EEG can be used to distinguish distressed and non-distressed conditions. The most informative features were obtained from the frontal cortex, which have also been identified as important to ER in the broader affective neuroscience literature. Our future work will include a study to investigate the generalization of distressed vs non-distressed condition classification across individuals.

4.Significance: Such a BCI could be used to monitor brain activity in youth with ASD and be closely coupled with a clinical treatment method as an intervention tool.

5.Acknowledgement: This work is supported by NSF grant # 1844885, DoD grant # W81XWH-18-1-0284 and Edith L. Trees Charitable Trust.

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Concordant SSRI use Effects Recovery of Hand Function in Stroke Survivors Using a BCI

L. Williams[1*], A.B. Remsik[1], M. Lin[1], C. Rivera[1], P. van Kan[1], J.C. Wiliams[1], V. Nair[1], K. Caldera[1], and V. Prabhakaran[1],
[1]*University of Wisconsin Madison, Madison, WI, USA*
*1111 Highland Avenue, Madison, WI, USA. E-mail: lwilliams25@wisc.edu

Introduction: Evidence from the FLAME trial [1] and other research suggests that pharmaceutically increased serotonin levels in the brain during BCI interventions may promote or enhance recovery in stroke survivors [2] with acquired motor disability. ***Materials***: Data from participants' medical records and primary outcome measure data (Arm Reach Action Test (ARAT)) and secondary outcome measures of Hand Grip Strength and Stroke Impact Scale Hand Function subdomain were used to analyze whether greater motor recovery was realized in participants taking SSRIs concurrently with BCI-FES intervention than those in the study who were not taking SSRIs. ***Methods***: 29 stroke survivors– for whom medical records were available - with varying levels of impairment, chronicity and lesion location participated in a maximum of 30 hours of a closed-loop BCI intervention for upper extremity motor recovery. Participants taking SSRIs as a part of their standard of care (n=9) while enrolled in the study and those not taking SSRIs (n=12) were grouped accordingly and analyzed for group mean differences at baseline and completion. ***Results***: A main effect for concurrent SSRI use on recovery was not observed in any of the outcome measures of functional capacity (see Fig 1-6). The results did show group mean differences however, these differences were marginal and not statistically significant.

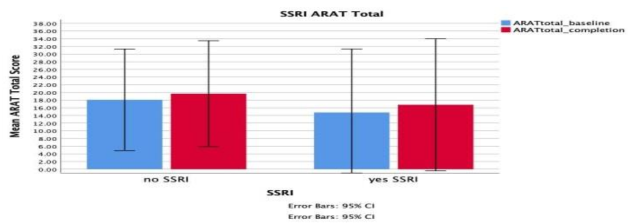

Figure 1. *Participants not concurrently taking SSRIs during BCI intervention (n=12) realized on average 1.5 point increases in total ARAT score change following BCI intervention, whereas (n=9) participants taking SSRIs concurrently with BCI intervention on average realized 2.0 point increases in total ARAT score change following BCI intervention*

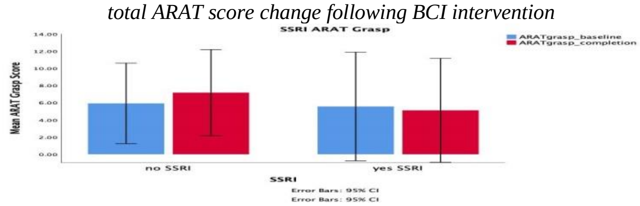

Figure 2. *Participants not concurrently taking SSRIs during BCI intervention (n=12) realized on average 1.2 point increases in ARAT Grasp subdomain score change following BCI intervention, whereas (n=9) participants taking SSRIs concurrently with BCI intervention on average realized 0.4 point decrease in ARAT Grasp subdomain score change following BCI intervention.*

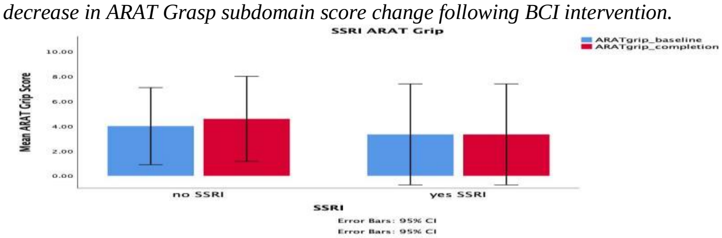

Figure 3. *Participants not concurrently taking SSRIs during BCI intervention (n=12) realized on average 0.5 point increases in ARAT Grip subdomain score change following BCI intervention, whereas (n=9) participants taking SSRIs concurrently with BCI intervention on average realized 0.0 point increases in ARAT Grip subdomain score change following BCI intervention.*

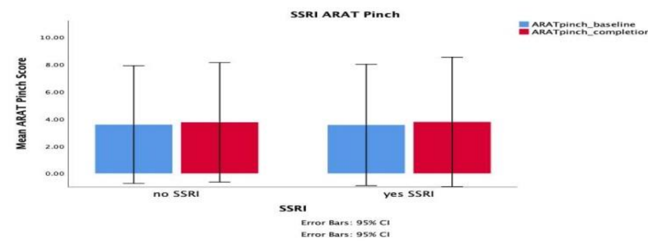

Figure 4. *Participants not concurrently taking SSRIs during BCI intervention (n=12) realized on average 0.2 point increases in ARAT Pinch subdomain score change following BCI intervention, whereas (n=9) participants taking SSRIs concurrently with BCI intervention on average realized 0.2 point increases in ARAT Pinch subdomain score change following BCI intervention.*

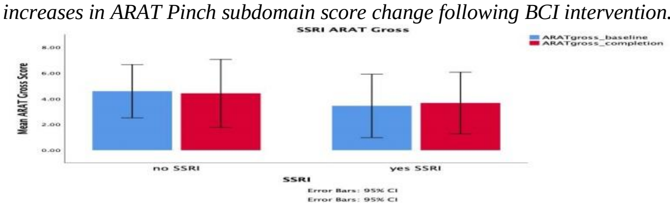

Figure 5. *Participants not concurrently taking SSRIs during BCI intervention (n=12) realized on average 1.1 point decrease in ARAT Gross subdomain score change following BCI intervention, whereas (n=9) participants taking SSRIs concurrently with BCI intervention on average realized 0.2 point increases in ARAT Gross subdomain score change following BCI intervention.*

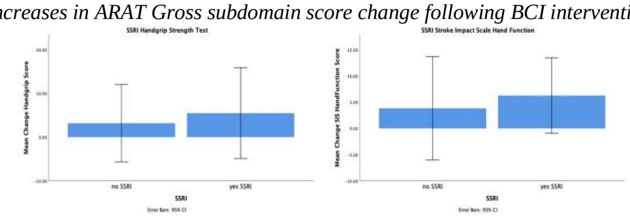

Figure 6*: Group mean change from baseline to completion for secondary outcome measures of Handgrip Strength and Stroke Impact Scale Hand Function subdomain within groups.*

Discussion: These data cannot fully support the findings of the FLAME trial that increased serotonin levels in the brain as a result of pharmaceutical admiration of SSRIs during motor intervention will result in greater functional capacity gains. However, these data but do suggest concurrent SSRI use may promote greater group mean change from baseline to completion, compared to BCI alone. ***Significance***: Such findings suggest that pharmaceutical administration of SSRIs during intervention may increase recovery potential for stroke survivors however; more targeted research efforts are needed to understand this relationship in a conclusive manner before adjusting standard of care practices.

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Convolutional Neural Network based EEG classifier for early detection of Dementia

Vinay K R Chimmula[1,2*], Lei Zhang[1,2], Dhanya Palliath[1]

[1]*University of Regina, Saskatchewan, Canada, S4S 6A7;* [2]*Saskatchewan Center for Patient oriented Research (SCPOR) Saskatchewan, Canada*

E-mail: vinayreddy911@gmail.com

Introduction: Signals generated from human brain are nonlinear and chaotic in nature which makes them difficult to analyse through traditional signal processing methods. EEG signals are resultant of Electrical pulses between neurons inside the brain and they can be processed to diagnose several neurological diseases. Dementia is a neurological disease primarily effects elderly people. It influences daily life activities like language, ability to think, and sudden changes in behaviour are most common symptoms. Dementia is a progressive neurological disease; it gets worse day by day if not detected at its early stages. EEG is being used as a tool for early diagnosis as it is a non-invasive method through which we can access the spatial and temporal features of brain activity. These signals reflects the superposition of spiking activity between the neurons. By finding the spiking patterns of the subjects, features can be extracted from the data and further analysed to classify the people with Dementia. Many scientific methods used for EEG analysis have used Machine learning to extract the meaningful information from the data. Recent advances in data storage devices like cloud GPUs and rise of Deep Learning era led to improvement of classification accuracies near to perfection. Since its success in many fields, deep learning also achieved state of the art results in detecting several neurological diseases. Recent works on classifying EEG signals using deep learning methods have shown very promising results.

Material, Methods and Results: In this study, we have modelled an 8-layer deep Convolutional Neural Network (CNN), inspired from standard AlexNet architecture [1]. EEG data for this experiment was obtained from an open source EEG database created by University of Bonn. In order to preserve the time-frequency components, EEG data is preprocessed using wavelet transformation. After preprocessing, data is directly fed into CNN layers which can extract features from the data without losing spatial components of input data. The network model used here has a total of 8 layers. In contrast with standard AlexNet architecture, we used 2 fully connected layers instead of 3. The other changes includes using LeakyReLU instead of ReLU because, negative gradients are neglected and approximated to zero in case of ReLu. Furthermore, LeakyReLU minimizes the loss occurs due to parameter updates. In our first experiment, we used sigmoid activation as output function to predict whether the subject was diagnosed with Dementia (1) or not (0). Our 8 layer deep CNN achieved peak classification accuracy of 92.39% which is better than previous state of the art CNN models performances [2, 3]. In order to find the severity of Dementia, we used Softmax as an output function where outputs range between 0 to 5 (value close to 0 means less prone to Dementia and close to 5 means higher chances of being affected). To our knowledge, this is the first work to use the Softmax non-linear function to predict the severity of the Dementia.

Significance: The CNN architecture proposed in this paper was able to extract features without losing temporal components of EEG data. We also proved an 8-layer deep CNN performs significantly better than previous state of the art methods. Although results are encouraging, the only drawback of our networks is the calibration time (training period) which is slightly longer than previous works. However, it can be improved with better hardware devices like GPU's. In future we would like to investigate the trade-offs between accuracy and training time.

Acknowledgements: This work is partly funded by Saskatchewan Center for Patient Oriented Research (SCPOR).

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Modified adaptive Fourier decomposition for SSVEP-based BCI

Z. Wang[1,2], Y. Peng[1,2], C.M. Wong[1,2], F. Wan[1,2*], and T.P. Jung[3]

[1]*Department of Electrical and Computer Engineering, Faculty of Science and Technology, University of Macau, Macau*

[2]*Centre for Cognitive and Brain Sciences, Institute of Collaborative Innovation, University of Macau, Macau*

[3]*Swartz Center for Computational Neuroscience, Institute for Neural Computation, University of California, San Diego*

*E-mail: fwan@um.edu.mo

Introduction: This study applies the adaptive Fourier decomposition (AFD) to pre-processing the EEG training signals for improving SSVEP-BCI performance. With the adaptive nature of the AFD [1], the key SSVEP signals can be extracted without losing individual details while the conventional AFD works unsatisfactorily because it cannot extract all the harmonic components due to large energy differences among them. To overcome this difficulty, this study proposes to modify the adaptive basis searching process of the AFD based on the characteristics of the SSVEP signals.

Material, Methods and Results: In the proposed scheme, the training EEG signals are first transferred to the frequency domain and then sent to the modified AFD to reconstruct the template signals using the extracted key components that contain large energy around the flickering frequency and its harmonics. Finally, these reconstructed template signals are applied to train the spatial filters. The key process of the AFD is to find a suitable parameter a_n array of the adaptive basis by scanning the whole spectrum [1]. However, for the SSVEP training signals, the AFD only needs to focus on the signals near the corresponding flickering frequency and its harmonics. Thus, a constraint that limits the phase of a_n is added to the objective function of searching a_n. For evaluation, this study used the 30 subjects' SSVEP signals from the 3rd China BCI Competition. Fig. 1 illustrates the average classification accuracies of the multi-stimulus task-related component analysis (ms-TRCA), the ms-TRCA with the proposed modified AFD, the combination of the multi-stimulus canonical correlation analysis (ms-CCA) and the ms-TRCA, and the combination of the ms-CCA and ms-TRCA with the proposed modified AFD [2]. Fig. 1 with one-way ANOVA indicates that the modified AFD could significantly improve the performance of the ms-TRCA and the combination of the ms-CCA and the ms-TRCA for the SSVEP-based BCI ($p<0.05$).

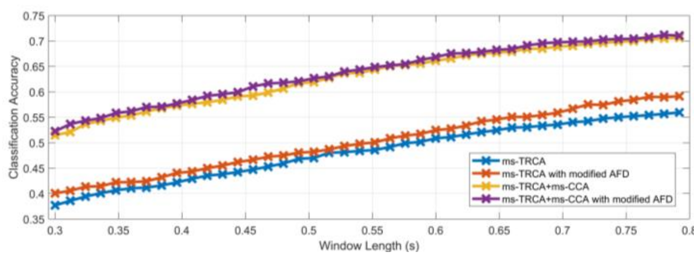

Figure 1. Average classification accuracies under different window lengths.

Discussion and Significance: This study modifies the AFD based on the characteristics of the SSVEP signals. The study results show that the modified AFD could enhance the performance of some cutting-edge spatial filter computation methods. To enhance the denoising effect, further modifications on the AFD to directly extract common basis from the multi-channel SSVEP signals will be included in future work.

Acknowledgement: This work is supported in part by the Science and Technology Development Fund, Macau SAR (File no. 055/2015/A2 and 0045/2019/AFJ), the University of Macau Research Committee (MYRG projects 2016-00240-FST and 2017-00207-FST), the National Natural Science Foundation of China (Grant No. 61961160705).

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An Adaptive Approach for Task-driven BCI Calibration

Frida Heskebeck[1,*] and Carolina Bergeling[1]
[1]*Department of Automatic Control, Lund University, Lund, Sweden*
[*]Email: frida.heskebeck@control.lth.se

Introduction One of the most significant obstacles for the every-day use of systems based on Brain-Computer Interfaces (BCIs) is the tediousness of calibration. Successful improvements on calibration, particularly the time needed and the user-experience, have been made with, e.g., transfer learning, gamification, and task estimation [1, 2, 3]. In this work, we present an adaptive approach to BCI systems' calibration with a model that evaluates if more calibration is needed. We inspect the model in its simplest form to showcase its versatility.

Material, Methods, and Results The model is built as a Markov Decision Process (MDP) with actions in each state and transition probabilities after each action (see Figure 1) [4]. The states s_{si} and s_{di} represent if the user is satisfied or dissatisfied with the BCI system's outcome. The number of updates of the classification algorithm is denoted through the index i. Two actions are possible: a_e - listen to the user intent and respond accordingly, and a_u - update the classification algorithm. Transition probabilities reflect the accuracy of the classification algorithm. In the case of model analysis, these can be estimated from data. There is an associated reward for each state transition: positive if reaching any of the states s_{si} and negative otherwise. Moreover, action a_u is considered expensive since it includes collecting more training data and training the classification algorithm.

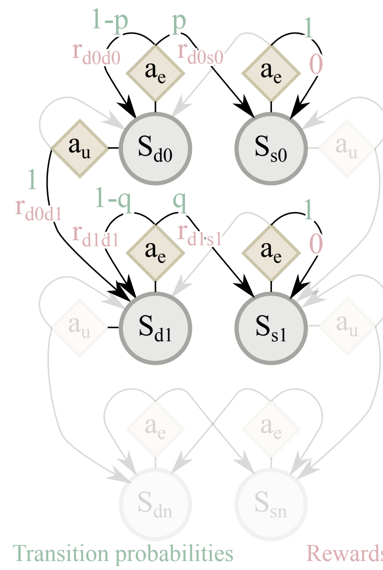

Figure 1: *Graphical outline for the model. The opaque parts are the simplest form of the model.*

Based on this model, the aim is to construct a policy (choice of action in each state) by which the system reaches any of the states s_{si} with maximum total reward. The best action to take will depend on the rewards and the expected value for the transition probabilities. Given the simplest model (opaque in Figure 1), one reaches inequality (1) with γ denoting the discount factor. Action a_u is best in state s_{d0} if (1) is true. The results from this analysis are intuitive. Given the rewards as stated above, (1) is true if $q > p$, i.e., action a_u is best if the classification algorithm is better at classifying the user intent after an update.

The model description is independent of the task to be solved, the BCI paradigm, and the classification method. A more tailored model could be constructed if these aspects were accounted for. The model is not intended to choose the best classification algorithm or preprocessing methods for the BCI system. Instead, it adapts the calibration to the current situation.

Discussion The simplest model can be extended in several ways (see transparent parts in Figure 1). For instance: 1) the user can change their mind, 2) the classification accuracy is not improved after the action a_u, 3) action a_u is possible also from a state s_{si}, and 4) n number of classification algorithm updates are possible (more states). Finally, it is not necessarily true that the BCI system knows the current state. This can be addressed through the theory of Partially Observable MDPs [5, 6]. The approach of reinforcement learning is also compelling for the extended model [7].

$$\frac{(1-p)r_{d_0d_0} + pr_{d_0s_0}}{1-\gamma(1-p)} < r_{d_0d_1} + \gamma\left(\frac{(1-q)r_{d_1d_1} + qr_{d_1s_1}}{1-\gamma(1-q)}\right) \quad (1)$$

Significance The model facilitates the decision of when to use the BCI system and when to calibrate it. We believe that it can be combined with other calibration approaches to create the next-generation autonomous BCI systems.

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Source-space based decoding of hand movement trajectory during a pursuit tracking task

Nitikorn Srisrisawang[1], Gernot Müller-Putz[1*]
[1]*Institute of Neural Engineering, Graz University of Technology, Graz, Austria*
[*]Stremayrgasse 16/IV, 8010 Graz, Austria E-mail: gernot.mueller@tugraz.at

Introduction: In our recent work [1]–[3], we gained insights about the brain regions contributing to the decoding of hand trajectory during a pursuit tracking task (PTT) which we could incorporate this information to explore a new possibility of decoding the hand trajectory from the source-space signals.

Material, Methods and Results: There are 15 subjects from 2 PTT studies [1], [2]. Subject controlled a robotic arm with shared control between LeapMotion (LM) hand movement and EEG signals to track the cursor on the screen with a gradual decrease of LM %. The EEG was transformed from the sensor-space signals into the source-space signals (ICBM152 head model, unconstrained sources, 5000 vertices, sLORETA with Brainstorm package [4]). Multi-lag (-300 to 0 ms) mean signals were computed from the 16 region-of-interests (ROI) according to the Mindboggle atlas [5] corresponding to the frontoparietal network. Partial Least Squares (PLS) (explaining 95% of variance) and a square-root unscented Kalman filter (SR-UKF) were trained to reconstruct 6 movement parameters: position and velocity in 2D, distance, and speed. We used the following metrics to compare this approach to the sensor-space approach: correlation, signal-to-noise ratio (SNR), and decoded-signal-to-signal ratio (DSSR) [3]. Both approaches achieved similar performance, but the source-space decoding indicated slightly lower performance for all three metrics. Multi-way repeated measures ANOVA revealed no statistically significant differences for correlations ($F(1,14)=3.58$, $p=0.0791$), but significant differences in terms of SNR ($F(1,14)=3.90$, $p=0.0058$) and DSSR ($F(1,14)=9.56$, $p=0.008$).

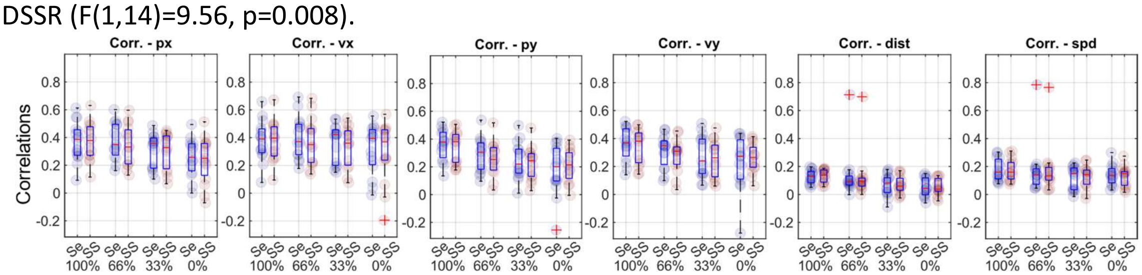

Figure 1. *Subject-averaged correlation between the decoded and the true movement parameters for measurement blocks from 100% to 0% LM control. The blue and red dots indicate the correlation of the sensor-space (**Se**) and the source-space decoding (**SS**), respectively.*

Discussion: Transforming the sensor-space signals into the source space increases the number of signals greatly (around 60 to 15,000 signals). However, our reduction approach might reduce too much information as reflected in the lower performance. Nevertheless, we see that the source-space decoding is possible, but it needs more elaborate investigation for its merits over the sensor space.

Significance: To the best of our knowledge, this is the first study that investigates the possibility of source-space decoding of hand movement trajectory in the PPT task.

Acknowledgements: Research supported by funding from the European Research Council (ERC-CoG-2015 681231 'Feel Your Reach'), the author N.S. received funding from the Royal Thai Government.

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Optimizing P300 flashboard design based on partial word and character context

Nithin Parthasarathy, Corey Arnold, Nader Pouratian, William Speier
University of California, Los Angeles, CA, USA
Email: nithinparthasarthy@gmail.com

Introduction: ALS, a progressive neuromuscular degenerative disease [1], restricts patients' communication capacity a few years after onset resulting in a severe degradation in their quality of life. Non-invasive brain-computer interfaces (BCI) can restore communication by allowing direct translation of electric, magnetic, or metabolic brain signals into control commands of external devices [2]. The P300 speller is a common BCI communication system that works by presenting stimuli to produce an evoked response that can be used to type [3].

The conventional P300 Speller interface has characters organized alphabetically and stimuli group characters either based on this organization (e.g., row/column flashing) or pseudorandomly (e.g., checkerboard paradigm). When using dynamic stopping, however, typing speed can be increased by presenting higher probability characters earlier. Also, by forcing characters that appear in similar contexts to flash separately, we can more easily distinguish between these characters, reducing the chance of making errors. We propose a virtual diagonal flashboard design as shown in Figure 1. At the beginning of each new character, prior probabilities are determined using a language model and high probability characters are aligned diagonally so that they do not share a row or column. Flashing groups are chosen based on rows and columns of this virtual flashboard so no two high probability characters are ever flashed together, making them easier to distinguish. When combined with word prediction techniques, performance is shown to be far superior to classical schemes.

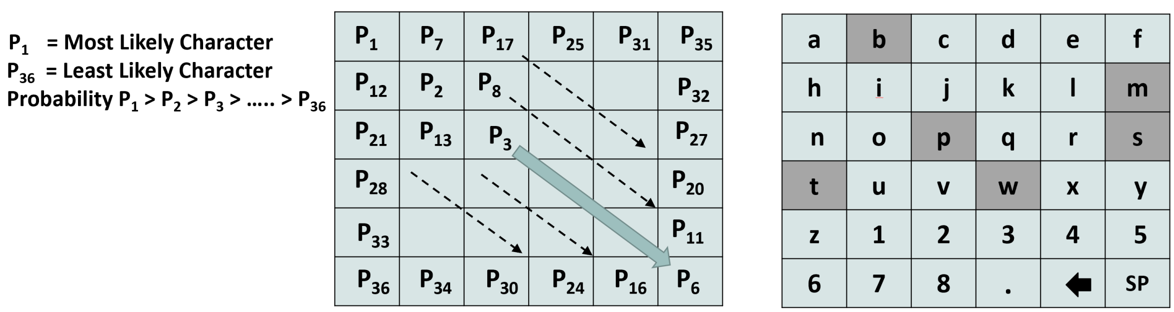

Fig. 1: Diagonal virtual flashboard design and highlighting of virtual flashboard characters on a static flashboard

Material, Methods and Results: Multiple levels of language models are fused by smoothing algorithms which allow for out-of-vocabulary character probability prediction. Full word predictions based on partial words is also performed using Djikstra's algorithm as a form of predictive spelling. Simulations using random sampling of real EEG subject responses are performed using the text of the "Declaration of Independence" as a target string. Using the proposed method, the average ITR across subjects improved from 63.17±4.78 bits/min to 70.72±4.5 bits/min. The manual error correction rate (using backspace) also decreased from 2.6% to 1.9%.

Discussion EEG lab results were collected from 48 subjects and was used in long simulations evaluating performance through the Information Transfer Rate (ITR). Results demonstrate that probabilistic highlighting on a diagonal along with effective word prediction provide major improvements over static flashboards.

Significance Using multi-level language models and smoothing techniques, this paper shows how conventional P300 spellers can be vastly improved with probabilistic ordering using virtual flashboards.

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Investigation of Graded Event-Related Desynchronization of the Sensorimotor Rhythm for BCI Applications

C. Haddix[1] and S. Sunderam[1*]

[1]F. Joseph Halcomb III, MD Department of Biomedical Engineering, University of Kentucky, Lexington, KY, USA

[*]522 RMB, 143 Graham Ave, Lexington, Kentucky 40506, USA. E-mail: ssu223@uky.edu

Introduction: Brain-computer interfaces (BCIs) are limited in performance by the need to elicit and discriminate between brain signals associated with multiple distinct mental tasks to control an external device. We seek to alleviate this problem by using the degree of effort in a single task – isometric handgrip – extracted from the electroencephalogram (EEG) as a scalable control signal. A model of graded event-related desynchronization (ERD) of the sensorimotor rhythm (SMR) could bridge the gap between intent and fine control and play a vital role in protocols aimed at recovery of function

Material, Methods and Results: Fourteen healthy human subjects (9 male, 5 female) participated in an IRB-approved study with informed consent in which they responded to cues by squeezing a hand dynamometer to different levels of predetermined force, guided by continuous visual force feedback. The ERD was calculated from the EEG in 14 locations over sensorimotor cortex and modeled to predict exerted force. Using a linear discriminant classifier trained offline on the ERD vector for five distinct grip force targets, mean classification accuracies across subjects of 53% and 55% were obtained for the dominant and non-dominant hand, respectively.

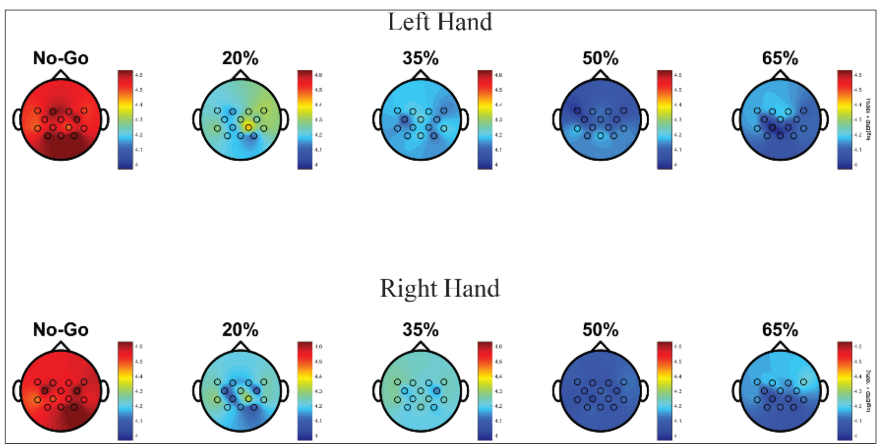

Figure 1. Grand median log scaled ERD values across all subjects (n = 14) for the five conditions. During No-Go, subjects remained at rest, which resulted in minimal ERD. The target forces expressed as a percentages of their maximum voluntary contraction (MVC). ERD appears to broaden and peak at 50% MVC.

Discussion: In this study, we found that modulation of the SMR of the electroencephalogram (EEG) is separable for different degrees of motor effort. Future work will investigate ERD gradation in the pre-movement period and in individuals with hemiparetic stroke.

Significance: Measurable changes in brain activity during a graded task can serve as commands that bridge the gap between intent and fine control and thereby play a vital role in therapeutic protocols aimed at recovery of function.

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Detecting mental workload from fNIRS signals using a simulated project planning task

Liucija Svinkunaite[1*], Frauke von der Haar[1], Marianne J. Floor-Westerdijk[1], Jörn M. Horschig[1]
[1]*Artinis Medical Systems B.V., Elst, The Netherlands*

* 6662 PW, Einsteinweg 17, Elst. E-mail: liucija@artinis.com

Introduction: Passive Brain-Computer Interface (pBCI) refers to monitoring cognitive or emotional states of a user interacting with the environment [1]. In daily workplace surroundings, a pBCI could assist in identifying sub-optimal workload and providing interventions leading to improved efficiency and general well-being. Functional Near-Infrared Spectroscopy (fNIRS) is one of the techniques suitable for detecting brain activation changes induced by different task demands [2, 3]. Mental workload is commonly investigated in the context of laboratory tasks, e.g., n-back [4], Stroop tasks [5] or domain-specific activities, e.g., piloting [6] and driving [7]. The former might fail to provide an ecologically valid representation of the everyday work while the latter is only applicable to a sample with a certain set of skills. In this study, we aimed to demonstrate the feasibility of detecting changes in mental workload using domain non-specific, ecologically more valid task.

Material, Methods and Results: We developed a task resembling project planning activities. In each experimental trial, a panel with available resources was presented. The participants were asked to distribute the available resources according to three requirements: deadline, workload and necessity of resources. The tasks had limited solutions. Participants had 35 seconds to solve each task. Subjective ratings after the task presentation were collected using a NASA-TLX questionnaire [8]. The activation changes in the prefrontal cortex were measured using a portable fNIRS system. After the pre-processing, we applied machine learning algorithms to achieve reliable detection of mental workload.

Discussion: In this study, we demonstrated the feasibility of using fNIRS for detecting different engagement levels in a task resembling common workplace activities.

Significance: The study is a step towards bridging the gap between simplified, highly controlled laboratory tasks and uncontrolled real-world settings.

Acknowledgements: This work has been supported by the research grant (PROJ-00900) under the Operational Programme European Regional Development Fund (OP ERDF) of the European Union.

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Movement-Related Cortical Potential during post-stroke motor recovery: preliminary study for a novel hybrid BCI paradigm

F. Pichiorri[1*], V. De Seta[1,2], E. Colamarino[1,2], J. Toppi[1,2], F. Cincotti[1,2], D. Mattia[2]
[1]Neuroelectrical Imaging and Brain-Computer Interface Lab IRCCS, Fondazione Santa Lucia, Rome, Italy; [2]Department of Computer, Control, and Management Engineering, Sapienza University of Rome, Italy
*Via Ardeatina 306, 00179. E-mail: f.pichiorri@hsantalucia.it

Introduction: Movement-Related Cortical Potentials (MRCP) are recorded from the scalp sensorimotor areas during movement execution or attempt (in the case of motor impairment eg. after stroke). Here, we present preliminary results on MRCP characteristics in subacute stroke patients who underwent motor rehabilitation including a motor imagery (MI) training as in [1] with the aim of addressing the design of a novel hybrid Brain-Computer Interface (BCI) that would exploit relevant information encoded by different EEG-derived motor-related phenomena (eg. Event Related Desynchronization, ERD and MRCP) together with muscular activation.

Material, Methods and Results: EEG (61 channels) and EMG (1 bipolar channel on extensor digitorum muscle) data were collected from 7 subacute stroke patients. EEG and EMG recordings were obtained before (PRE) and after (POST) one-month of motor rehabilitation which included imagery (MI) training as in [1], during attempted (with the affected hand; AH) and executed (with unaffected hand; UH) finger extension. EEG data were pre-processed (band-pass filter [0.1-1]Hz, common average reference) and segmented in [0-7]s windows. MRCP amplitude (Fig. 1a) was extracted from artifacts-free trials aligned to the EMG onset and averaged for each patient. All patients displayed a significant POST-training improvement in the Fugl-Meyer Assessment (FMA) clinical scale (n=7 patients; p=0.018). Statistical analysis (Wilcoxon matched pairs test) revealed a significantly smaller MRCP peak amplitude (over the hemisphere contralateral to the movement) for AH condition as compared with UH in PRE session, Fig. 1; such difference was no longer present during POST session; a significant difference in the MRCP peak amplitude was seen only for AH condition over the ipsilesional hemisphere between sessions (PREvsPOST; Fig.1b).

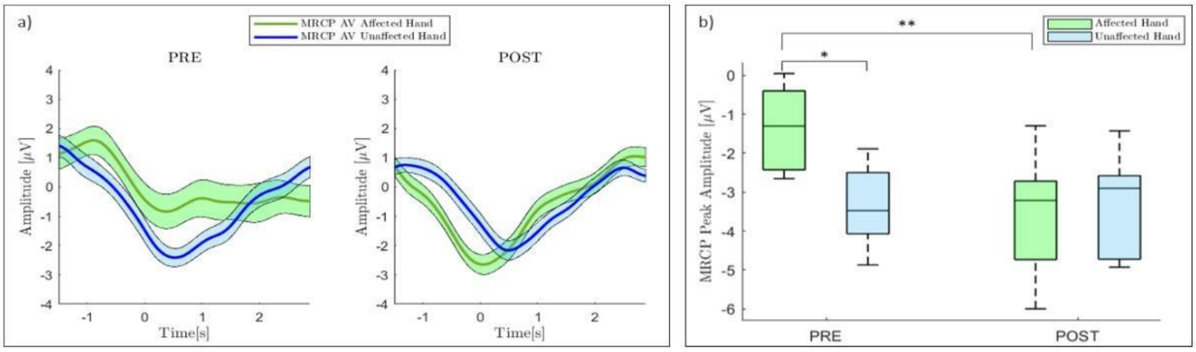

***Figure 1.** a) Grand average MRCPs (± SE) estimated over C1 and C2 electrodes for AH and UH conditions respectively and PRE-POST training. EEG data were flipped (lesioned hemisphere on the left – C1); b) Boxplot of MRCP Peak Amplitude for both AH and UH conditions in PRE and POST sessions (*p=0.028,**p=0.042).*

Discussion: Our findings indicate that ipsilesional MRCP amplitude elicited during AH turned into "more" physiological range (no asymmetry between AH and UH conditions at POST) after one month of rehabilitation. This preliminary evaluation provides hints on which MRCP characteristics encode cortical motor-related changes underlying favorable motor recovery in subacute stroke patients. Our ultimate goal is to implement such characteristics in a novel hybrid BCI paradigm which includes different motor-related signals from the brain (EEG) and the periphery (EMG).

Significance: MRCPs could probe functional motor recovery after stroke [2] and thus, encode relevant information for the implementation of a hybrid BCI system aiming at re-establishing a close-to-normal brain and muscular activity.

Acknowledgements: This work is partially supported by the Italian Ministry of Health (GR-2018-12365874, RF-2018-12365210).

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BCI-assisted Motor Imagery training to promote functional recovery in cervical Spinal Cord Injury patients: preliminary data

E. Colamarino[1,2*], F. Pichiorri[2], M. Masciullo[3], F. Tamburella[3], I. Pisotta[3], G. Scivoletto[3], M. Molinari[3], F. Cincotti[1,2], D. Mattia[2]

[1] *Department of Computer, Control, and Management Engineering Antonio Ruberti, Sapienza, University of Rome, Italy;*
[2] *Neuroelectrical Imaging and Brain-Computer Interface Lab, Fondazione Santa Lucia IRCCS, Rome, Italy*
[3] *Spinal Cord Unit, Fondazione Santa Lucia IRCCS, Rome, Italy*
* Via Ariosto 25, 00185 Rome (Italy), E-mail: emma.colamarino@uniroma1.it

Introduction: Brain-Computer Interface (BCI)-assisted Motor Imagery (MI) training has been validated as an effective intervention to promote brain plasticity, leading to an improvement of hand motor function in subacute stroke patients [1]. Since evidence for structural and functional reorganization of the brain have been observed after Spinal Cord Injury (SCI) [2] suggesting their potential role in promoting functional sensorimotor recovery, the use of BCI technology has been recently explored in chronic SCI patients [3]. Preliminary findings of the transfer of the BCI-driven MI training [1] to the rehabilitation path of cervical SCI patients are presented.

Material, Methods and Results: Eight subacute cervical SCI patients admitted to the Spinal Cord Unit of the Fondazione Santa Lucia underwent BCI-supported MI with the Promotoer (Fig. 1, panel a). All patients were trained to perform bilateral MI of hand movements (grasping and finger extension). Patients' neurophysiological and clinical evaluation was performed PRE and POST - BCI training. Electroencephalographic (EEG) data were collected from 31 electrodes placed over the central and parietal areas of the scalp, according to an extension of the 10-20 International System, and sampled at 200 Hz. Data were notch filtered (50 Hz), re-referenced to the common average reference and divided into 1s long epochs. Spectral features were extracted using the Maximum Entropy Method (16th order model, 2 Hz resolution, no overlap). For each feature, the R-square index was computed to statistically compare spectral features between task and rest conditions. As shown in Fig.1 panel b, the POST-training group statistical map revealed a stronger bilateral desynchronization over the centro-parietal areas during MI tasks. For the clinical assessment, performed with Upper Extremity Motor Score (UEMS) of the International Standards for Neurological Classification of Spinal Cord Injury (ISNCSCI) and Graded Redefined Assessment of Strength, Sensibility and Prehension (GRASSP), the Wilcoxon matched pairs test for bilateral UEMS showed significant improvement ($p<0.01$), as well as all GRASSP subscores ($p<0.01$).

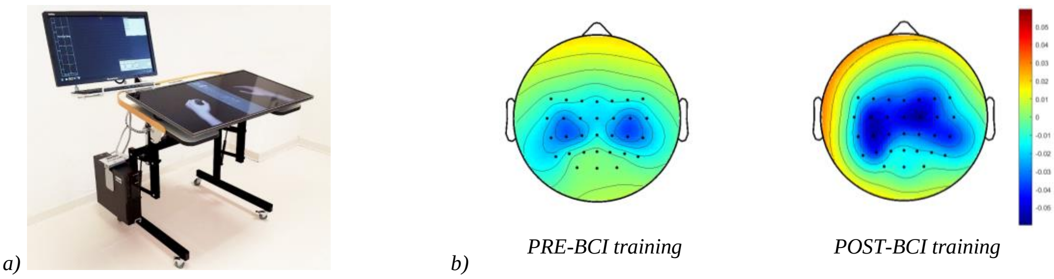

***Figure 1**. Panel a) The Promotoer, i.e. the BCI-supported Motor Imagery (MI) training station currently available at Fondazione Santa Lucia. Panel b) Neurophysiological assessment results presented as group (N=8) statistical maps of R-square values, rest vs bilateral hand MI, PRE - left side- and POST - right side- BCI training sessions (15 ± 5 sessions). Positive (negative) values of R-square reveal the increase (decrease) of the spectral power of the EEG signal during MI. Statistical maps, evaluated at 11 Hz (mean frequency across subjects of the BCI control features), revealed a stronger bilateral desynchronization during the MI task after the BCI training over the centro-parietal areas.*

Discussion: BCI-assisted MI training led to a reinforcement of MI-associated EEG patterns. We will assess the impact of such intervention on upper limb sensorimotor functional recovery in cervical SCI patients in the framework of an ongoing registered randomized controlled trial.

Significance: This work provides the basis to optimize the BCI application in SCI as a *top-down* therapeutic intervention for the upper limb sensorimotor recovery beyond the canonical BCI use for the neuroprosthetic control.

Acknowledgements: This work was partially supported by Ricerca Corrente from the Italian Ministry of Health (RF-2018-12365210, RF-2019-12369396).

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Short Distance Channel Validation: Recommendations for (Online) Systemic Activity Correction Methods in fNIRS.

F. Klein[1,2*], A. Benitez-Andonegui[3], M. Lührs[3,4], P. Roehn[1], C. Kranczioch[1,2]

[1]Neurocognition and Functional Neurorehabilitation Group, Carl von Ossietzky University of Oldenburg; [2]Neuropsychology Lab, Carl von Ossietzky University of Oldenburg; [3]Faculty of Psychology and Neuroscience, Maastricht University; [4]Brain Innovation B.V., Maastricht, The Netherlands

*Oldenburg, Germany. E-Mail: franziska.klein@uol.de

Introduction Functional Near Infrared Spectroscopy (fNIRS) is a promising tool for BCI and neurofeedback applications. Especially for clinical populations it is an eligible choice because it has good spatial specificity and is relatively robust to gross motion. Moreover, it is comparably cheap, and mobile versions are available. However, in terms of preprocessing standards, fNIRS lags way behind well-established methods like EEG or fMRI. An extensive problem in fNIRS signal processing is its contamination with evoked systemic cerebral and extracerebral hemodynamic activity (in short: systemic activity, SA). This contamination results from the fact that on its way from source to detector, the transmitted near-infrared light does not only penetrate the cortical brain tissue but also passes through highly vascularized extracerebral layers (i.e., scalp and skull tissue). SA frequency overlaps with the task frequency, it is not constantly distributed over the head, and its strength varies between channels and tasks within and across subjects. For these reasons, conventional temporal filters fall short of removing SA from the data. This is a general problem, but even more so for BCI and neurofeedback, where insufficient correction of artefacts means running the setup on noise instead of brain activity.

Short distance channels (SDCs) are the favorable method for SA removal. With a source-detector distance of <1cm, a SDC measures only the SA and can be used to correct the data for systemic contributions.

So far, SDC correction is rarely performed. This might be due to restricted awareness of the problem, but more likely to limited access to the necessary hardware. However, if SDCs are not available, alternative approaches to SA correction exist. One such approach is called global component removal (GCR) [1, 2], a spatial filter combining Gaussian kernel smoothing and singular value decomposition [1]. In a recent study [2] we showed that GCR significantly improved single trial data quality in terms of spatial specificity and temporal consistency as compared to conventional temporal filters alone. Other alternatives that are particularly suitable for online implementations include common average referencing (CAR) [3] and baseline principal component analysis (PCA) [4]. Data on how these approaches perform on single trial data compared to SDC correction have not been published so far.

Material, Methods & Results We compare the SA correction algorithms GCR, CAR and PCA with the outcome of the SDC correction methods simple regression, global GLM filter and local GLM filter. The analysis is based on a neurofeedback data set collected from N = 26 elderly subjects (58-71 years) performing two blocks of motor execution, separated by two blocks of each, motor imagery with[1] and without neurofeedback. The optodes (8 sources, 8 detectors and 8 short distance detectors) covered bilaterally M1 and SMA areas. Preliminary analysis of SDC corrected concentration changes indicated an effect of neurofeedback on Δ[HbR], but not Δ[HbO]. Further analyses will investigate the stability of this finding across GCR, CAR, and PCA as well as the three SCR approaches. Moreover, for all methods, offline single trial data quality will be considered in terms of spatial specificity, temporal consistency and classification assessments (e.g., accuracies, ROC, AUC) of a 2-class (left vs. right hand) classifier.

Significance This study will validate selected SA correction algorithms designed for use without SDC with corrections based on SDC. Based on the results, recommendations will be deducted regarding correction algorithms with and without SDCs. This will make an important contribution to the field of fNIRS-based BCI and neurofeedback, but also more generally to the ongoing efforts to define standards for fNIRS data processing.

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Interbrain Synchrony and the Prisoner's Dilemma Game: An Approach to Social Anxiety

Marcia Saul[1*], Xun He[1], Stuart Black[2], Fred Charles[1]

[1]Bournemouth University, Poole, United Kingdom [2]BrainTrainUK, Farnborough, United Kingdom

* E-mail: msaul@bournemouth.ac.uk

Introduction: Interbrain synchrony (IBS) has been increasingly studied in accordance with the conceptual development of two-person neuroscience, which views neural activities from interacting individuals as a single functional unit [1]. IBS is usually found to be stronger in collaborative than non-collaborative interactions. However, this approach has not been employed in social anxiety (SA) research. The current study investigated the relationship between IBS and SA using a prisoner's dilemma game [2] with a focus on the frontal lobe.

Materials, Methods & Results: Seven healthy participant pairs (4 males and 10 females; mean age 25.36) who did not know each other prior to the experiment participated in 20 rounds of a prisoner's dilemma game with EEG being recorded at 64 locations on each head. The game was defined as *splitting* or *stealing* lottery tickets from the respective other player. After the game, each round was labelled *co-operative* (if both participants split) or *defective* (if one or both participants stole), with the intervals between rounds as a baseline. SA trait scores were taken before and after the game using the Liebowitz Social Anxiety Scale (LSAS) and state scores were taken after each round. EEG data was FIR filtered and Hilbert-transformed for each frequency band (θ: 3-7 Hz, α: 8-12 Hz, β: 13-29 Hz, γ: 30-40 Hz). Phase-locking values (PLVs) [3] were computed for each interbrain channel combination (from 26 frontal channels per head) and statistically assessed using Kruskal-Wallis tests with Bonferroni correction. Higher IBS was found for both co-operative and defective conditions vs. the baseline (> 99% combinations, $p < 4.88e^{-06}$). The co-operative rounds also showed higher IBS than the defective rounds (> 80% combinations, $p < .001$). However, no state or trait SA scores could predict the PLVs (Spearman's correlations: ps > .08).

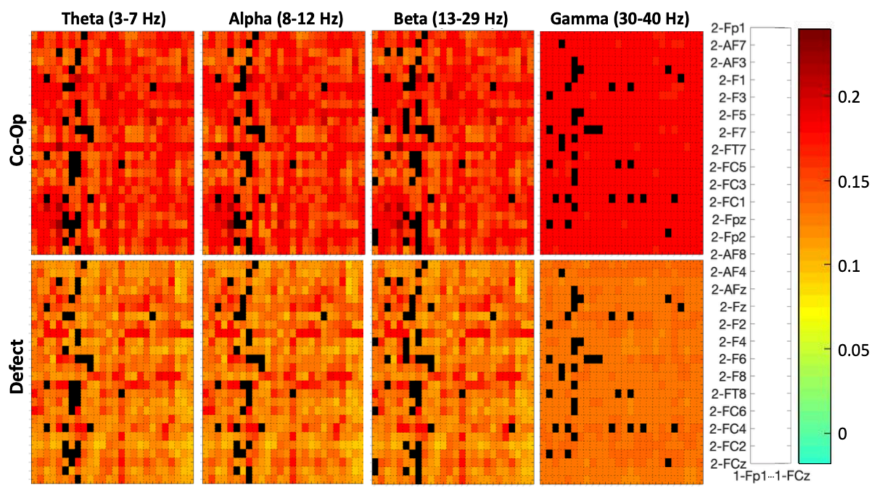

Figure 1. Mean PLVs in the co-operative and defective conditions (statistically assessed against the baseline) across frontal channel combinations. Higher PLVs are observed in the co-operative than the defective conditions. Black pixels indicate non-significant PLVs from the baseline.

Discussion: Co-operation has been associated with the alleviation of SA [4]. In this experiment, significantly greater IBS was present interpersonally over the frontal channels when the participants co-operated than when they defected. Significant interpersonal interaction was also revealed in higher PLVs in both conditions against the baseline. However, no relationship was found between the SA scores (both state and trait) and the IBS. This suggests the lack of power in predicting interbrain connectome with SA scores in the current dataset and demands further research.

Significance: In sight of the very limited research incorporating both SA and IBS, the current study made an early attempt to investigate (interpersonal) SA within the two-person neuroscience framework. Future research will increase statistical power and incorporate channels from other scalp regions.

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Application of composite CSP to enhance motor imagery classification accuracy while reducing training time

A. Esposito[1,2*], P. Arpaia[2,3], E. De Benedetto[2,3], M. Imbò[2,3], N. Moccaldi[2,3], M. Parvis[1]
[1]Politecnico di Torino, Turin, Italy; [2]Augmented Reality for Health Monitoring laboratory (ARHeMlab), Naples, Italy; [3]Università degli Studi di Napoli Federico II, Naples, Italy;

* E-mail: antonio.esposito@polito.it

Introduction: The performance of a brain-computer interface can be enhanced with the application of transfer learning. Especially for motor imagery, the accuracy in classifying brain signals can improve while reducing the long training time required for a new user [1]. To this aim, one exploits the brain activity information shared among different users to increase the amount of available data. This shortens system calibration and hence reduces the stress for the BCI user. The present work considers features extraction from brain signals with "common spatial pattern" (CSP), notably merging the EEG data from a new user with the data of other users through a linear combination. This approach is known in literature as "composite CSP".

Material, Methods and Results: Composite CSP is an improvement of the well-known CSP features extractor. Indeed, the spatial projection of CSP are derived from the covariance of multi-channel EEG data. In composite CSP, the EEG covariance matrix of the new user is linearly combined with the covariance matrix of all other users taken as a whole. The sum of these two matrices is weighted multiplying by λ and (1- λ), respectively [2]. The regularization parameter λ is chosen with cross-validation. The implementation of composite CSP within a "filter-bank common spatial pattern" approach was validated on three different datasets: the dataset 2a from BCI competition IV, the dataset 3a from BCI competition III, and a dataset with 52 healthy subjects from GigaScience. Classification was conducted with a support vector machine (SVM), and the mean classification accuracies before applying transfer learning were 73%, 72%, and 60% respectively. In all three cases, 40% of the new user's data was used for training together with data from other subjects, while the remaining data (60%) was used for testing. This data imbalance aimed to demonstrate that a shorter system calibration is feasible for a new user. As a result, the mean classification accuracies increased with respect to the use of CSP without transfer learning: on the datasets 2a the increase was 2%, on dataset 3a it was 5%, and on the GigaScience dataset the increase equaled 4%.

Discussion: Although an accuracy increase was obtained in all three cases, only the improvement on the GigaScience dataset was statistically significant (p-value: 0.022). This would indicate that the composite CSP is more effective when the starting accuracy is low, and indeed, in such a situation, performance increase is mostly needed. On the other hand, subjects from BCI competition were a few (12 in total) if compared to the GigaScience ones, and this also affects the results significance.

Significance: The results reported above justify the usefulness of composite CSP in increasing accuracy and diminishing calibration time. However, more work is needed to extend the transfer learning beyond the CSP features extraction, so to also consider the other processing steps. It is foreseen that applying transfer learning to the classifier training would still increase the performance.

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Predicting Postoperative Delirium Using Riemannian Geometry on Intraoperative Frontal EEG Data

Vera Röhr [1*], Susanne Koch [2], Claudia Spies [2], Benjamin Blankertz [1]

[1] Neurotechnology, Technische Universität Berlin, Berlin, Germany; [2] Anesthesiology, Charité Berlin, Berlin, Germany;

[*] Sekr. MAR 4-3, Marchstr. 23, 10587 Berlin; E-mail: v.roehr@tu-berlin.de

Introduction Postoperative delirium (POD) is the most frequent cerebral dysfunction after general anesthesia in elderly patients, leading to adverse longterm complications as increased mortality, prolonged hospital stay and persisting cognitive impairments [1]. Intraoperative EEG guided anesthesia has been recommended to reduce POD incidence, by avoiding deep stages of anesthesia, as burst suppression activity [2]. However POD is often overlooked, due to the hypoactive clinical aspect [3]. We therefore propose a data-based approach to evaluate the risk of a POD, using intraoperative frontal EEG data. This would allow for appropriate measures to be taken already during or directly after the general anesthesia.

Material, Methods and Results We extracted and re-analyzed the raw EEG data set of a randomized, singel-center study done 2009- 2010 at the Charité-Universtätsmedizin Berlin, Department of Anesthesiology and surgical Intensive Care Medicine [4], registered at ISRCTN 36437985. Frontal 4-channel EEG was recorded with the BIS Monitor (Covidien / Medtronic, Minneapolis / USA) from the start of anesthesia until extubation of the patient, with a mean duration of general anesthesia of 168 ± 101min. In total 1277 patients were included, of which 219 developed POD. The cross-subject classifier presented here, uses the covariance matrices calculated from the filtered operation data as a representation for each patient. The covariance matrices are then grouped using the time frame of the operation and their geometric mean is calculated. We use the framework proposed in [5] and train various classifiers on the corresponding tangent space of the Riemannian manifold of positive definite matrices. If we only consider the raw EEG data, we achieve at least 60% accuracy in cross-validation on a balanced data set. The alpha band and delta band are particularly important for the classification. How these results are improved by including clinical data into the classification, will also be presented.

Discussion Classification of EEG data based on Riemannian geometry of covariance matrices substantially improves performance compared to other state-of-the-art methods on this clinical EEG data. Combining that knowledge with other clinical data and further improving the machine learning techniques used on the tangent space, might bring us one step closer to integrating BCI into daily clinical practice.

Significance This study is a further step towards a tool giving an objective evaluation of the risk for a delirium after operations. It is easily applicable, without adding an additional measurement to the operating room, because EEG monitoring is already used during most operations.

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Online SSVEP based Controller using Adaptive Riemannian Geometry

Tushar P. Kendre[1], Tharun K. Reddy[1], Madhur D. Jain[1], Satyam Kumar[2] and Laxmidhar Behera[1]*

[1]*Indian Institute of Technology Kanpur* [2] *The University of Texas, Austin*

*WL-212, Academic Area, IIT Kanpur, UP, India-208016 Email:lbehera@iitk.ac.in

Introduction: Steady State Visually Evoked Potential (SSVEP) signals are naturally generating responses to visual stimulation. The brain generates signals of the same (or harmonics of the same) frequency as that of a flickering visual stimulus. Brain-computer interface (BCI) based on SSVEP has been primarily studied owing to their high classification performance with little training [3]. The goal of this study is to develop an online SSVEP based system to actuate a mobile robot. Our approach reduces the complexity of parameterization and optimization by use of Riemannian geometry [1]. Furthermore, the system also adapts according to the user response.

Materials and Methods and Results: The experiment used single graphics stimuli which are displayed on an LCD screen. Every trial consists of a rest screen followed by a cue and then followed by the stimulus screen on an LCD monitor (Fig. 1). The system is pre-trained using the runs obtained in offline phase and then deployed online for adaptation and robot actuation.

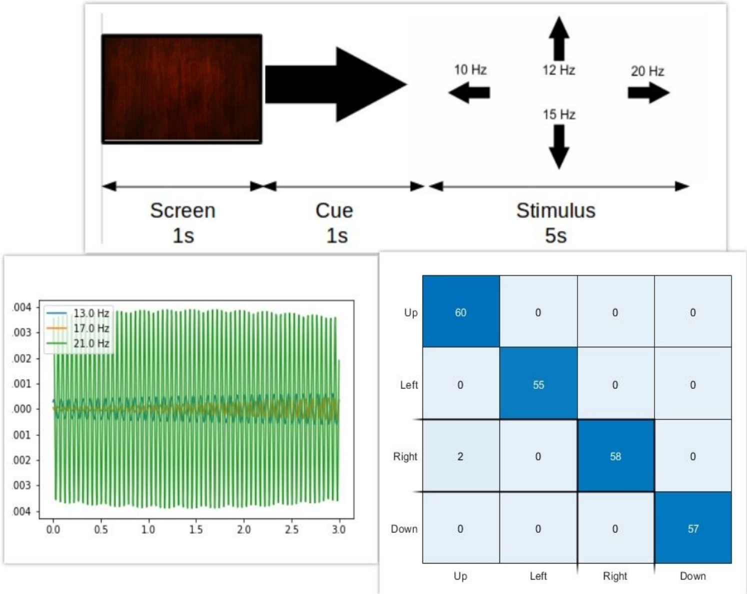

Figure 1: *The timeline of the experiment stimulus, The narrow bandpass filtered signals(as evident, the 21Hz signal is dominant) and the confusion matrix obtained for a subject*

Riemannian methods work on the covariances between classes to evaluate results [1]. As SSVEP signals are not spatially separated corresponding to their location in the brain (compared to motor imagery where they are lateralized), the whole signal is narrow bandpass filtered about the stimulus frequencies. The filtered signals thus generated are concatenated and an extended signal is generated. After this, covariances were extracted and mapped onto the Riemannian manifold [1]. For classification, we use Minimum Distance to Mean(MDM) [2] classifier to predict the results. The whole system was synchronized using Lab Streaming Layer(LSL). During the online operation of the system, the early predictions are made based on the pre-recorded data. As the operation proceeds, new data is added and the classifier is retrained thus, adapting according to the user. The system is tested on two datasets: a) an In-House dataset recorded according to above-mentioned protocol b) Publicly available dataset[4]. The system gave an accuracy of 99.1% on the recorded dataset(as seen in the confusion matrix (Fig 1). To preserve integrity during operation, a few trials were cut off from the start and end of each run. Furthermore, these predicted labels were then exported via LSL on a robot connected to the local network and actuated based on it. The feedback was given to the user via a webcam mounted onto the robot and projecting the picture onto a screen. The 'resting' class is not included from the original research [2], as the robot simulation switch is in control of the user and could be paused anytime the user wanted. The system also showed a good generalization over trials for a subject, as one does not have to record the pretraining runs on different days of conducting the experiment.

Significance: To the best of our knowledge, this is the first study that systematically investigates the impact of adaptive Riemannian learning for SSVEP based mobile robot actuation. The study paves the way to the development of further applications in technology for the disabled.

Discussion: Riemannian approaches have been successfully applied to EEG signals for brain-computer interfaces. Conventional classifiers such as Minimum Distance to Mean provided competitive results with state-of-the-art methods, without requiring meticulous parametrization or optimization. Working on covariance matrices in Riemannian spaces over a broad spectrum of distances embeds desirable invariances. Thus, it has been possible to avoid the computation of user-specific spatial filters which were sensitive to artefacts and outliers. Nonetheless, the estimation of the Riemannian geometric means has had a strong impact on the classifier accuracy.

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Towards Deep Learning in BCI: Automatic labeling of large natural data sets

Anja Meunier[1*], Moritz Grosse-Wentrup[1]

[1] *Research Group Neuroinformatics, University of Vienna, Vienna, Austria*

*Hörlgasse 6/9, 1090 Wien, Austria. E-mail: anja.meunier@univie.ac.at

Introduction: An abundance of data in our digitalized world, together with ever-increasing computational capacities, has brought back neural networks from the AI winter, and led to sharp increases in performance in many decade-old problems. In the BCI field, data is still scarce due to traditional set-ups with randomized individual trials, which severely restricts the number of data points obtained per session and thus limits the power of complex deep learning architectures. One remedy for this data scarcity is moving to continuous natural real-world stimuli, which in turn poses the challenge of efficient data labeling. Herff et al. [1] have used a traditional speech recognition pipeline for this task. In our approach, we use the end-to-end deep neural network DeepSpeech [2] to automatically label large amounts of EEG data during perception of natural speech, resulting in almost 400.000 labeled data points per subject.

Material, Methods and Results: In our experiment, we recorded the neural activity of four healthy subjects with 126 EEG-channels (Brain Products EasyCap, Bittium NeurOne Tesla amplifier) at a rate of 1000 Hz in four sessions each. Sessions began with a 10 minute resting state recording (5 minutes eyes open/closed), followed by six blocks of approx. 15 minutes listening to an audio book with closed eyes, separated by short breaks and followed by another 5 minute resting state recording (eyes closed). Participants were asked to relax and focus on the story, and answered a question about each preceding block during breaks to encourage paying attention. We thus recorded 6 hours of data per subject during the listening task. To account for any inaccuracies in playback speed, we simultaneously recorded the presented audio via a bipolar channel of the amplifier. The original audio was down sampled to 1000 Hz and aligned with the recorded audio channel by maximizing their cross-correlation for snippets of 2 seconds.

The original text corresponding to the 6 hour audio book contains 294.938 characters (including spaces, excluding punctuation), which makes the labeling by hand infeasible. In our approach, we automated labeling by making use of the open source deep neural network DeepSpeech [2] for speech recognition, trained on 7.380 hours of transcribed audio. We modified the system to directly output characters (a – z, space and ' or unknown, represented as #) for every 20 ms window, instead of passing decoded sequences to a language model, and fed the audio stimulus presented to the subjects to the DeepSpeech network [2]. We thereby obtained 399.801 labeled windows (excluding #) per subject, an even larger number than characters in the original text, since many characters are repeated more than once, when their utterance spans several windows (see Figure 1).

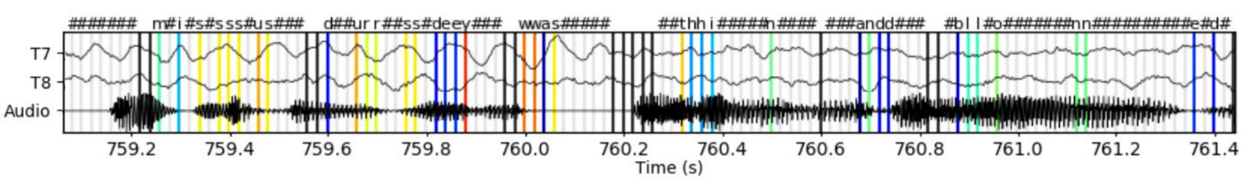

Figure 1. *EEG channels T7 and T8 and audio stimulation channel, including character labels (# for unknown) and colors.*

Discussion: The presented method makes automatic labeling of large natural data sets possible and thus opens up new possibilities in the use of complex models such as deep learning. The use of an AI system for labeling does however introduce label noise into the dataset. As shown in Figure 1, the decoded characters do not always correspond exactly to the original written text, and slight shifts between utterance (audio channel) and character labels can be observed. The impact of these aspects on model training remains to be evaluated. Another drawback of this approach is the fact, that character distributions in natural language are not i.i.d. and classes are highly imbalanced, which needs to be taken into account when making statistical inferences based on this data.

Significance: As the interest in non-traditional paradigms such as speech decoding grows, the need for larger training sets in BCI will only increase further. We have shown that labeling training data with existing AI systems is possible. In addition, our method is not restricted to listening tasks, but can readily be used for speech, and even multi-speaker settings. With this, we hope to further promote the use of data intensive methods such as deep learning in BCI.

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Reliable outlier detection by spectral clustering on Riemannian manifold of EEG covariance matrix

Maria Sayu Yamamoto[1,2*], Khadijeh Sadatnejad[1], Md. Rabiul Islam[2], Fabien Lotte[1]
Toshihisa Tanaka[2]

[1] *Inria Bordeaux Sud-Ouest, Talence, France;* [2] *Tokyo University of Agriculture and Technology, Koganei-shi, Japan*
*200 avenue de la Vieille Tour, 33405 Talence cedex, France. E-mail: yamamoto18@sip.tuat.ac.jp

Introduction: Automatically identifying and rejecting artifact-contaminated trials is a key problem to design robust BCIs. Here, we propose a novel outlier detection method based on Riemannian Geometry (RG), a promising approach for BCI classification [1]. With RG, EEG signals are represented and processed as Sample Covariance Matrix (SCM), which is also known to reduce EEG artifacts influence. State-of-the-art outlier detection methods in RG include *Riemannian Potato* (RP) [2] and *Median-Based Trimming* (MBT) [3]. However, both suffer from the need of a threshold to determine outliers, and both always reject some samples as outliers, even when there is none. Thus, we propose *Riemannian Spectral Clustering* (RiSC), to detect outliers by clustering SCMs into non-outliers and outliers by similarity, without thresholds.

Material, Methods and Results: First, RiSC computes the graph of SCMs similarities using the Riemannian distance between SCMs. Then, the graph nodes are clustered using spectral clustering [4], and all clusters except the most numerous one are rejected as outliers. We compared the classification accuracy of a *Minimum Distance to Mean* classifier [1] without outlier rejection (baseline) and after rejecting outliers from each class training data using RP, MBT and RiSC. We used EEG signals from 78 subjects from [5, 6], who performed right or left-hand motor imagery. The first two runs were used for training and the remaining runs for testing. Results showed no significant differences between methods (repeated measure ANOVA, $p = 0.093$). Mean classification accuracy (%) was 59.5±10.2, 59.8±10.1, 59.4±9.99 and 59.5±10.1 for the baseline, RiSC, RP and MBT respectively. RiSC did not detect any outlier for most (68 out of 78) subjects. However, when it removed outliers, this increased accuracy for all but one subject (mean gain: 2.39 ± 2.24 %). On the other hand, RP and MBT detected outliers in all subjects, but this decreased accuracy for 46 and 34 out of 78 subjects respectively.

Discussion: RiSC did not detect outlier for most subjects, which may suggest EEG contamination was already reduced using SCM. Thus, RiSC might be useful on more contaminated data. Contrary to RP and MBT, RiSC did not inadvertently reduce accuracy by rejecting clean data as outliers.
Significance: Describing EEG as SCMs and detecting their outliers by spectral clustering seem to be a robust method that usually does not lead to inadvertent decrease in classification accuracy.

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Improved decoding of intended gaze from lateral prefrontal cortex using deep neural networks

A. Rouzitalab[1,2*], C.B. Boulay[1,2], M. Leavitt[3], J. Martinez-Trujillo[4], A.J. Sachs[1,2]

[1]Ottawa Hospital Research Institute, Ottawa, Canada; [2]University of Ottawa, Ottawa, Canada; [3]McGill University, Montreal, Canada; [4]Robarts Research Institute, University of Western Ontario, London, Canada

*725 Parkdale Ave., Ottawa, Ontario, Canada. E-mail: arouz097@uottawa.ca

Introduction: Neurons in the lateral prefrontal cortex (LPFC) encode sensory and cognitive signals, as well as commands for goal directed actions. This brain region might be a good signal source for a cognitive brain-computer interface (BCI) that decodes the intended goal of a motor action previous to its execution. Recent work has demonstrated performance gains using deep artificial neural networks to decode movement intentions from motor cortex. In this work we examine if deep learning is similarly applicable to decoding of intended gaze targets from pre-saccadic LPFC neuronal activity.

Material, Methods and Results: We recorded neuronal spiking activity from microelectrode arrays implanted in area 8A of the LPFC of two adult macaques while they made visually guided saccades to one of a pair of presented targets. The rewarded target was indicated by a transient colour cue and we changed periodically the association between colour and rewarded direction. In total, four different target pairs and three different colours were used. Analyzed data comprised 4 sessions from monkey JL and 4 sessions from monkey M. Behavioural performance was poor at the onset of each new cue-target rule; analyzed data are limited to trials with demonstrated high-performance running d' > 1.0).
Threshold crossing events were convolved with an alpha kernel, low-pass filtered, and decimated to 100 Hz. Trial segments were extracted from -0.25 s to +1.45 s after target onset, terminating at least 0.08 s before saccade onset. Baseline classification accuracy was evaluated using within-session 10-fold cross-validated support vector machines (SVM). Chance accuracy was 41.1 ± 2.9% with pre-target data only and 50.2 ± 2.8% with data including the target period, but before the colour cue. Classification of the full segment including the cue period and delay period yielded 67.4 ± 3.7% accuracy. We next tested a deep artificial neural network which includes layers similar to EEGNet [1] with additional recursive neural network (RNN) layers. Our model comprised blocks for time-axis convolution, channel-axis convolution, recursive time-axis signal processing, a bottleneck layer, and finally a softmax classifying layer. Average within-session improvement over SVM was 22.6 ± 2.3%, with a minimum improvement of 14.6% and a maximum improvement of 34.1% across all sessions. Random forests and regularized linear regression were also added to comparison (Figure 1). Principal component analysis (PCA) and t-distributer stochastic embedding (t-SNE) methods show the low-dimensional projections of the input signal compared to the RNN layer output in figure 1. The projections of input signal showed the 4 different target pairs, but the model separates the pairs into 8 targets before passing the outputs to the bottleneck and classifier layers.

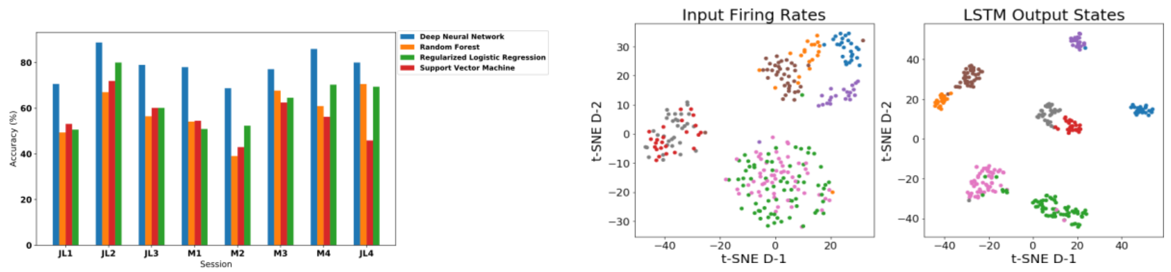

Figure 1. Left panel: Classification accuracies across all sessions compared between 4 methods. Right panels: Low dimensional projections of activations from input signal and RNN layer outputs.

Discussion: Our previous efforts to decode intended saccade targets from LPFC with shallow machine-learning methods yielded classification accuracies that were better than chance yet did not cross the threshold for acceptable BCI performance (i.e., < 70%). Here, using a deep neural model, classification accuracy was greatly improved. Crucially, all sessions were improved compared to previous methods. Moreover, only one session did not cross the 70% accuracy threshold missing with 1.25% margin, still improving 17.2% over the best compared method. These results suggest that the LPFC may be a good signal source for a BCI that decodes intention, even in the absence of reliable eye movements.

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Move Apart: A Geometrical Learning Approach for Training of Motor Imagery

Satyam Kumar[1], Hussein Alawieh[1], J. del R Millán[1]

[1]The University of Texas at Austin, TX, USA

*2501 Speedway avenue, Austin, Texas, United States of America. E-mail: satyam.kumar@utexas.edu

Introduction: Motor imagery (MI) is one of the most popular modalities used for controlling Brain-Computer Interfaces (BCIs) in applications ranging from neurorehabilitation to assistive devices. However, training a subject for producing stable and discriminable motor imagery patterns is a challenging task. Recently, new frameworks are being designed to balance the need for adaptation of the used computational models with the training requirements of subjects in order to promote the learning of robust MI [1]. Moreover, longitudinal training of subjects on MI proved to be effective in producing discriminable patterns even in an out-of-the lab real-life competitive scenario [2]. Nevertheless, previous studies addressed this mutual learning problem as a trade-off between subject and machine learning. Here, we explored the possibility of designing machine learning methods that facilitate subject learning. In particular, our approach provides feedback based on a modified feature space designed to increase the discrimination of motor imagery patterns.

Material, Methods, and Results: The Pilot Study was conducted over 4 subjects using two different methods, a) the classic protocol, b) the proposed framework. In each method, 4 online sessions were conducted after an initial calibration session. We used real time online rebiased riemannian geometry classification framework [3]. In the classic protocol (*baseline*), we trained a minimum distance to mean (MDM) classifier on the covariance features from offline data, which was further used to provide feedback using a moving bar in all the following online sessions of corresponding methods. In the proposed framework (*Shifted*), we shifted the feature distributions by 15% of riemannian distance between class covariances along the geodesic connecting the class-wise covariances, so as to increase the distance between the two class prototypes, followed by training of an MDM classifier on the shifted data. To assess the motor imagery performance by the subjects, we used the riemannian distance between the class-prototypes and the kappa value of each online session (Fig. 1).

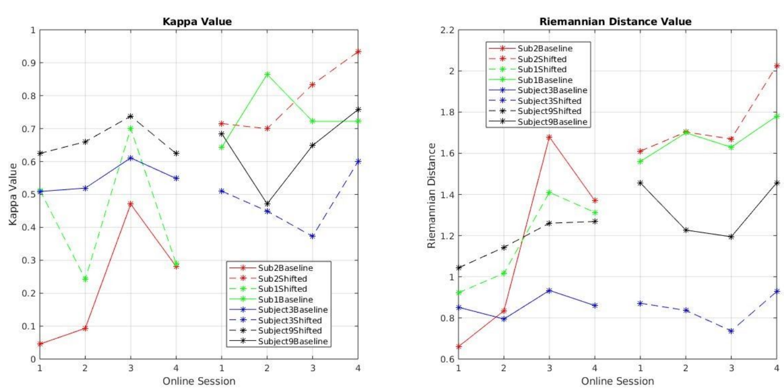

Figure 1. *Comparison of Metrics: Experiments are plotted in the order of temporal chronology. Vertical line separates the crossover between two experiment modalities*

Discussion: Results of longitudinal training in crossover study over 8 sessions showed a sustained or increasing trend in metrics in riemannian distance, kappa value pointing to a possible effect of learning in longitudinal training. Nevertheless, given the short number of subjects, no differences can be observed between the two methods.

Significance: Validating the pilot study results on a statistically significant number of subjects in a crossover study will contribute to a new effective training protocol for MI-BCI.

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Electrophysiology-guided deep brain stimulation targeting in Tourette syndrome complements anatomical targets for improved outcomes

J. Cagle[1], R. Eisinger[1], E. Opri[1], K. D. Foote[1], M. S. Okun[1], A. Gunduz[1*]

[1]*University of Florida, Gainesville, FL, USA*

*Biomedical Sciences Building J283, Gainesville, FL 32611, USA. E-mail: agunduz@ufl.com

Introduction*:* Tourette syndrome (TS) is a continuous lifelong condition that is highly prevalent and socially embarrassing. Deep brain stimulation (DBS) has emerged as a promising treatment option for addressing tics in appropriately screened cases. In our patient cohort, two 4-contact macroelectrodes are placed during DBS surgery in the centromedian-parafascicular thalamic (CM-Pf) region bilaterally, which is known to suppress tic activity in TS patients. However, due to different imaging techniques, patient brain conditions, and clinician preferences, the final target locations vary from patient to patient even within the same structure. Herein, we identify the anatomical correlate of Tourette syndrome using both imaging techniques and neurophysiological recordings from DBS electrodes for the better understanding of Tourette syndrome and improved targeting in future DBS interventions.

Material, Methods and Results*:* Each patient received bilateral Activa PC+S implants for chronic neural recordings in the study. Pre-operative T1 magnetic resonance imaging (MRI), and post-operative computed tomography (CT) were obtained for each patient. For functional recordings, we propose the use of attention task to elicited visual evoked potential present only in CM-Pf nuclei instead of other nuclei in thalamus. A modified Go/No-Go task [1] was given to each patient. The patients were instructed to press on yellow/blue stimuli and avoid pressing on yellow/orange stimuli. Motor tasks will also be used to differentiate nearby motor nuclei from the target structure. Figure 1 shows the functional recording results.

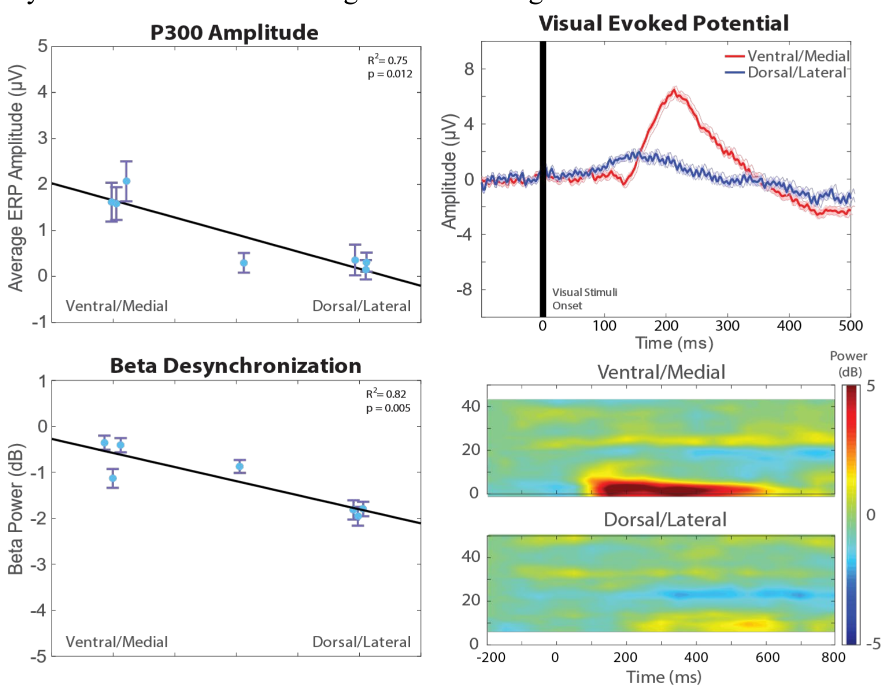

Figure 1. The P300 visual evoked potential during the modified Go/No-Go task was stronger in CM-Pf nuclei than other thalamic nuclei on the trajectory. The signature beta desynchronization in motor nuclei was not seen in CM-Pf nuclei. The spectrogram shows significant difference between nuclei that help identifying the CM-Pf nuclei during intraoperative procedures.

Discussion*:* Our results show that CM-Pf nuclei can be differentiated using functional recordings. The functional mapping can be applied during intra-operative procedure accompanied with anatomical localization to improve DBS targeting.

Significance*:* Better understanding of target specific neural activity in Tourette syndrome can improved targeting in future DBS interventions and improve treatment outcomes.

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Bi-directional modeling between LFP and screw ECoG Activity

***Y.-J. CHANG[1], Y.-I. CHEN[1], H.-C. YEH[1], J. M. CARMENA[2,3], S. R. SANTACRUZ[1,4]**

[1]Biomedical Engineering, University of Texas at Austin, Austin, TX, USA;[2]Electrical Engineering & Computer Sciences, University of California at Berkeley, Berkeley, CA, USA; [3]Helen Wills Neuroscience Institute, University of California, Berkeley, CA, USA;[4]Institute for Neuroscience, University of Texas at Austin, Austin, TX, USA

*P.O. Box C0800. Email: derek706586@utexas.edu

Introduction: Local field potentials (LFP), postsynaptic activity of hundreds of neurons recorded using microelectrodes, are a signal type commonly used for both neuroscientific studies and therapeutic applications. The primary disadvantage of using LFP signals is that they require invasive technology. Here we developed the NeuroBondGraph Network (NBGNet), a bi-directional signal translation model between two distinct measurements, to estimate LFP data using signals recorded from screw electrocorticography (screw ECoG) which acquire high SNR data in a less invasive way. We found original and reconstructed screw ECoG signals exhibit both high correlation (**Fig. 1b**) and phase synchronization (**Fig. 1c**).

Material and Methods: LFP and screw ECoG signals are recorded simultaneously in awake behaving rhesus macaques (n = 2) performing a center-out behavior task. LFP data is recorded from one hemisphere, whereas screw ECoG signals are acquired across both hemispheres. A 50-Hz low-pass filter is applied to both signals. Forward and inverse models are derived to capture the system dynamics of the neural activity. NeuroBondGraph (NBG) approach [1], a sparse-connected recurrent neural network, is introduced to model both the system dynamics and nonlinearities via state-space representation. Data from 100 sessions with varying lengths of time is used for model training. Two evaluation metrics, (1) cross-correlation and (2) phase synchrony, are employed to quantify the performance of our model.

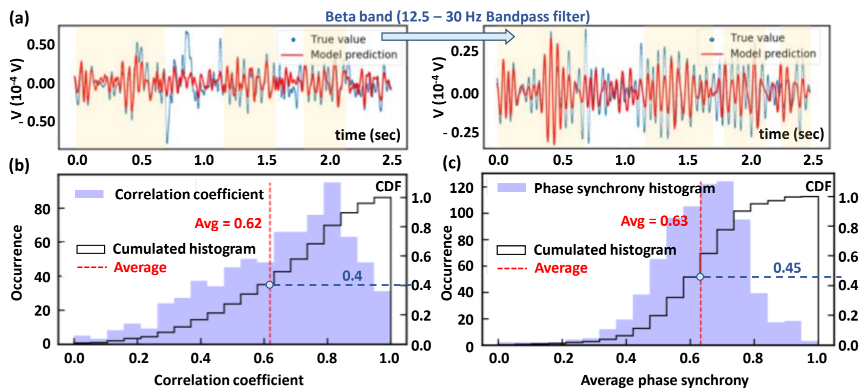

Fig 1. *Results of forward model. (a) One representative session presented before bandpass filtering (left) and after bandpass filtering (right). (b) Histogram and cumulative density function (CDF) of cross-correlation coefficients among all sessions. (c) Histogram and CDF of average phase synchrony among all sessions.*

Results: The underlying dynamics in the beta band (12.5 – 30 Hz) were captured accurately by the model during colored regions (**Fig. 1a**). Similar shape of oscillation (60% had cross-correlation coefficient greater than 0.62; **Fig. 1b**) and phase (55% had phase synchrony greater than 0.63, indicating less phase difference than $\pi/4$; **Fig. 1c**) between model predictions and original signals validate the model performance.

Discussion: We have demonstrated that screw ECoG signals can be well estimated from LFP signals with NBGNet. Interestingly, decreased amplitude in our predictions indicates that our approach acted as a noise reduction tool to remove the sharp edge artifacts in the signals. The development of both forward and inverse models allows us to uncover neural dynamics. Our next goal is to study the reliability of reconstructed LFP signals for closed-loop neuroprosthetic applications. We believe that this model can be implemented in the neuroscience study such as investigation of brain dynamics for neuropsychiatric disorder treatment.

Significance: The proposed bi-directional models could not only significantly improve the performance of LFP-based closed-loop neuroprosthetic applications without increasing the LFP channel count, but also inform intrinsic dynamics and cross-level network dynamics in both forward and inverse directions.

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Differential effects of neurofeedback latency on the incidence rate, amplitude and duration of alpha-bursts

N. Smetanin[1], A. Belinskaia[1], M. Lebedev[1], A. Ossadtchi[1*]

[1]*Centre for Bioelectric Interfaces, NRU Higher School of Economics, Moscow, Russia*

E-mail: ossadtchi@gmail.com

Introduction: Latency of the feedback has been hypothesized to play a crucial role in reinforcement learning [1]. It has been suggested that the latency of 250-350 ms between a neuronal event and the corresponding feedback is optimal to form an efficient neurofeedback and produce desired neural activity changes [2]. Here, we employed the P4-alpha neurofeedback paradigm to examine how different feedback latency values affect the changes in oscillatory neural activity that occur during neurofeedback training.

Materials, Methods and Results: To investigate the effect of feedback latency we trained four groups of subjects (10 people in each group, in sum 13 males; 24.58 ± 5.3 years) with three different artificially imposed additional feedback signal latency values (0, 250 ms and 500 ms) which resulted into (250 ms, 500 ms and 500 ms) total delay and mock feedback group to upregulate their occipital alpha-rhythm power. All three feedback groups demonstrated a reliable increase in the average alpha power as compared to the mock feedback group.The detailed analysis of neurofeedback induced changes revealed that in the zero-additional latency group significant differences (w.r.t. the mock feedback condition) occurred only in the incidence rate of alpha-spindles leaving average alpha bursts duration and their amplitude intact, which agrees with [3]. 500 ms of additional latency caused further morphological changes in alpha bursts duration and mean amplitude of alpha bursts.

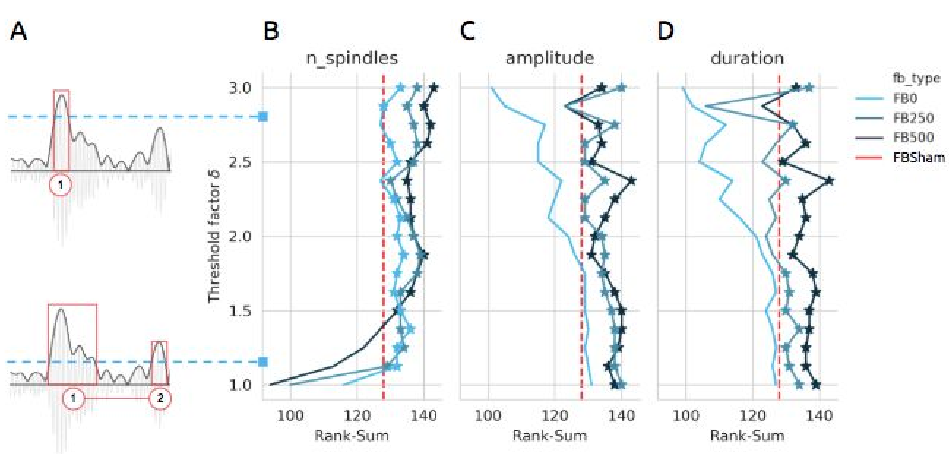

***Figure 1.** P-values for the Wilcoxon rank-sum test exploring the effect of feedback latency on different morphological characteristics of the P4 alpha rhythm. A: Threshold factor illustration, B: Number of alpha-bursts per unit time, C: Alpha-burst duration. D: alpha-burst amplitude. Separate tests are performed for each threshold value calculated. Asterisks indicate statistical significance based on the FDR(0.1) corrected $p<0.05$. Dotted lines bracket the non-significant zone for the Wilcoxon rank-sum test.*

Discussion: We conclude that feedback delay even when varied within the range of large values typical to commercial NFB systems causes differential effects on the morphology of occipital alpha rhythm. Therefore, the delay is to be considered as an additional parameter of NFB intervention and NFB equipment manufactures should include the possibility for physicians to adjust feedback latency depending on the particular case. Methodological developments to reduce the fundamental delay encountered when assessing brain-rhythm instantaneous power are also warranted as reduction of latency may unleash additional power of neurofeedback and facilitate real-time brain-rhythms contingent studies.

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Dry EEG-based Pre-processing Pipeline for a Clinically Feasible Sensor Array with P300-speller Applications

J. J. Podmore[1*], T. P. Breckon[2, 3], U.R. Beireholm[1]

Department of {[1]Psychology | [2]Computer Science | [3]Engineering}, Durham University, Durham, U.K.

[*]DH1 3LE, Durham City, U.K., E-mail: joshua.j.podmore@durham.ac.uk

Introduction: The past decade has seen significant enhancements in communication-based Brain-Computer Interfaces (BCI), known as spellers. These devices harness brain-based bio-signals for speller control [1]. The P300 waveform describes a time-locked positive deflection in electroencephalogram (EEG) time-series in response to deviant stimulus augmentations [2]. Typically, letters and numbers are displayed via a computer monitor and paired with a visual augmentation such as a colour inversion [3]. Crucially, P300-based spellers have demonstrated the most success in real-world patient trials [4], with typical subjects achieving accuracies >95% [5]. To achieve this performance, dense (8+) sensor wet-EEG arrays are paired with common average referencing [6] and multi-channel averaging to extract P300 waveforms embedded within the EEG data [5]. These techniques are not clinically feasible for end-point users as they fail to accommodate for patient comfort, cognitive fatigue or wearable assistive device hygiene requirements. To overcome these issues, we propose here a custom pre-processing pipeline for low-density (1-3 sensor) dry EEG setups. This compromises an 8-step package for zeroing, detrending, data-splicing, high-pass/ low-pass notch filtering, referencing and normalizing.

Methods: To evaluate our pre-processing pipeline we first present subjects with a localization task during concurrent dry EEG (Cognionics Quick-20) acquisition over sensors: Fz, Cz, P3, P4, O1, O2 and A2. This involves displaying an array of 7 emoji on-screen programmed with a typical P300 oddball design. At the start of each trial, subjects are informed of the target emoji and instructed to maintain fixation on this stimulus throughout. Each trial consists of 5 flash-sequences. These are averaged offline to generate P300 and Non-P300 datasets. Separate Linear Discriminant Analysis (LDA) classifiers are then trained using these data. One dataset passes through an industry-standard pre-processing pipeline using all sensors to harness above-mentioned averaging techniques. Further, a second model is generated using a low-density (Fz, Cz & A2) sensor dataset and our custom pre-processing pipeline. To evaluate the computational efficiency of both pipelines, subjects are presented with an extended version of the localization task. EEG data collected in real-time is fed to both LDA models and used to assess the relative performance of each technique.

Results: Our low-density-specific pre-processing pipeline demonstrates comparable performance with industry-standard techniques. Crucially, computational demands across both methods are non-significantly different. Our custom pre-processing pipeline was also combined with current sophisticated averaging techniques offline and was shown to outperform both above-mentioned methods. This suggests that our pipeline also demonstrates significant potential as a pre-processing pipeline for dry EEG-based P300 research outside of the BCI speller field.

Discussion: These results indicate that dry EEG calibration techniques for low-density EEG sensor arrays can produce high-quality data for BCI-speller classification. This suggests it is possible to accommodate the clinical requirements of end-point users without compromising on classification accuracy or incurring a time-lag penalty.

Significance: Currently available EEG signal-processing tools are geared specifically for the detection of P300 waveforms collected via wet-EEG. This dry EEG-based pre-processing pipeline is crucial to enhance data quality for these more clinically and experimentally feasible applications. These techniques will reduce setup times, lower hardware costs, decrease user discomfort and enhance patient life quality.

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Hand movements classification for a hybrid rehabilitative BCI: study on corticomuscular and intermuscular coherence

V. de Seta[1,2*], E. Colamarino[1,2], F. Pichiorri[2], J. Toppi[1,2], M. Masciullo[3], F. Cincotti[1,2], D. Mattia[2]

[1] Department of Computer, Control, and Management Engineering, Sapienza University of Rome, Italy;
[2]Neuroelectrical Imaging and Brain-Computer Interface Lab, Fondazione Santa Lucia IRCCS, Rome, Italy;
[3]Spinal Cord Unit, Fondazione Santa Lucia IRCCS, Rome, Italy
*Via Ariosto 25, 00185. E-mail: deseta@diag.uniroma1.it

Introduction: Hybrid Brain-Computer Interfaces (hBCIs) for upper limb motor rehabilitation after stroke pursue the reinforcement of "more normal" brain and muscular activity [1]. Here, we propose the combination of corticomuscular coherence (CMC) and intermuscular coherence (IMC) as control features for a novel rehabilitative hBCI.

Material, Methods and Results: EEG (31 electrodes above the sensorimotor scalp areas) and EMG (5 upper limb muscles per side) signals, sampled at 2400 Hz, were collected in 17 healthy participants performing finger extension (Ext) and grasping (Grasp) with both dominant and non-dominant hand (60 trials). Data were pre-processed and segmented in epochs, selecting windows of 2s each for rest and task condition. Single-trial CMC and IMC were estimated for each EEG-EMG and EMG-EMG pair in the frequency bands of interest: alpha (8—12 Hz), beta (13—30 Hz), gamma (31—60 Hz) and high frequency (HF, 61—100 Hz). For each movement and frequency band, CMC/IMC values were extracted at the characteristic frequency in both task and rest condition [2] and used as features to classify each task vs rest, and Ext vs Grasp in each limb, by means of a single-subject 10-iteration cross-validation. CMC and IMC values across frequency bands were considered both together (full-spectrum classifier) and separately (band-specific classifiers) in the feature space of different classification models. We obtained task-rest classification performances (Area Under the receiver operating characteristic Curve, AUC) ranging on average from 0.87 to 0.98, while Ext-Grasp classification showed AUC values higher on average than 0.90. When considering task vs rest classification, a two-way repeated measures ANOVA (rmANOVA) on AUC of the full-spectrum classifier revealed a significant effect for *Movement ($F(1,16)=14.49$, $p=0.002$)* and *Movement x Side* factors (Fig. 1a). Similar results were obtained for the band-specific classifiers. As for Ext vs Grasp classification, the two-way rmANOVA on AUC of both the full-spectrum and the band-specific classifiers showed a significant effect only for *Frequency Band* factor (Fig. 1b).

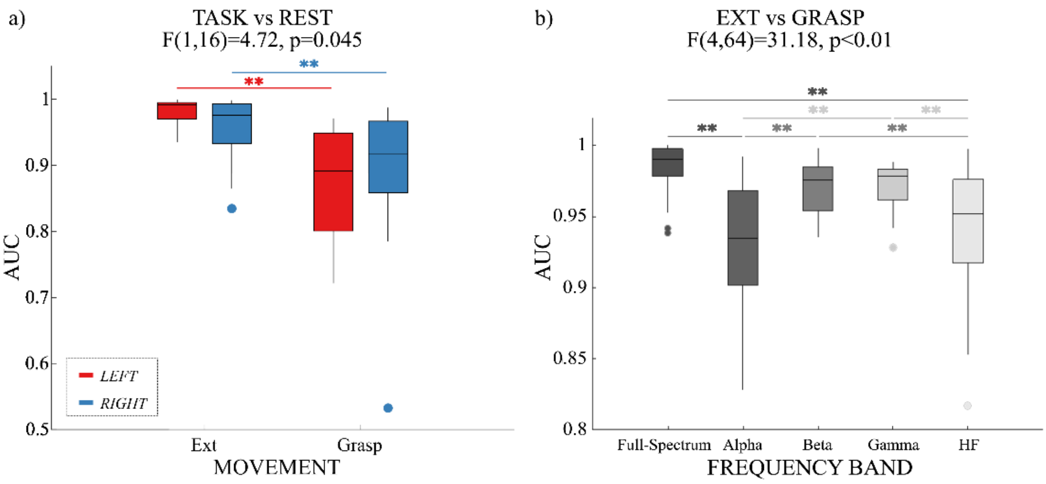

***Figure 1** Boxplot reporting results of the two-way rmANOVA on AUC values. a)* Movement x Side *effect of the full-spectrum task-rest classification considering as within main factors the* Movement *(2 levels: Ext, Grasp) and the* Side *(2 levels: right, left) b)* Frequency Band *effect of Ext-Grasp classification considering as within main factors the* Side *(2 levels: right, left) and the* Frequency Band *(5 levels: full-spectrum, alpha, beta, gamma and HF band). Markers (**) indicate significant differences ($p<0.01$) resulting from the Tukey post-hoc test.*

Discussion: Our preliminary findings indicated that the combination of CMC and IMC features can allow for classification of both Ext and Grasp movement vs rest with higher performance for Ext, and for classification of Ext vs Grasp with higher discriminability in beta and gamma frequency bands.

Significance: The combination of CMC and IMC is a promising candidate to inform the design of a hBCI system for post-stroke rehabilitation.

Acknowledgements: This work is supported by the Italian Ministry of Health (GR-2018-12365874 and RF-2018-12365210) and by Sapienza University of Rome- Progetti di Avvio alla Ricerca 2020 (AR120172B8B5B405).

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Brain Drain: Understanding fatigue in brain-computer interfaces (BCI) for children and adults

E. Kinney-Lang[1,2*], D. Kelly[1,2], J. Wrightson[1,2], and A. Kirton[1,2]

[1]*University of Calgary, Canada;* [2]*Alberta Children's Hospital, Calgary, Canada*

* 28 Oki Dr NW, Calgary, AB T3B 6A8. Email: eli.kinneylang@ucalgary.ca

Introduction: Despite fatigue's influence on successful BCI use [1], [2], limited research has explored how and why fatigue and fatigability manifests after BCI use, particularly in children. Fatigue is especially problematic for young BCI candidates with neurological impairments as they are more likely to feel chronic fatigue [3]. Fatigue and fatigability associated with BCI use in children is a critical concern which needs to be understood before BCI clinical potential can be fully realized. To date, no systematic study of the factors associated with BCI fatigue has been performed despite anecdotal reports of fatigue in pediatric BCI. This pilot project aims to assess fatigue outcomes following two common BCI paradigms and a negative control scheme. Outcomes reported here reflect a work-in progress in an ongoing study of adult and children.

Material, Methods and Results: Figure 1 outlines a flowchart of the methods in this study.

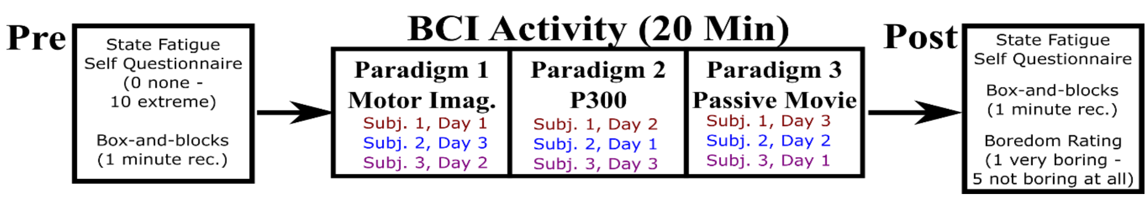

Fig. 1. Participants (n = 3, ongoing) were recruited to attend 3 sessions on separate days to evaluate fatigue following BCI use. Each session began with assessment of current state fatigue using a self-report scale and clinical motor task (non-dominant hand box-and-blocks (BB) [4]). Participants then engaged in 20 minutes of - (1) imagined motor imagery (MI); (2) oddball visual stimulus (P300) or (3) passive watching. Afterwards, self-reported fatigue and the BB task were repeated, alongside a perceived boredom questionnaire (1 very – 5 not at all) for the specific BCI task.

Healthy subjects were recruited from the community. Task EEG data was recorded using gel electrodes with a g.tec USB amplifier (samp. rate = 256 Hz). Task order was varied across subjects using a Latin Square to minimize potential learning affects for both BCI and the box-and-blocks task. Preliminary results from adult participants (n = 3) indicate potential fatigue in the motor BB task following the MI-BCI paradigm (-2.57 ± 0.58%) compared to P300 (4.17 ± 0.19%). Changes were found in BB following the passive video (-2.19 ± 0.39%) but may be due to boredom as the activity was rated as the most boring by all individuals (2 ± 1).

Discussion: These early results support the feasibility of assessing fatigue during BCI including apparent fatigability in 2 of 3 participants. Video recordings from the BB task will be analyzed to assess changes in kinematic movements using advanced motion tracking analytics. Changes in EEG data will also be analyzed to assess potential features of fatigue development during BCI, similar to [5].

Significance: Identifying potential differences in fatigability following two common BCI tasks (P300 and MI) will provide insight on probable underlying mechanisms contributing to BCI-induced fatigue and yield potential options for mitigation for both adult and pediatric BCI users.

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BCI-at-Home: Exploring the Technical Feasibility of a Home BCI Program for Children with Cerebral Palsy

E. D. Floreani[1,2*], E. Kinney-Lang[1,2], D. Kelly[1,2], D. Rowley[2], I.Robu[2], A. Kirton[1,2]
[1]University of Calgary, Calgary, Canada; [2]Alberta Children's Hospital, Calgary, Canada
*Corresponding Author. Email: edflorea@ucalgary.ca

Introduction: Brain-computer interfaces (BCIs) are emerging as an access technology for children with severe physical disabilities, such as quadriplegic cerebral palsy (QCP) [1]. However, BCI still faces significant barriers preventing translation into daily life [2]. Previous literature investigating BCI use in the home for adults illuminates a plethora of challenges facing BCI home integration, including complex setup requirements, limited usability of BCI systems, and a noisy user environment [3], [4]. We faced these challenges head-on when the COVID-19 pandemic necessitated that we move our clinical pediatric BCI program, BCI4Kids, into participants' homes. To support this translation, we developed a user-friendly BCI control terminal paired with comprehensive documentation to enable caregivers to easily and independently utilize a commercial EEG headset for BCI at home.

Methods and Results: *BCI Hardware:* Each family (n=3) was provided with an at-home kit for our pilot home-based program that included an Emotiv Epoc X headset and a tablet computer with pre-installed BCI software. The Epoc X was chosen due to its relative ease of setup and cleanup. *BCI Software:* Emotiv's proprietary BCI application was used to connect the headset, check electrode impedances, and train the BCI to detect "mental commands". Emotiv's Cortex API was used to interface mental command outputs with applications through Node-RED, a JavaScript-based visual programming tool that offers a way to flexibly integrate APIs, web services and IoT devices. A friendly user interface, the Emotiv Games Dash, was designed to provide caregivers an intuitive means to adjust BCI system settings, quickly map key bindings to distinct mental commands and suspend/resume key mappings to an active application. The UI system was wrapped with the underlying Node-RED and Cortex backend into a clean, executable application through Electron. *Technical Support:* Each family was provided with a comprehensive onboarding package for initiating BCI-use at home, which included a detailed setup guide and an initial virtual orientation. Additional virtual support via Zoom was offered as needed. *Assessment:* Participating families were interviewed biweekly following initial delivery of the system to assess their BCI at home use. *Results:* Enrollment for the home-BCI pilot program began in August 2020. Each family enrolled had previous exposure to BCI but had no prior experience setting up BCI or using BCI at home. All families reported success in setting up and independently using the BCI system at home and reported using BCI at home 2-8 times over a two-week period, for 15min-2hour sessions. Setup was reported as the most challenging aspect of using BCI at home only in the first follow-up interview. Utilizing the Emotiv Games Dash UI was not reported by any family as a challenge.

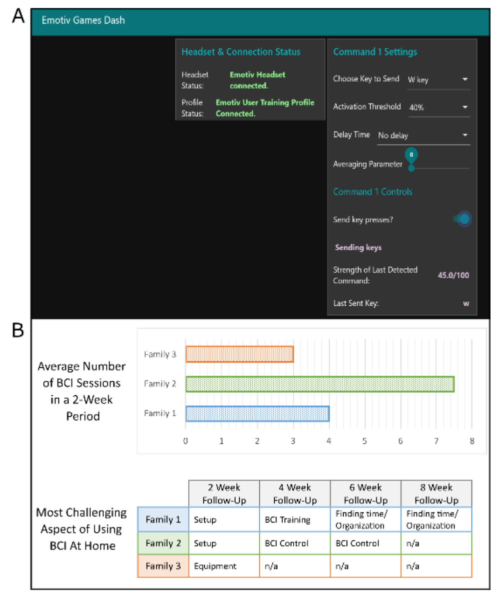

Figure 1: A) The Emotiv Games Dash. The UI displays the connection status of the headset, allows the user to select which key to send and adjust BCI system settings. It also provides feedback on mental command "activation strength" and which key was sent last.

B) The average number of at-home BCI sessions in a 2-week period for each family, as well as the reported most challenging aspect of using BCI at home by each family.

Discussion and Significance: The early success of this home BCI pilot program demonstrates that at-home BCI is feasible for independent use by families. Intuitive BCI control terminals like the Emotiv Games Dash can support BCI use at-home by alleviating caregiver's required knowledge of BCI systems. Our next steps will be to recruit more families and undergo comprehensive usability testing of the home BCI technology. Testing the feasibility of BCI in the home with intended end-users and incorporating their goals and opinions are essential steps toward translating BCIs from the lab to daily life.

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Controlling a virtual vocal tract for real-time speech synthesis using a speech-motor imagery brain-computer interface

J. S. Brumberg[1*]

[1]*Department of Speech-Language-Hearing, University of Kansas, Lawrence, KS, USA,*

**Dole Human Development Center, Room 3001, 1000 Sunyside Ave, Lawrence, KS, USA. E-mail: brumberg@ku.edu*

Introduction: This work extends previous efforts for real-time synthesis of speech sounds using a limb-based non-invasive sensorimotor rhythm brain-computer interface (BCI) [1] to a more ecologically valid paradigm that is similar to natural speech production by controlling a continuous speech synthesizer as a “virtual vocal tract.” In doing so, learning to control the BCI virtual vocal tract becomes very similar to the known process for typical speech motor that emphasizes individuals’ (previous) familiarity with speaking. This approach also avoids lexical orthography (e.g., “typing what you think”) due to the complex representation of language in the human brain [2] in favor of the more direct process of speech motor control [3]. Further, brain networks that support speech motor learning and control may be leveraged for BCI-based communication (e.g., speech motor networks, feedback and feedforward articulatory control; [3]).

Methods: One participant without impairments took part in an offline BCI pilot study (without feedback) to determine the feasibility of decoding EEG responses to imagined speech movements (2 s duration). The tested movements included 30 imagery trials of each: tongue advancement (e.g., /i/, /d/, /n/, /s/), tongue retraction (e.g., /A/, /u/), lip protrusion & spreading (e.g., /u/ and /i/), and jaw opening & closure (e.g., /A/, /æ/, /b/, and /m/). A g.HIamp (g.tec) was used to record 62 EEG electrodes at 512 Hz referenced to the left earlobe and four bipolar surface EMG electrodes placed along the Masseter m. (jaw closer), Orbicularis oris inferior m. (lip pursing), Risorious m. (lip spreading), and below the jaw longitudinally to record the submental muscles Mylohyoid m., Geniohyoid m., Digastric m. (jaw openers), Genioglossus m., and Hyoglossus m. (tongue advancement & retraction) to ensure task compliance. A Kalman filter decoding algorithm was used to predict articulatory trajectories from sensorimotor rhythms (mu and beta), which were then visualized and synthesized using the Maeda speech synthesizer.

Results: Decoded correlation coefficients for all tasks to targets were 0.61, 0.62, and 0.60 for tongue, jaw, and lip, respectively. Fig 1 shows the decoded articulatory parameters Jaw Height, Tongue Position, and Lip Protrusion (right three columns) for the tongue advancement & retraction task (top row), jaw opening & closure task (middle-row) and lip pursing & spreading task (bottom row). The left column shows a graphical representation of the combined average decoded virtual vocal tract configuration with the tongue, jaw, and lower lip represented in light and dark orange, and superior and posterior vocal tract boundaries in black.

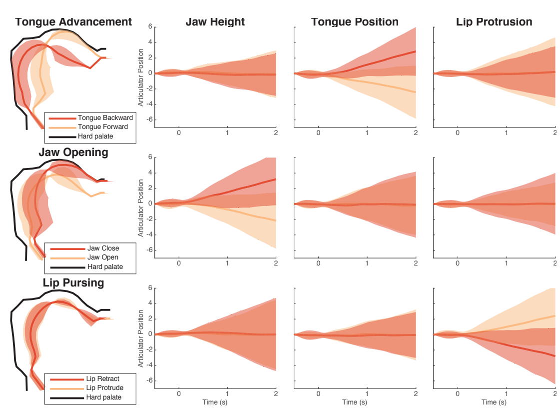

Figure 1: The mean (95% CI) decoded Jaw Height, Tongue Position, and Lip Protrusion for each task. Left colum shows the virtual vocal tract, and right columns the parameter timecourses.

Discussion: The BCI correctly decoded tongue advancements (row 1, col 1: forward toward the right, backward toward the left), jaw opening and closing (row 2, col 1: opening away from the superior border, closing toward the superior border), and lip pursing and spreading (row 3, col 1: lips forward and backward) with no extraneous decoding prior to start of imagery at 0 s and task crossover. The successful confirmation of EEG-based decoding of orofacial (speech) motor imagery supports matching control and output modalities for a speech BCI and warrants further investigation.

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Guiding the Future Design of BCI Restorative Assistive Technology Devices: A Literature Review Study

Geraldine Light

Walden University, Minneapolis, MN, USA

Abstract

Although research of Brain Computer Interface (BCI) technology has been ongoing for over fifty years, there still exists a scarcity of restorative BCI assistive technology devices at the consumer level. How might the recent and expanding use of recreational (BCI) technology devices influence the use of restorative BCI technology devices by individuals with rare disorders such as Amyotrophic Lateral Sclerosis (ALS)? This poster represents preliminary study results based on a review of BCI literature. The intention of this study was to complete a synthesis of the literature on recreational BCI technology devices and their influence on user acceptance of restorative BCI technology devices. The literature review was completed by using international databases covering the period from June 1970 to December 2019. Thirty articles were thoroughly reviewed and integrated into this review. Negative attitudes held by individuals with rare disorders as well as by the care givers of these individuals related to the use of restorative BCI devices are likely to influence patient expected outcomes. By creating positive experiences with recreational BCI technology devices it might be possible to reduce the stigma related to restorative BCI physical devices and promote greater understanding of how the brain and the computer device interact to produce a positive outcome.

Zero-training plug-and-play for cVEP BCI

J. Thielen[1,2*], J. Farquhar[2], P. Desain[1,2]

[1]*Radboud University, Donders Institute for Brain, Cognition and Behaviour, Nijmegen, the Netherlands*

[2]*MindAffect, Nijmegen, the Netherlands*

*P.O. Box 9104, Nijmegen, the Netherlands. E-mail: jordy.thielen@donders.ru.nl

Introduction: For a typical state-of-the-art brain computer interface (BCI) training is an important phase. This step is necessary for the BCI to learn about the user-specific brain signals. If this training step is performed properly, the BCI will ultimately be able to generalize to a testing phase, in which the user can use the system to operate a certain application (e.g., a speller). At this point, a trade-off arises. On the one hand, from a user perspective one would like the training phase to be short to allow quick use of the BCI-driven application. On the other hand, from a machine learning perspective one would like a long training phase to collect a large amount of brain data for proper calibration of the classifier. Here, we present a zero-training approach that fully eliminates the training phase. We show that our algorithm can classify single-trials without any prior data. We additionally show that by allowing the classifier to learn from previously classified trials it becomes faster over time, ultimately learning the data distribution like a fully trained classifier. This opens up the opportunity for a plug-and-play BCI.

Material, Methods and Results: We performed an online experiment with 11 human participants who operated a BCI speller application. In two runs participants performed a copy-spelling task and in a third run they performed a free-spelling task. We recorded the electroencephalogram (EEG) with eight water-based electrodes (Fz, T7, T8, POz, O1, Oz, O2, Iz) amplified by a TMSi Porti. The speller application presented 29 cells that alternated between black and white using a set of modulated Gold codes which upon fixation evoke code-modulated visual evoked potentials (cVEPs) [1, 2]. To learn user-specific brain signals, a canonical correlation analysis (CCA) is performed that learns both a spatial as well as a temporal filter to individual flashes [1, 2, 3]. By performing the CCA in parallel for all 29 hypothesized stimulation sequences, the most likely attended cell can be identified by maximizing the explained variance over models [3]. A dynamic stopping procedure was adopted to emit the most likely symbol as soon as possible [3]. From the 11 participants, 9 participants completed the full experiment. One participant was excluded from the analysis due to a broken electrode and another participant did not complete the full design. All 9 remaining participants could operate the BCI very well. Averaged over all three runs, participants spelled with an information transfer rate (ITR) of 66.4 bits per minute and a symbols per minute rate (SPM) of 13.4 symbols per minute (including a 1-second inter-trial interval). Three participants made one error during spelling which they could correctly correct. The best participant achieved an ITR of 106.7 bits per minute and an SPM of 22.0 symbols per minute. These numbers include the first few slow trials: the first two took on average 9.3+1 seconds, while the last 10 trials were produced within 3.3+1 seconds, which demonstrates the need for a warm-up as well as quick convergence of the classifier.

Discussion: We have shown the potential of a fully calibrationless paradigm for cVEP-based BCI. We have evaluated the performance in an online experiment where participants successfully operated a BCI speller.

Significance: We have shown one of the first zero-training cVEP BCI achieving high-speed online performances for communication and control. This opens up avenues for practical plug-and-play BCI applications.

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MEG Features for Fast Detection of Intentional Eye-Gaze Dwells in an Eye-Brain-Computer Interface

S.L. Shishkin[1,2*], A.N. Vasilyev[1,2,3], A.O. Ovchinnikova[1,2], I.P. Zubarev[4], A.V. Butorina[1,5], B.L. Kozyrskiy[2,6], Y.O. Nuzhdin[2], I.A. Dubynin[1,2], E.P. Svirin[2,7], A.E. Ossadtchi[8], B.M. Velichkovsky[2], T.A. Stroganova[1]

[1]Moscow State University of Psychology and Education, Moscow, Russia; [2]NRC Kurchatov Institute, Moscow, Russia; [3]M.V. Lomonosov Moscow State University, Moscow, Russia; [4]Aalto University, Aalto, Finland; [5]Skoltech, Moscow, Russia; [6]Department of Data Science, EURECOM, Biot, France; [7]University of Würzburg, Würzburg, Germany; [8]NRU Higher School of Economics, Moscow, Russia

* Shelepikhinskaya Naberezhnaya, 2A, 2, Moscow, 123290, Russia. E-mail: sergshishkin@mail.ru

Introduction: We aim at developing a noninvasive highly responsive eye-brain-computer interface (EBCI) for experimenting with fluent human-machine interaction. An EBCI is an interface that issues commands when the user's gaze dwells on designated locations for a short time, but only when an intention marker is observed in a brain signal [1, 2]. Here, we explore intention-sensitive features from the gaze dwell-related magnetoencephalogram (MEG) that might be used to enhance the EEG-based EBCI.

Methods: 306-channel MEG was recorded in 33 healthy participants who played *EyeLines* game [2] by making moves using gaze dwells. Intentional dwells where identified as ≥ 500 ms gaze dwells on game objects quickly followed by a special confirmatory dwell. Generalized additive model [3] was applied to control for non-linear effects of saccade amplitude and gaze coordinates on fixation-related MEG. Linear mixed model (LMM) was used to find sensors and sources with significant ($p<0.05$, FDR corrected) effect of intention while controlling for linear contaminating effects. LF-CNN and VAR-CNN [4] were applied to pre-feedback fixation-related single-trial gradiometer data to classify intentional vs. spontaneous dwells.

Results: Sensor level analysis and source modeling identified several cortical areas that were activated when eyes were kept at game objects intentionally (compared to spontaneous fixations). Classification ROC AUC was 0.66±0.07 for LF-CNN and 0.67±0.07 for VAR-CNN. In an additional study in five participants, mean ROC AUC increased by 0.8 when several times larger training sets were used.

Discussion: The observed activation differed by its time course (Fig. 1) / localization from the EEG marker [2] of intentional dwells. Thus, the MEG may serve as a complement to the EEG in the EBCI.

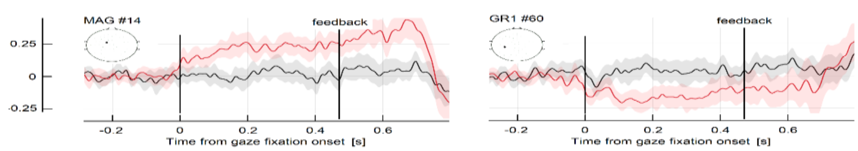

Figure 1. *Examples of fixation-related brain magnetic field (recorded with magnetometers, MAG, and with planar gradiometers, GR1) time courses at sensors where LMM revealed intention effect. Group average (n=29) M (solid lines) ± 95% conf. int. (shadow) for signals normalized using [-300..-100] individual baseline: red, intentional dwells; black, spontaneous dwells. Dots on the heads show sensor positions.*

Significance: The results suggest the utility of MEG for the development of an effective EBCI.

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Hybrid Motor Imagery BCI using Error-Related Brain Activity

M. Mousavi[1*], L. R. Krol[2], V. R. de Sa[1]

[1]*UC San Diego, California, USA;* [2]*TU Berlin and BTU Cottbus-Senftenberg, Germany*

*9500 Gilman Dr, La Jolla, CA, USA, 92093-0515. Email: mahta@ucsd.edu

Introduction: Motor imagery (MI) BCI systems read and infer brain activity directly from the brain. Movement imagination of different body parts can be used, for instance, to move a cursor on a screen towards a target. Earlier in an offline study, we proposed a hybrid MI-BCI to simultaneously incorporate both the MI signal and the user brain response to the BCI output (feedback) – e.g., the cursor's direction of movement [1]. In this work [2], we show the efficacy of our proposed MI-BCI in real-time control, and compare its accuracy and reliability in comparison to a conventional MI-BCI.

Material, Methods and Results: We recorded data from 12 healthy participants using a 64-channel EEG system. The experiment comprised 9 blocks each with 20 trials during which participants were instructed to control the movement of a cursor towards a target on the screen in front of them using right/left hand motor imagery [1,2]. The first three blocks were used for calibration during which the cursor moved according to a predefined set of movements; however, participants were led to believe that they were in control of the cursor. On the calibration data, three classifiers were trained: one MI classifier detecting the right/left hand motor imagery (R/L) using common spatial patterns (CSP) [3] as well as two error-related brain activity classifiers, one using CSP and another using windowed means on central channels [2]. The latter two classifiers were trained to detect whether the last cursor movement was perceived by the user as a good or bad movement (G/B). We compared two types of control: a conventional MI control using the R/L classifier only and a hybrid (R/L+G/B) control that combined the scores of the R/L and the two G/B classifiers using logistic regression to determine the next cursor movement. In blocks 4-9, participants controlled the cursor movement with either of the two control types. The control type in each block was alternating and its order was counterbalanced across participants. We used Wilcoxon signed-rank tests for statistical comparisons. Our results showed that across participants the R/L+G/B control had an average target hit rate of 0.75 which was significantly better than the R/L hit rate of 0.62 ($p<0.003$). Furthermore, across participants, the average information transfer rate (ITR) in R/L+G/B blocks was significantly higher than the ITR in R/L blocks ($p=0.007$). Moreover, the accuracy of the G/B classifiers were not significantly different when trained and tested on calibration blocks (using cross-validation) compared to their online performance when trained on calibration and tested on the online blocks (across participants, $p>0.6$). However, the accuracy of the R/L classifier was significantly worse when transferred from calibration to online control ($p<0.001$).

Discussion and Significance: Different from the existing work that uses the error-related brain activity sequentially in a corrective or adaptive way upon encountering an error [4], our proposed hybrid BCI [2] combines the scores of the R/L and G/B classifiers simultaneously and performs significantly better than a conventional MI-BCI improving hit-rate and ITR. We showed that this is in part due to the G/B classifiers being more reliable compared to the MI classifier when transferred from calibration to online control.

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The effects of frontal cortex lesions on SMC BCI features

Z. Freudenburg[1*], M.J. Vansteensel[1], E.J. Aarnoutse[1], K.J. Miller[2], N.F. Ramsey[1]
UMC Utrecht Brain Center, Dept. of Neurology and Neurosurgery, UMC Utrecht, The Netherlands; [2]Dept. of Neurosurgery, Mayo Clinic, Rochester, MN, USA

*Universiteitsweg 100, 3584 CG Utrecht, The Netherlands
E-mail: Z.V.Freudenburg@umcutrecht.nl

Introduction: The sensoriMotor Cortex (SMC) is a frequently targeted brain area for the development of implantable Brain-Computer Interfaces (BCIs) for communication in people with severe paralysis and communication problems. It is widely acknowledged that this area displays an increase in high-frequency band (HFB) power and Event Related Desynchronization (ERD) in the lower frequency band (LFB) during movement, as well as low-frequency Event Related Synchronization (ERS) upon cessation of movement [1,2]. The ability to modulate the neural signal in the SMC by imagining or attempting to move is crucial for the implementation of sensorimotor BCI in people who are unable to execute movements. However, most common causes of loss of motor function, such as stroke, are themselves associated with significant damage to the brain, potentially affecting the functional modulation of HFB, LFB ERD, and LFB ERS control features. While BCIs aim to target non-compromised brain regions, LFB functional features are often driven by remote brain regions and thus may be affected even when HFB control features are present. Here we investigated whether MRI abnormalities remote to the SMC are associated with differences in LFB features as recorded with electrocorticography (ECoG).

Material, Methods and Results: We analyzed data from 24 subjects implanted with ECoG electrode grids for epilepsy monitoring who were evaluated to be MRI negative (no indications of cortical or sub-cortical lesions; 9 subjects) or who had MRI abnormalities that were evaluated to be either focal to the frontal cortex (6 subjects) or not (9 subjects). Electrode positions and HFB power were used to identify electrodes over the primary motor and primary somatosensory cortices with significant functional responses to overt motor tasks. We found that the mere presence of a cortical lesion does not lead to disruption of the LFB ERD or ERS in SMC electrodes. However, subjects with a frontal cortical lesion did show significantly decreased LFB ERD and ERS functional responses in the SMC.

Discussion and Significance: Evidence is mounting that LFB ERD [3,4] and ERS [5] can be disrupted by stroke, but the disruption has not yet been linked to lesion location. We feel this work can help link cortical abnormalities to possible LFB disruption, which could be important for determining the likelihood for successful functioning of implantable BCIs in severely paralyzed subjects.

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Detecting Fluctuations of the Patients with Disorders of Consciousness using Vibro-tactile Brain-Computer Interface system

C. Guger[1,2*], N. Murovec [1,2], R. Xu[1], R. Ortner[3], Y. Miao[4], J. Jin[4],

[1]Guger Technologies OG, Graz, Austria; [2]g.tec medical engineering GmbH, Schiedlberg, Austria; [3]g.tec medical engineering Spain S.L., Barcelona, Spain; [4]Department of Automation, East China University of Science and Technology, Shanghai, China

*Sierningstraße 14, 4521 Schiedlberg, Austria. E-mail: guger@gtec.at

Introduction: Diagnosis of the patients with disorders of consciousness (DOC), who typically suffer from motor and cognitive disabilities, presents a challenging task. Neurobehavioral tools used for clinical diagnosis, such as the Coma Recovery Scale-Revised (CRS-R) [1] are highly dependent on voluntary motor control and fluctuation in responsiveness [1]. Recent research has shown that non-invasive brain-computer interface (BCI) technology could help assess these patients' cognitive functions and command following abilities [2].

Material, Methods and Results: In this study, we repeated a vibro-tactile BCI paradigm on 10 DOC patients. 5 were diagnosed with minimal conscious state (MCS) and 5 with unresponsive wakefulness syndrome (UWS) and all were in a chronic stable condition. With 8 repetitions of the BCI paradigm on 10 consecutive days, we attempted to investigate if these patients were able to follow the vibro-tactile BCI paradigm and if the fluctuations observed in neurobehavioral assessments could be observed in the BCI accuracy. Each patient was evaluated with CRS-R score before and after the intervention. Each session took about 1 hour, EEG signals were recorded from eight channels (FCz, C3, Cz, C4, CP1, CPz, CP2, and Pz). The paradigm consists of 3 vibro-tactile stimulators that were placed on right wrist, left wrist and foot to provide target and non-target stimuli to the patients. The patients were asked to silently count and concentrate on the target vibrations while ignoring the non-target ones. A linear discriminant analysis was used to distinguish EEG features between target and non-target stimuli. A cross-validation resulted in a classification accuracy of 56±34% for the first run, and reached the maximum accuracy of 89±16% at the best run. Statistical difference using Wilcoxon sign-rank test between first and max accuracy was found with $p=0.031$. The median accuracy of all the repetitions was 22.5±14%. More importantly, 6 out of 10 patients improved the accuracy after the first vibro-tactile BCI session.

Discussion: The study shows that BCI systems can detect command following abilities of the patients with DOC and results can show fluctuations when the measurements are repeated. However, due to the small sample size, the authors believe that this should be further validated involving more patients.

Significance: Observed differences in the accuracies found with vibro-tactile BCI system show fluctuations in responsiveness of the DOC patients when using BCI systems and it emphasises the importance of repeated measurements.

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Evaluating a Longitudinal BCI Training Paradigm with a Lower-Limb Exoskeleton and its Induced Cortical Changes

Kevin Nathan[1,2*], Atilla Kilicarslan[1], Robert Grossman[2], Jose L Contreras-Vidal[1,2]

[1]NSF IUCRC BRAIN, University of Houston, Houston, TX, USA

[2]Houston Methodist Research Institute, Houston, TX, USA

*4800 Calhoun Drive, Engineering Building 2 E409, Houston, TX 77006. E-mail: kcnathan@uh.edu

Introduction: Brain-computer interfaces (BCIs) have been developed to enable cognitive control of computers and robotic devices. Such technology might potentially lead to restoring movement for persons with motor disabilities by allowing them to control robotic prostheses or orthoses naturally with their mind. However, BCIs are still in their infancy, and long-term usage with closed-loop systems has not been thoroughly studied, nor the subsequent changes in the brain induced by cortical plasticity.

Material, Methods and Results: Eight able-bodied subjects were recruited for a longitudinal BCI training paradigm with the Rex lower-limb robotic exoskeleton. The paradigm consisted of nine sessions in which users developed their ability to use kinesthetic motor imagery to initiate the walking and stopping of the Rex's gait as a Go-No Go task. The BCI consisted of active EEG with dynamic eyeblink and motion artifact removal [1] processed through a Localized Fisher Discriminant Analysis dimensionality reduction and a Gaussian Mixture Model classifier on time-lagged delta band amplitudes [2]. Training data were accumulated to update the decoding model over the first five sessions, after which model parameters were fixed so that subjects could adapt to their personalized model. Subjects underwent a final session with simultaneous EEG-fMRI recording while watching video playback of themselves walking in the Rex performing the same motor imagery, allowing for fMRI-constrained source localization of the EEG [3].

Discussion: BCI decoding for control of the Rex's gait varied among the subjects, with at least some achieving significantly above chance classification performance by the end of training. The fMRI scans showed contrasts in activation between the Walk and Stop conditions localized in the parietal lobule among other areas associated with motor imagery [4]. Offline EEG analysis identified ERPs corresponding to the walk cue, but these may not have been reliably detected by the classifier.

Significance: The novelty in this study is the extended use of a subject pool continuously for many sessions of BCI training to control a walking exoskeleton. The longitudinal aspect provides insights into how much training subjects may need to achieve reliable classification, what factors separate good BCI operators from poor ones, and what other features may be more relevant in future BCI applications.

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Utilizing Goal-Related Information from Medial Prefrontal Cortex in Brain-Machine Interfaces

Zhiwei Song[1*], Xiang Zhang[1*], Xiang Shen[1*], Yiwen Wang[1,2*]

[1]*Department of Electronic and Computer Engineering,* [2]*Department of Chemical and Biological Engineering, The Hong Kong University of Science and Technology, Hong Kong, China;*

*Clear Water Bay, Hong Kong. E-mail: eewangyw@ust.hk

Introduction: Brain-machine interfaces (BMIs) aim to help paralyzed people restore their motor functions. The decoders in BMIs interpret the movement intention from neural activities to control the neuro-prosthesis as a substitute for their real limbs. An efficient way to train decoders is to use a known trajectory, which is not available for paralyzed people, or using external reward [1], which is not autonomous. We are interested in designing an autonomous decoder using internal critics. In this study, we propose to extract goal-oriented information from medial prefrontal cortex (mPFC) as an internal critic to train a RL BMI decoder as an actor-critic structure [2].

Material, Methods and Results: We apply the actor-critic structure as an autonomous decoder on a rat brain control lever-pressing task, in which rats need to continuously change brain states to reach the target within multiple steps. The decoder takes in the primary motor cortex (M1) activities as input and outputs the expectation of movement. The internal critic takes the neural signals from mPFC as input and outputs the movement state value. The temporal difference of the state value is used as internal guidance to train the decoder every time instance.

In Fig. 1(a), The x-axis is the movement state and y-axis represents a neuron's spike rate in mPFC averaged across trials. It shows that as the rat approaches the target, this neuron in mPFC demonstrates a positively related modulation, which indicates the possibility to use mPFC activity as the state value. In Fig. 1(b), The x-axis represents the time index and y is the movement, in which 1 stands for pressing lever and 0 for rest. The movement reconstruction by actor-critic structure (black dashed line) has a mean squared error (MSE) of 0.1085 comparing with ground truth (red). In comparison, the single actor, which uses the external reward by the end of each trial, has an MSE of 0.2883. The results Illustrate that the critic's internal feedback is more effective to interpret movement intention for multi-step tasks.

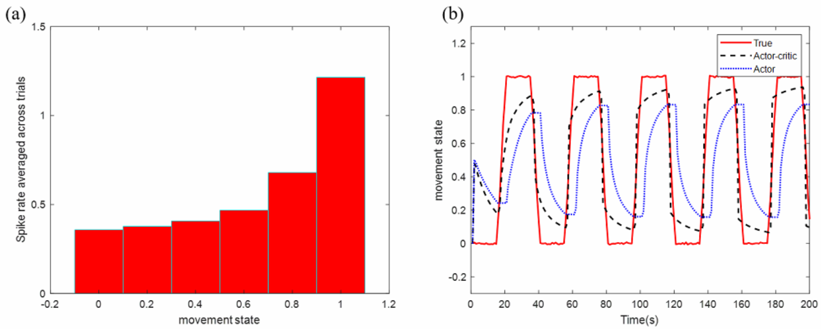

Figure 1. *(a) The neuronal modulation as rat approaches the target. (b) The decoding performance comparison*

Discussion: The proposed method shows superior decoding performance on the ever-pressing multi-step task. In the future, we will further validate it across different subjects.

Significance: This abstract shows that mPFC could be utilized as a critic to evaluate the goal-related information. Also, critic's supervision contributes to an effective decoder for multi-step tasks.

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Speech Activity Detection from Intracranial Recordings: A Pilot Study

P. Z. Soroush[1*], M. Angrick[2], J. Shih[3], T. Schultz[2], D. J. Krusienski[1]

[1]Virginia Commonwealth University, Richmond, VA, USA; [2]University of Bremen, Bremen, Germany; [3]UCSD Health, San Diego, CA, USA

[*]ASPEN Lab, Virginia Commonwealth University, 737 N 5th St, 23219, Richmond, VA, USA. Email: zanganehp@vcu.edu

Introduction: Brain-Computer Interfaces (BCIs) are a promising tool for restoring communication to those who have lost this ability because of neurological disease or injury. While several previous studies have investigated mapping brain activity to speech using different experimental designs, features, window lengths, etc. [1, 2], there are still many obstacles on the way to reaching a practical, real-time speech BCI. As an initial step toward improving performance, we propose to study the differences that distinguish speech and silence states in brain activity more systematically to find the features and model parameters that best perform in speech-silence distinction (SSD). Here, using stereo Electroencephalography (sEEG) data [3] recorded during continuous speech, we focus on alpha band energy [1, 4] over different temporal windows and offsets around each speech segment to determine the parameters that best represent the difference between the speech and silence states.

Materials, Methods, and Results: sEEG recordings were obtained from a patient being monitored as part of treatment for intractable epilepsy at UCSD Health. Ninety sEEG channels (located on the left hemisphere) and the patient's voice were recorded simultaneously during a continuous speech task. To better represent the fast changes of speech signal and nonstationary nature of brain signals, the speech signals were segmented into 10 ms frames labeled as speech or silence. The sEEG signals were bandpass filtered around each frame (±300 ms) in the 8-12 Hz alpha band for use as model features.

Different feature extraction configurations were tested, including different temporal window lengths, numbers of windows, and using windows of the brain signals from pre-frame up to the end of the frame (PFF) (to emulate causal, real-time performance) or windows from both pre- and post-frame (PPF), to determine what combination best works for SSD. Signal energy over 10, 20, 50, and 100 ms windows was computed on each channel from 300 ms prior to each 10 ms frame to 300 ms following the frame. Next, a logistic regression model with a 10-fold cross-validation analysis was trained and tested on features extracted for the various configurations.

Fig. 1 shows the results of best PFF and PPF models for each window length. For both PFF and PPF configurations, the models trained using 10 ms window length achieved the best performance (accuracy was 93.2% for PPF model and 90.5% for PFF model vs. 50% chance level). On average, for different window lengths, the best PPF model outperformed the best PFF model by about 3%.

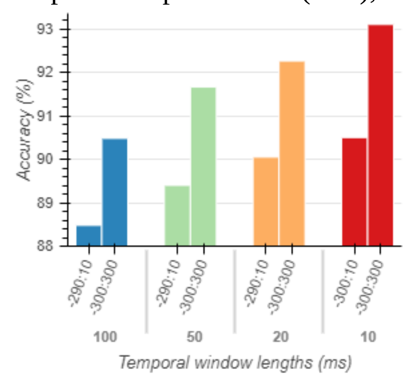

Figure 1. Best results of both PFF and PPF configurations (x-axis indicates the feature extraction window in ms).

Discussion: We have shown that alpha band energy from sEEG recordings can be used to design an accurate SSD model. We found that 10 ms windows represent the nonstationary nature of brain activity better than longer windows, and pre-speech windows can be used for a real-time SSD model. It was found that using a larger number of windows (either on one side or both sides of the frame) improves the performance of the trained model.

Significance: This is a pilot study towards a speech activity detection model using alpha-band activity from intracranial signals with the goal of designing a practical speech synthesis BCI for patients without the ability to speak.

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Intracortical microstimulation of human somatosensory cortex integrates optimally with vision

Vahagn Karapetyan[1,2*], Michael L Boninger[1,2,3], Jennifer L Collinger[1,2,3], Aaron P Batista[2], Patrick J Loughlin[2], Robert A Gaunt[1,2,3]

[1]Rehab Neural Engineering Labs, [2]Department of Bioengineering, [3]Department of Physical Medicine and Rehabilitation, University of Pittsburgh, Pittsburgh, USA

*3520 Fifth Avenue, Suite 300, Pittsburgh, PA 15213, USA. Email: vak53@pitt.edu

Introduction: Many activities of daily living involve object manipulation, which depends on intact visual and haptic feedback. These feedback modalities integrate to construct a rich representation of the external environment[1]. Attempts to restore motor function using implanted brain-computer interfaces (BCIs) have relied almost exclusively on visual feedback, despite the growing appreciation that maximizing BCI performance will likely require somatosensation. To address this need for multisensory feedback in BCIs, intracortical microstimulation (ICMS) of primary somatosensory cortex in humans has recently been shown to elicit tactile percepts and potentially improve BCI performance[2]. However, it remains unclear whether, or to what extent, ICMS interacts with vision to form a more useful representation of the external environment.

Material, Methods and Results: Using a two-alternative forced choice task, we investigated how vision and ICMS combine in a human with quadriplegia who had microelectrode arrays implanted into motor and somatosensory cortex. The visual stimulus consisted of dynamically generated random dots arranged into a sinusoidal grating, with dot coherence controlling visual noise. The ICMS stimulus consisted of a 100 Hz biphasic pulse train, where pulse amplitude was modulated in a sinusoidal pattern representing the underlying grating amplitude. Vision and ICMS stimuli were administered simultaneously to present two sequential sinusoidal patterns ranging from 4 to 20 Hz (visual angle of 204 to 41 minutes of arc). The participant had to identify which grating had the higher frequency. The sinusoidal frequency was congruent across both modalities during one interval, but during the other interval, vision and ICMS stimuli were delivered incongruently. The separation between visual and ICMS frequencies allowed us to assess the independent contribution of each modality to the overall percept and to probe how the interaction compared to predictions under a Bayesian integration model.

We found that ICMS and visual feedback were integrated in a manner consistent with Bayes' minimal-variance optimality. Further, as visual feedback noise decreased, the participant's point of subjective equivalence during multisensory stimulation became significantly biased towards the visual modality, in accordance with model predictions. This effect was replicated on two electrodes, projecting to different somatotopic locations, without additional training. Our results show that representing tactile feedback using ICMS in a cutaneous region of the cortex enables multisensory integration to occur without requiring substantial training[3].

Discussion: Our data support the hypothesis that direct cortical stimulation can engage similar multisensory integration mechanisms as other tactile sensory inputs including peripheral nerve stimulation in amputees[4] and visuo-haptic exploration in able-bodied individuals[1]. These results help establish a foundation for interpreting the ways in which ICMS feedback operates in conjunction with other sensory modalities.

Significance: Given that ICMS conforms to predictions of multisensory integration based on intact sensory systems, BCI performance stands to benefit from ICMS as a sensory feedback modality, improving natural object interactions during tasks of daily living, particularly in situations where visual feedback is obstructed or unreliable.

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Towards Closed-Loop Speech Synthesis from Stereotactic EEG using a Unit-Selection Approach

M. Angrick[1*], M. Ottenhoff[2], L. Diener[1], D. Ivucic[1], G. Ivucic[1], A. J. Colon[3], L. Wagner[3], D. Krusienski[4], P. L. Kubben[2], T. Schultz[1], C. Herff[2]

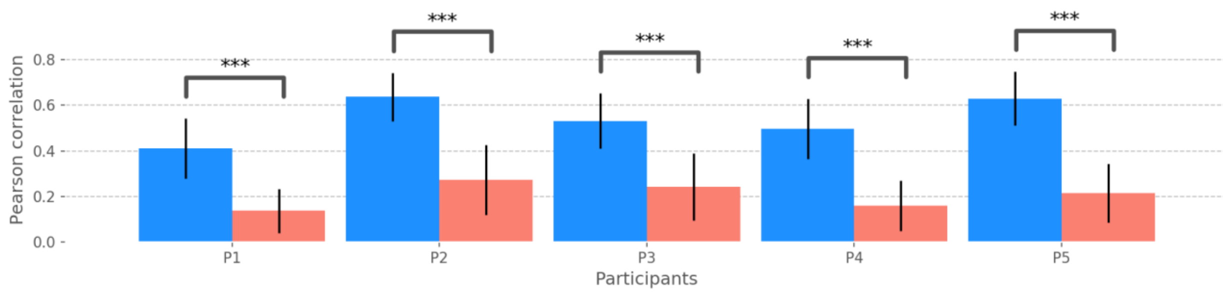
[1]University of Bremen, Bremen, Germany; [2]Maastricht University, Maastricht, Netherlands; [3]Epilepsy Center Kempenhaege, Netherlands; [4]Virginia Commonwealth University, Richmond, VA, USA;

*Enrique-Schmidt-Str. 5, 28309 Bremen, Germany. E-mail: miguel.angrick@uni-bremen.de

Introduction: Speech-related Brain-Computer Interfaces have received increasing interest in recent years, demonstrating different approaches [1, 2] to reconstruct audible audio from intracranial recordings. Our team recently developed the first closed-loop BCI that addresses imaginary speech processes using a real-time decoder capable of outputting continuous acoustic feedback to the user [3]. While we achieved very promising results, the audio quality was limited by simplified linear mappings and it is likely that more complex approaches, particularly those published in [1, 2], can generate more intelligible speech. Here, we incorporate a decoding approach based on a unit selection strategy [2] from the speech synthesis domain into our closed-loop decoder. This approach creates acoustic feedback through concatenation of short units (150 ms) of actual speech. We evaluate the resulting real-time decoder on open-loop recordings of Dutch sentences from a speech production task to assess its decoding capabilities and computational cost before deployment in a closed-loop experiment.

Material and Methods: We adapted the decoding scheme from [2] and implemented each step as a self-contained node to constitute a stream processing pipeline, which considers a window of neural data every 10 ms and outputs an acoustic waveform. In the training phase, the system stores time-aligned pairs of neural and acoustic data. In the decoding phase, the closest pair gets selected with respect to the cosine similarity between stored and incoming neural data.

Results: We used the Pearson correlation to compare the speech spectrograms of the generated audio with the original speech and achieved significantly higher ($p < 0.001$, Mann-Whitney-U test) correlations across all 5 participants than a random chance level (see Figure 1). The complete decoding pipeline is applicable for real-time scenarios and has a processing cost of 6.6 ms for each 10 ms window of neural data.



1. *Correlation results for each participant (blue bars) and random chance level (red bars).*

Discussion: We show that the proposed method in [2] can be incorporated in a real-time decoding pipeline and achieves significantly higher correlation scores with respect to a chance level on stereotactic EEG recordings on sentence tasks.

Significance: This is a first step towards synthesizing audible speech in real-time with a non-linear decoding approach for closed-loop experiments.

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Toward adapting feedback for MI-BCI user training to learners' traits and states

L. Pillette[1,2*], B. N'Kaoua[3], F. Lotte[1,2]

[1]*Inria, Bordeaux, France;* [2]*LaBRI (Univ. Bordeaux, CNRS, Bordeaux-INP), Bordeaux, France;* [3]*Handicap, Activity, Cognition, Health, Univ. Bordeaux, Bordeaux, France*

*200 Av. de la Vieille Tour, 33400 Talence, France. E-mail: lea.pillette@ensc.fr

Introduction: Along with signal acquisition and processing, Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) user-training should be improved to enable a wider development of the technology [1]. The user-training relies on the use of feedback, which have variable effects [2]. These variations have notably been associated with the different characteristics of feedback. Many researchers have attempted to clarify which characteristics enhance the positive effect of feedback [1, 3]. Also, it seems that adapting the feedback to the learners' profiles, e.g., level of autonomy, might be necessary [3, 4].

Objective & Method: The use of standard definitions and classification of the different feedback could enable a better understanding of the current state of the literature and the challenges that remain to be overcome. Beyond that, assessing how feedback impacts people differently might enable to better understand the between-studies and between-participants differences. Through a review of the literature, this work aims to contribute to the answer of these challenges.

Results: Based on our analysis of the literature, we defined three main characteristics of the feedback: (1) its *content*, or what information is conveyed by the feedback, e.g., performance-related information, (2) its *modality* of presentation, or how this information is conveyed, e.g., using a visual extending bar, and (3) its *timing* of presentation, or when this information is conveyed, e.g., after each trial. *R*ecommendations regarding each of these three characteristics can be made based on the literature. For instance, the feedback should have a supportive dimension taking into account the level of autonomy of the learners [4]. Also, a tactile and visual feedback seems preferable compared to a visual one [5,6]. Even though, the level of expertise of the learner might influence the modality of feedback to favor [3,6].

Discussion: Beyond recommendations regarding the type of feedback to use, our analysis also revealed several leads for future research. For instance, we argue that taking into account learners' state might provide relevant information to adapt the feedback. In particular, the timing of the feedback, that has been scarcely studied, might benefit from being adapted to the learners' attentional state. Attentional characteristics of the learners have been associated with BCI performances [6,7]. It might be representative of the amount of attentional resources necessary and available to process the feedback (See chapter 8 of [6] for more details). Thereby, feedback might benefit from being adapted to the attentional state of the learners.

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Design of a Magnetoencephalography Compatible Hand-Exoskeleton for BCI Based Neurorehabilitation of stroke patients

Prayagadhwaj Yadav[1]*, Sujit Roy[2], Ashish Dutta[3], Girijesh Prasad[4]
*Indian Institute of Technology Kanpur, Kanpur, India. E-mail: prayagy@iitk.ac.in

Introduction: Motor impairment of the upper limb, in terms of loss of ability to use the fingers due to stroke, is a major cause of disability worldwide. Recently [1] it has been shown that stroke survivors may have enhanced recovery if they undertake a BCI based therapy with a hand exoskeleton, involving both physical and mental practice. However existing exoskeletons [2] have motors, metallic parts, etc. and cannot be used in MEG systems. Hence there is a need to develop hand exoskeletons that are compatible with MEG systems for BCI based neurorehabilitation involving a robotic hand exoskeleton.

Material and Methods: We present the design of a MEG compatible robotic hand-exoskeleton for finger movement and a challenge-based neuro-rehabilitation strategy. The exoskeleton is designed to reproduce natural human fingertip motion during extension and flexion, with minimal kinematic complexity. It has a force adaptation based assistance control strategy by switching between active non-assist and passive assistance modes. In the active non-assist mode, the exoskeleton motion follows the applied fingertip forces based on a force position model. If the applied fingertip forces are inadequate, the passive assistance mode is triggered. It has been designed using two pneumatic artificial muscles (PAM) along with two solenoid valves as shown in fig 1. As the exoskeleton is for continuous finger flexion and extension, different solenoids have been used for both motions respectively. For position feedback in real-time, a flex sensor measures the finger position.

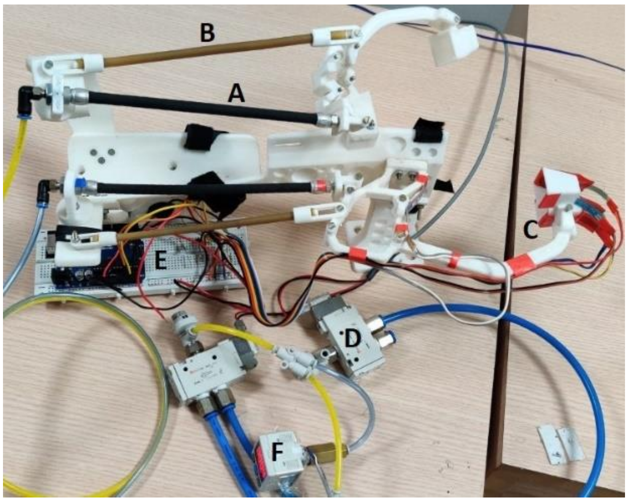

Figure 1. MEG compatible Exoskeleton with PAM(A) as actuators, elastic element (B), Force sensor attached fingertip holder(C), Solenoid valve(D), Arduino(E) and Pressure feedback sensor(F).

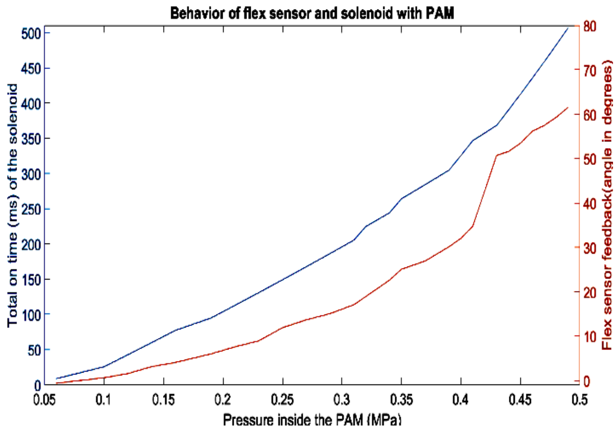

Figure 2: Experimental Plot of pressure vs time and pressure vs change in angle of arm for flexion and extension

Result and Conclusion: The exoskeleton is made using Polylactic Acid (PLA) using rapid prototyping, PAM, elastic element and plastic screws which does not add significant noise to the MEG signals (Fig 1). The exoskeleton is controlled using an Arduino microcontroller which is kept outside the magnetically shielded room. A paradigm has been designed such that the patient is first shown a cue (open hand/closed hand) and if he/she thinks correctly the MEG system activates the hand exoskeleton. The opening and closing of the fingers of the exoskeleton are controlled by suitably controlling the displacement of PAM actuators. The extension and flexion motions have been validated for smooth opening and closing of the fingers with force and position feedback (Fig 2).

Significance: We present the first MEG compatible BCI based robotic hand-exoskeleton which has potential for neurorehabilitation of stroke patients.

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Brain-computer interfacing with OPM-MEG

B. Wittevrongel[1]*, N. Holmes[2], E. Boto[2], R. Hill[2], M. Rea[2], B. Hunt[2], E. Khachatryan[1], A. Libert[1], M. Brookes[2], R. Bowtell[2], M.M. Van Hulle[1]
[1]KU Leuven, Leuven, Belgium; [2]University of Nottingham, Nottingham, UK

*Herestraat 49 box 1021, Leuven, Belgium. Email: benjamin.wittevrongel@kuleuven.be

Introduction: The vast majority of non-invasive BCI studies rely on electroencephalography despite that the complementary magnetic signals offer clear advantages in the spatial and spectral domains [1]. Recently, a new-generation of MEG sensors based on optically pumped magnetometers (OPMs) have been developed, which operate at room temperature [2] and offer the same flexibility in sensor positioning as traditional scalp-EEG [3]. In the current study, we investigated the potential of OPMs for adoption in a BCI context.

Material, Methods and Results: One male subject (28 years old, right handed) was shown 9 crosses, arranged in a 3-by-3 matrix design (Fig. 1A), which expanded and contracted for 150 ms in a non-overlapping fashion with a jittered inter-stimulus interval of 150±75 ms. The subject was asked to focus on a cued target and his brain responses were recorded with 38 OPM- and 32 EEG sensors in two sessions on separate days. Both OPM- (Fig. 1B) and EEG-recordings (Fig. 1C) exhibit a clear motion-onset visual evoked potential (i.e., N200), with a maximal signal-to-noise ratio of 18.9 dB (95% confidence interval [12.3, 22.8]) and 13.5 dB (95% confidence interval [9.0, 19.6]), respectively, both over the right parieto-occipital scalp region. Further offline analysis, as described in [4], reveals accurate decoding of the gazed target for both modalities (Fig. 1D and E).

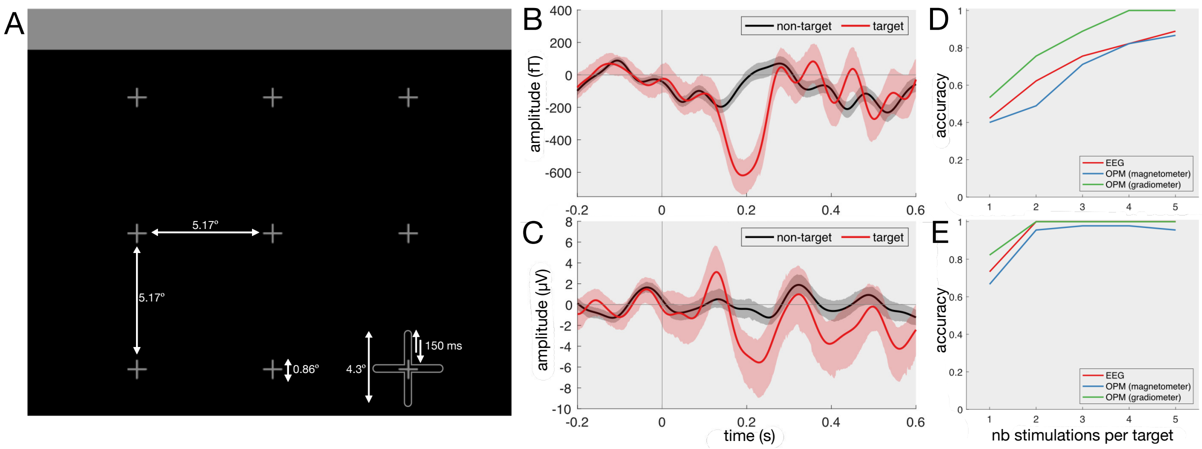

Figure 1: (A) Experimental interface. (B,C) Time-locked response obtained from OPM (B) and scalp-EEG (C). (D,E) Accuracy of decoding the gazed target with respect to the number of times each target was stimulated for single-channel (D) and multi-channel (E)

Discussion: With the current work, we showed the possibility to use OPM-MEG for accurate communication using a BCI. As the magnetic responses have an advantage in SNR compared to scalp-EEG, we believe that OPM-MEG will contribute to the development of a new generation of BCIs for communication and control.

Significance: OPM-MEG is a promising new technology that allows the exploitation of the neuro-magnetic responses in a practical and flexible manner, and opens up new avenues for a wide range of brain-computer interface applications.

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Introducing Tactile P300 Brain-Computer Interfaces to a Locked-In Syndrome Patient with Amyotrophic Lateral Sclerosis

P. Ziebell*[1], M. Eidel[1], A. Kübler[1], S. Halder[2]

[1] *Institute of Psychology, University of Würzburg, Würzburg, Germany;* [2] *School of Computer Science and Electronic Engineering (CSEE), University of Essex, Colchester, United Kingdom;* * Marcusstraße 9-11, 97070 Würzburg, Germany, philipp.ziebell@uni-wuerzburg.de

Introduction: Locked-in syndrome (LIS), a condition of almost complete or even total paralysis of the human muscular system, severely affects the ability of interacting with the outside world. Brain-computer interfaces (BCIs) have emerged as a promising way for LIS patients to maintain selected activities, e.g. enabling them to engage artistically via "Brain Painting", thus improving quality of life [1]. However, "Brain Painting" and various other BCI approaches rely on vision, in case of "Brain Painting" on visual stimulation via flashes evoking the electroencephalographic event-related response P300. Since loss of vision has been pointed out as a limiting factor in LIS cases, alternative BCIs have been developed. For example, Halder, Käthner and Kübler could show successful use of an auditory P300 BCI in paralyzed patients [2]. Still, BCI research regarding potential LIS end-users remains scarce [3]. The present single-case-study intended to further explore P300 BCI use in LIS patients by involving recently developed tactile P300 BCIs [4, 5] (see Fig. 1), which proved feasible for healthy users, and to compare them to visual and auditory approaches.

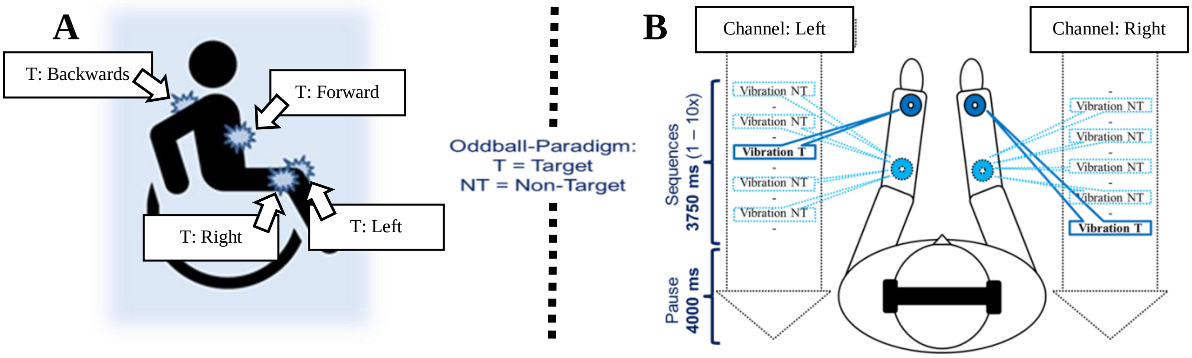

Figure 1. *Schematics of stimulation positions used in the two tactile P300 BCIs: 4-choice wheelchair (A) and 2-choice streaming-based (B).*

Material, Methods and Results: The participant was a LIS end-user (male, 55 years) suffering from loss of speech and near complete paralysis caused by amyotrophic lateral sclerosis diagnosed 8 years ago. Visual and auditory P300 BCIs were already tested in earlier sessions, with higher effectiveness and efficiency as well as lower subjective workload reported for the visual paradigm. In the current session, basic P300 elicitation oddball-paradigms still indicated the superiority of the visual modality. The patient experienced the newly introduced tactile P300 BCI 4-choice wheelchair approach as the second best option and reported the wish for additional sessions with this BCI.

Discussion and Significance: The feasibility of a tactile P300 BCI for a LIS end-user could be shown as a vision-independent communication alternative if a loss of vision should occur in the future. More sessions are planned to examine long-term development of BCI use in further detail following the user-centered design approach [6].

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Recognition Method of Mental States of Single-Task and Multi-Task Using EEG Signals

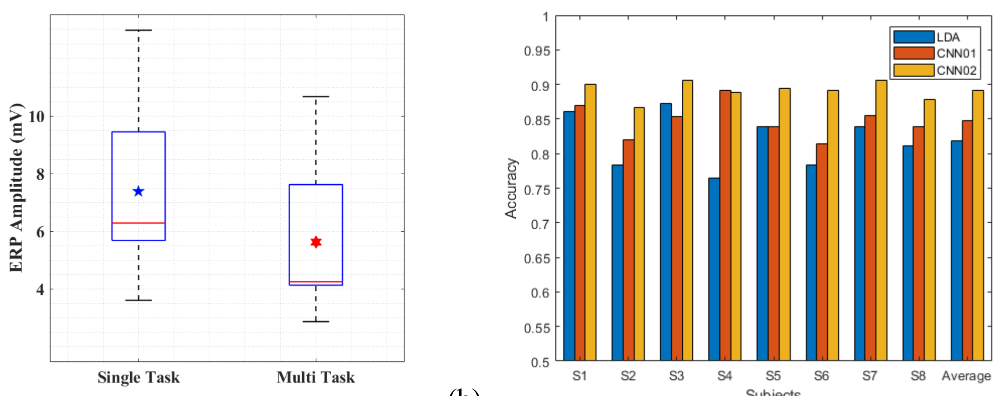
Luzheng Bi*, Shengchao Xia, and Xiaoguang Wang

[1] *Beijing Institute of Technology, Beijing, China;* E-mail: bhxblz@bit.edu.cn

Introduction: Brain-computer interface (BCI) systems can decode brain activity into control signals to operate external devices to assist people with some disabilities or healthy people to complete a certain task [1, 2]. Different decoding and control models need to be involved in single-task and multi-task situations. Therefore, it is necessary to distinguish which state the person is in a single-task state or a multi-task state. Since electroencephalogram (EEG) signals can reflect the state of brain activities, which precede observable behavioral actions, and studies have shown that it is feasible to use EEG signals to decode brain states and intentions [3]. In this paper, we proposed an EEG-based method to distinguish mental states given single- and multi-task conditions by using convolutional neural network (CNN).

Methods: Eight healthy subjects participated in the experiment. We used the addition task to elicit the single-task state of subjects. We used the combination of addition and upper limb movement to elicit the multi-task state, in which the upper limb movement was the primary task and the addition task was the secondary task. EEG potentials were measured from16 channels. The sampling frequency was 1000 Hz. Baseline correction, common average reference and downsampling were applied. There were two different CNN structures used for classification and compared with linear discrimination analysis (LDA).

Results and Discussion: The event-related potentials (ERP) P300 amplitudes under different task conditions are shown in Fig. 1 (a). The average amplitudes under the single- and multi-task conditions are 7.6 mV and 5.6mV, respectively. The classification performance is shown in Fig. 1 (b). The average classification accuracy obtained by using CNN with structure 1 is 84.76±0.03%, whereas the classification accuracy of the CNN with structure 2 is 89.13±0.01%, both higher than that by using LDA (81.91±0.04%).



(a) (b)

Figure 1. *(a) ERP amplitude given different task conditions (b) Classification performance of different methods.*

Significance: This work is the first to propose an EEG-based recognition method to distinguish single- and multi-task mental states, which is basic for developing adaptive assistive methods to improve performance.

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FBNet: A Filter-Bank Convolutional Neural Network for Motor Imagery BCI in Chronic Stroke Patients

R. Mane[1], N. Robinson[1], E. Chew[2], K. Chua[3], K. K. Ang[1,4], A. P. Vinod[5], C. Guan[1*]

[1]Nanyang Technological University, Singapore; [2]National University Hospital, Singapore; [3]Tan Tock Seng Hospital, Singapore ;[4]Agency for Science, Technology and Research, Singapore; [5]Indian Institute of Technology, Palakkad

* School of Computer Science and Engineering, Nanyang Technological University, Singapore. E-mail: ctguan@ntu.edu.sg

Introduction: Motor Imagery (MI) based Brain-Computer Interface (BCI) systems have emerged as a powerful tool for post-stroke motor rehabilitation. Deep learning architectures, particularly based on Convolutional Neural Networks (CNN), have shown promising results for MI-BCI classification in healthy subjects. However, their effectiveness in stroke patients has not been validated. In this work, we present one of the first reports on EEG-MI classification using deep learning in chronic stroke patients. Also, we propose a novel, neuro-physiologically, inspired CNN architecture named Filter-Bank Network (FBNet).

Material, Methods and Results: We evaluated the performance of existing deep-learning architectures named Deep Convnet[1] and EEGNet[2] for classification of hand-MI vs. rest condition in 34 chronic stroke patients (data details : [3]) in a subject-specific 10-fold cross-validation setting. The deep learning architectures were compared with Filter-Bank Common Spatial Patterns (FBCSP) algorithm[4], and the classification results are presented in Tab. 1. FBCSP algorithm resulted in significantly better performance compared to both deep learning architectures ($p<0.05$) when tested using Wilcoxon Singed-rank test.

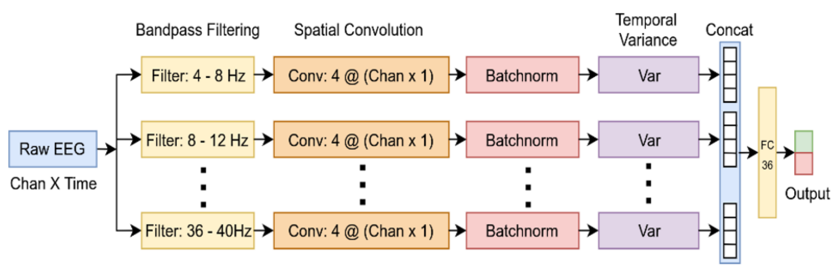

Figure 1. *The proposed FBNet architecture for MI-BCI in stroke patients.*

Architecture	Classification Accuracy (%)
FBCSP-SVM	72.25
Deep Convnet	67.71
EEGNet-8,2	67.59
FBNet	**75.71**

Table 1. *Classification accuracies*

Following the principles of FBCSP, we designed a novel CNN architecture named FBNet (Fig. 1). FBNet is designed to capture spectro-spatially localised signatures of MI (Event-Related De/Synchronization (ERD/ERS)). To do so, FBNet first creates a multi-view representation of the data by bandpass-filtering the EEG into multiple frequency bands. Next, spatially discriminative patterns for each view are learned using a CNN layer. Finally, the temporal information is aggregated using a temporal variance layer and a fully connected layer classifies resultant features into MI classes. Results indicate that FBNet significantly outperforms both EEGNet and DeepConvNet ($p<0.05$) and its classification accuracy is better than FBCSP.

Discussion and Conclusion: In healthy subjects, DeepconvNet and EEGNet have performed far better than FBCSP [1], [2]. However, opposite results were observed for stroke patients which may be caused by the post-stroke disruption of sensory-motor rhythms. The higher classification accuracy achieved by FBNet indicates that inclusion of neuro-physiological priors while designing deep learning architectures may offer better MI-classification results for stroke patients.

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A Neurophysiological Approach to Feature Selection for Adaptive Common Spatial Patterns

J. D. Bennett[1*], S. E. John[1], D. B. Grayden[1], A. N. Burkitt[1]

[1]*Biomedical Engineering, The University of Melbourne, Melbourne VIC 3010, Australia*

*203 Bouverie Street, Parkville, Victoria, Australia. Email: bennettj1@student.unimelb.edu.au

Introduction: Electroencephalography (EEG) recordings have the potential to be interpreted by a Brain-Computer Interface (BCI) to restore communication and control to people with severe motor disabilities. The widely used Common Spatial Patterns (CSP) algorithm is an effective method to overcome the poor spatial resolution of EEG and extract discriminatory features. Informed selection of CSP filters typically requires oversight from a BCI expert to accept or reject filters based on the neurophysiological plausibility of their time-invariant source patterns [1]. The aim of this study was to empirically reveal recurring CSP patterns, assess their influence on decoder performance, and determine whether they can be automatically categorized to inform spatial filter adaptation.

Material, Methods, and Results: Four publicly available motor imagery EEG datasets (1-4) were used consisting of 52, 5, 9, and 10 participants, respectively [2-5]. The six most relevant CSP filters and patterns were extracted from each participant across time, using a window of 80 trials. An unsupervised clustering technique was applied to the CSP patterns of Dataset 1 to identify the most common CSP patterns. Nine classes of prototypical CSP patterns were established, shown in Fig. 1.

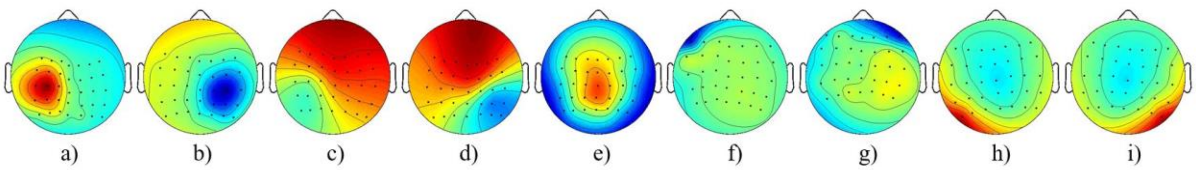

***Figure 1**. Nine classes of prototypical spatial patterns. Patterns observed were a) left motor cortex, b) right motor cortex, c) frontal/left parietal, d) frontal/right parietal, e) central, f) left eye artifact, g) right eye artifact, h) left parietal artifact, i) right parietal artifact.*

Patterns a) to e) were considered neurophysiologically plausible BCI targets. The correlation of the number of these patterns that a participant had in the calibration set with the Cohen's kappa of an adaptive linear discriminant analysis classifier was 0.68 ($p<0.001$). 27 participants possessed artifactual patterns (f-i). When the corresponding filters were discarded, they experienced a significant 7.4% decrease in average kappa ($p=0.007$). A Convolutional Neural Network (CNN) was trained to categorize the CSP patterns into the nine established classes plus an uncategorized class, and achieved an average test accuracy of 82.3±6.1%. A decoder that adapted CSP filters according to the categorization of their patterns significantly increased performance compared to state-of-the-art decoders.

Discussion: In this study, we revealed typical CSP patterns that BCI experimenters can expect. We showed that neurophysiologically implausible sources, such as ocular or muscular activity, can be a consistent indicator of task-related activity. Furthermore, we identified the topography of plausible sources that were associated with high performance. The automatic detection of such patterns can inform decoder adaption to increase performance which, benefited participants whose features became inseparable due to changing sensorimotor rhythm (SMR) patterns over time.

Significance: In the pursuit of effective BCI decoders that rely on neural activity only, this study highlights the importance of considering and reporting upon the source patterns of any spatial filters used. CSP filters can become ineffective in the presence of evolving SMR patterns and automatic detection of these emerging patterns can be utilized to inform decoder adaptation to restore feature separability.

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Interpreting deep network representations of EEG

N. Robinson*, C. Guan
Nanyang Technological University, Singapore
*N4-02a-32, 50 Nanyang Avenue, S639798. E-mail: nrobinson@ntu.edu.sg

Introduction: With the recent surge in application of deep learning in Brain Computer Interfaces (BCI), the need to explore neurophysiologically plausible interpretations of networks to justify its comparable or better performance than state-of-the-art approaches is becoming increasingly relevant [1-2]. Recently, we reported an average (N=54) cross-subject classification of 84.19 (+/-9.98) % for right vs. left hand motor imagery (MI) using EEG across 54 subjects [2]. This research investigates whether the patterns learned by the network can explain performance variation across subjects using localized EEG.

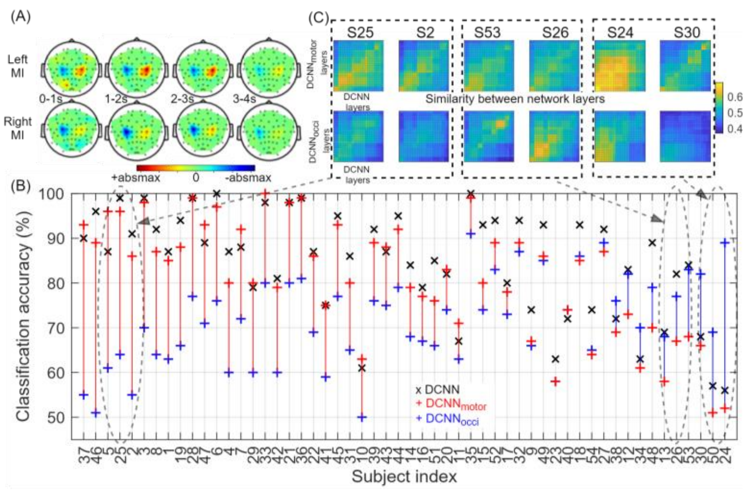

Figure 1. *(a) LRP relevance maps of correctly classified trials averaged across subjects. (b)Classification accuracy across subjects. The average accuracies are 84.69 +/- 11.75, 81.08+/-12.92 and 71.45 +/-10.01 respectively for DCNN, DCNN$_{motor}$ and DCNN$_{occi}$. (c) SVCCA similarity across networks for row1: DCNN vs DCNN$_{motor}$ and row2: row1: DCNN vs DCNN$_{occi}$.*

Material, Methods and Results: Data from 54 subjects MI is used to train deep CNN using a leave-one-subject-out strategy. From the trained models and correctly classified trials, we determine relevance patterns using layer-wise relevance propagation [3]. The heatmap averaged across all subjects across an epoch is indicated in Fig. 1(A). It can be observed that occipital along with motor region influences the network decision (0-1s). Based on this, we hypothesize that the network trained using EEG in motor and occipital regions may explain characteristic of certain subjects.
To explore this, we compared 3 variants of DeepConvNet [1] in which the input is given as whole head 62 channel EEG (DCNN), 20 channel motor EEG (DCNN$_{motor}$) and 8 channel occipital EEG (DCNN$_{occi}$). Fig. 1 (B) displays performance of subjects sorted according to difference in accuracy using DCNN$_{motor}$ and DCNN$_{occi}$. The red and blue lines indicate subjects with higher accuracy using DCNN$_{motor}$ and DCNN$_{occi}$ respectively. The performance with DCNN$_{occi}$ is better for 24% of subjects compared to DCNN$_{motor}$ and 11.11% subjects compared to DCNN. We use SVCCA tool [4] to compare the representation of data across network layers for DCNN and localized DCNN$_{motor}$/DCNN$_{occi}$ for 3 sets of subjects. In set 1, from left end of Fig. 1(B), the network DCNN and DCNN$_{motor}$ exhibits high similarity and high performance. Sets 2 and 3 from right end of Fig. 1(B), in which subjects perform well using DCNN$_{occi}$. In set 2, DCNN performs well and the patterns are correlated with DCNN$_{occi}$, whereas in set 3, it shows least similarity with DCNN$_{occi}$ and the performance is much lower than DCNN$_{occi}$.

Discussion and Significance: The results presented here indicates (1) the network trained on occipital EEG offers better performance compared to sensorimotor EEG for certain subjects. It may indicate that the subjects resorted to visual rather than kinetic motor imagery task and denote the ability of network to identify it. (2) DCNN may benefit from subject-specific localized EEG for certain subjects and hence networks that incorporate multiple localized regions might help to enhance BCI decoder further.

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BCI and AAC Language Representation Methods as Rate Enhancement Strategies

M. O'Leary[1]*, J. E. Huggins[2], K. Hill[1]

[1]University of Pittsburgh, Pittsburgh, PA, USA; [2]University of Michigan, Ann Arbor, MI, USA

*AAC-BCI Performance and Testing Lab, 6017 Forbes Avenue, Pittsburgh, PA 15260. E-mail: mso16@pitt.edu

Introduction: Brain-Computer Interface (BCI) is a rapidly developing technology that will allow an individual to access their augmentative and alternative communication (AAC) device using brain activity. Yet, the current research is severely lacking in implementing AAC language representation methods (LRMs) beyond spelling and word prediction. LRMs on an AAC device may be categorized in three ways: 1) text or alphabet based (spelling), 2) single meaning pictures, and 3) multi-meaning icons. Spelling tends to be slow for sentence formulation due to the increased number of selections required to generate an utterance. Other methods of utterance generation have been present in the field of AAC for several decades, but they have yet to make an appearance on BCI technology. This includes the use of single meaning pictures and multi-meaning icons. Such language or encoding methods may increase the communication rate of an individual, allowing them to generate a far greater number of words at a faster rate compared to traditional letter-by-letter spelling methods. Research on word prediction has shown that this method does not increase communication rate [1]. Research on multi-meaning icons used by AAC speakers has shown to increase communication rate [2]. The use of spelling, single meaning pictures and multi-meaning icons are accurately compared using Language Activity Monitoring (LAM) analysis.

Material, Methods and Results: LAM was developed with a focus on language sampling and reliability in the transcription process. The use of LAM allows a speech-language pathologist to monitor the language representation method utilized, the average and peak communication rates, the selection rate, rate index, and accuracy [2]. These data can then be used to determine treatment effectiveness including comparisons amongst appropriate access methods such as BCI [3]. Likewise, by maximizing the efficiency of how language is presented on the screen the AAC-BCI user is more likely to have increased participation in care and conversations, have reduced fatigue levels, increased communication rate, and an overall higher quality of life [4].

The LAM data were analyzed using the AAC Performance Report Tool (PeRT) [5]. Calculation methods have been tested and published for AAC performance measures. Data was extracted from the AAC Bank Repository. Performance data was collected from two picture description tasks and a conversational speech sample. Language sampling data revealed that users who utilized a combination of LRM's had increased average and peak communication rates compared to those with just spelling. They also produced a greater number of total words, mean length of utterance, and total utterances. For example, participant 1 only used spelling (36.4%) and word prediction (63.60%) on the picture description task versus Participant 2 who used a combination of methods such as multi-meaning icons (59.10%), spelling (4.50%), word prediction (18.20%), and single meaning pictures (18.20%). These methods allowed for Participant 2 to have an average communication rate of 12.75 words per minute (wpm) versus Participant 1 who generated 0.87 wpm.

Discussion and Future Directions: Currently, BCI as an access method is slow compared to other access methods [6] such as eye gaze or switch scanning. BCIs should take advantage of language displays with multiple LRMs to provide the user an opportunity to produce a higher communication rate.

Significance: Rate enhancement strategies through LRMs for an AAC-BCI system is imperative. Performance measurement to compare LRMs has been completed on multiple access methods and BCI should utilize the same features in order to maximize communicative output.

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Artifact subspace reconstruction with adaptive baseline procedure for SSVEP control application

Bo-Yu Tsai[1], Li-Wei Ko[1*], Shih-Chien Tang[2], Chia-Lung Yeh[2]

[1]*National Chiao Tung University, Hsinchu, Taiwan;* [2]*National Chung-Shan Institute of Science and Technology, Taoyuan, Taiwan*

*E-mail: lwko@mail.nctu.edu.tw

In BCI study, it is usual to use EEG for realize the activity in the brain. Due to its characteristic of time resolution, it is possible to decode our brain in real time and control something with our brain. However, not only information in brain would be record but also some artifact would be record. For example, blinking eye and grinding teeth causes some high amplitude and high frequency signal on the recorded EEG. Artifact subspace reconstruction (ASR) is a new artifact removal method proposed by Kothe and Jung [1]. The main idea of ASR is looking for principle components of clean data and apply these components and a cutoff parameter to reject some components of contaminated data. After multiplying inverse of truncated components to contaminated data, the big amplitude artifact of contaminated data will be eliminated. Besides, Chang and Hsu evaluate that the cutoff parameter used in ASR method should be 10 to 30 to ensure the brain activity will not be reduced so much but reduced most artifact components activity [2]. According to implementation, the process to finding clean segment from EEG data is just done once in the beginning. However, EEG signal is non-stationary signal, the components used in ASR process should not be same all the time. Therefore, adaptive ASR is proposed in this study to deal with this problem. The process to finding the clean data is not only done once during ASR process and clean data segment will be changed in specific time. This study focuses on applying adaptive ASR on SSVEP-BCI experiment data [3] and do a pilot test. After removing artifact with adaptive ASR, most subjects' performances are improved. Among thirty trials in SSVEP experiment, it can improve eighteen correct trials to twenty correct trials in average of ten subjects. Although it is not such subjects, it shows the impact of ASR in SSVEP performance. Besides, the large amplitude artifact can be removed in time domain given specific cutoff parameter. In the future, applying adaptive ASR method in real time could be a powerful tool for BCI field.

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BrainBraille: Towards 100+bpm Typing with a Haemodynamic Response-based Brain-computer Interface

Yuhui Zhao[1], Thad Starner[1*2], Abdelkareem Bedri[2], Qiuyue Xue[3], Benoit Corda[2], Vishwadeep Ahluwalia[1], Ankit Arora[1], Caitlyn Seim[4], Huanfen Yao[2], Richard Lyon[2], Alex Olwal[2], Melody Jackson[1]

[1]*Georgia Institute of Technology, Atlanta, GA, USA;* [2]*Google Research, Mountain View, CA, USA;* [3]*University of Washington, Seattle, WA, USA;* [4]*Stanford University, Stanford, CA, USA;*

*Technology Square Research Building, 85 5th St NW, Atlanta, GA 30308. E-mail: thad.starner@gmail.com

Introduction: Most high-speed non-invasive BCI typing systems require intense visual attention and feedback [1]. BrainBraille investigates a more open-loop approach similar to touch typing. BrainBraille enables communication at 20 characters per minute (cpm) by monitoring attempted movements in the motor cortex [2] using functional Magnetic Resonance Imaging (fMRI). Users attempt to tense the muscles for six body parts: the hands, the feet, the tongue, and the gluteus maximus. Those actions activate the corresponding six regions of the motor cortex, which map to the six dots in a Braille cell. When letters are separated by 3sec or more, words form unique signatures of activation in the brain. Figure 1 demonstrates the concept for HappyNewYear using pilot data using the hands, feet, and shoulders. The regions tensed are shown at the top, activations are shown in the middle, and the bottom shows the regions active at the end of the phrase. For locked-in users, whose attempted movements also activate the motor cortex [3], the eventual goal is to enable open vocabulary, phrase-level communication using functional near infrared spectroscopy (fNIRS) without needing visual attention.

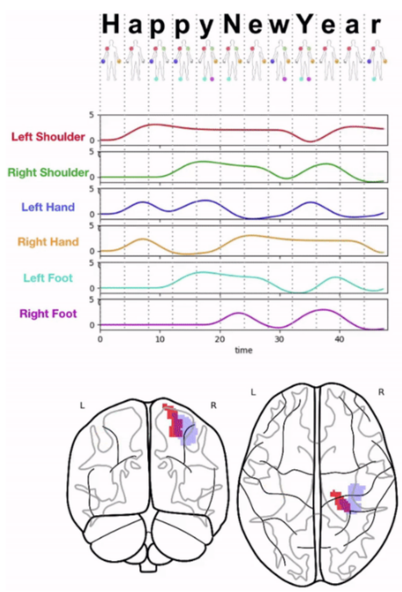

Figure 1: BOLD response while typing HappyNewYear. Synthetic curves are modeled on normalized, averaged and smoothed actual responses.

Material, Methods and Results: All experiments are conducted on a healthy male subject using a 3T MRI with a repetition time of 750ms. Pilot studies determined the most distinguishable body parts, mentioned above, and optimized the BrainBraille dot-pattern-to-letter mapping. For evaluation, we selected nine phrases in the MacKenzie & Soukoreff corpus [4]. In two 2-hour sessions, the subject performed 11 runs where the nine phrases are performed in random order with each letter appearing for 3sec. The fMRI data is collected and analysed offline. Leave-one-phrase-out cross-validation is used. Regions of interest for each body part are first identified with a Generalized Linear Model. To classify the transitions of activations of each body part and decode the letters, we applied Hidden Markov Models resulting in 89% letter accuracy, while a Support Vector Machine approach using Viterbi decoding reached 97% letter accuracy. Restricting the dictionary to the 38 words in the phrases resulted in 97% word accuracy with the SVM method; allowing all 1164 words in the full corpus resulted in 93% word accuracy.

Discussion: Data collection on more subjects is ongoing and initial tests indicate comparable results. We believe that the system can be further improved by adding more regions, reducing the time per letter and using stochastic grammars for disambiguation. Memorizing the BrainBraille alphabet may be accelerated for locked-in patients using passive haptic learning (PHL) [5]. Since the haemodynamic response is also observable using fNIRS, we are investigating whether similar rates could be enabled using portable fNIRS systems. Testing suggests that, due to the depth of the representation of the feet in the motor cortex, the shoulders may have to replace the feet for two dots in BrainBraille.

Significance: By using multiple regions of the brain simultaneously and detecting changes of activations in letter transitions, this work demonstrates a haemodynamic response-based BCI speller that can achieve ~100 bpm and 97% letter accuracy on typing at 20 cpm. These results point toward a potential non-invasive BCI for locked-in patients.

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The effects of using BCI software with posterior alpha rhythm neurofeedback (NFB) on cognitive processes underlying reading in persons with mild Alzheimer's disease (AD)

B. S. Oken, D. Klee, D. E. McLaughlin, T. Memmott, M. Fried-Oken
Oregon Health & Science University, Portland, OR USA Corresponding author: oken@ohsu.edu

Introduction: Prior BCI research suggests NFB may improve cognitive performance. In addition to memory deficits, AD is often associated with functional impairments in language and reading. The goal of this pilot study was to develop a BCI-based NFB paradigm to investigate the effect of NFB on cognitive processes underlying reading in people with mild AD.

Methods: NFB training included a P300 speller with rapid serial visual presentation (RSVP) of letters developed using BciPy software [1] and an 8-channel dry-electrode cap (VR300, Wearable Sensing). Calibrations consisted of 100 sequences. Each calibration sequence presented a target letter followed by a series of 10 letters, including the target letter, presented at a rate of 3 Hz. Machine learning was trained on 500 msec of EEG data following target and non-target letters. A regularized discriminant classifier was implemented following dimension reduction using a principal components analysis. The best parameters for the classification were obtained using a 10-fold leave-one-out cross-validation.

Posterior alpha rhythm amplitude, an attentional marker [2], was used for feedback. NFB was presented after each trial based on estimated posterior rhythm (8.0-10.0 Hz) power spectral density. Feedback was presented as 5 horizontally oriented rectangles ranging from red to green. The trial feedback was presented for 2 s as a highlighted border around 1 rectangle. Posterior rhythm amplitude thresholds for the 5 levels were individualized for each person based on prior calibration data. We provided more positive than negative feedback and selected category 1 as the lowest 15th percentile up to category 5 as the top 30th percentile. A single case experimental design was implemented, with 5 people. Participants completed 3-7 baseline calibrations before starting the 6-week NFB phase, with 3 visits per week. Besides the AUC outcome measure, cognitive outcome measures related to reading were administered weekly: reading processing speed (*WJ Sentence Comprehension*), selective attention (letter cancellation task with 2 difficulty levels), and working memory (letter span forwards & backwards). Summative measures at the beginning and end of the study are: *WJ Discourse Comprehension Test* and *WAIS-IV Digits Forward, Digits Backward and Sequencing Digit Span.*

Results: Two participants with mild AD completed the study; three are enrolled (age 53 – 79 years and MOCA scores 19 – 29). For individualized NFB, we successfully delivered feedback at the 5 levels in approximate target distributions. On the BCI RSVP task, participants with mild AD achieved a mean correct classification rate (AUC) at baseline of 0.76 $\pm$ 0.05. Improvements in one participant are shown in the Figure.

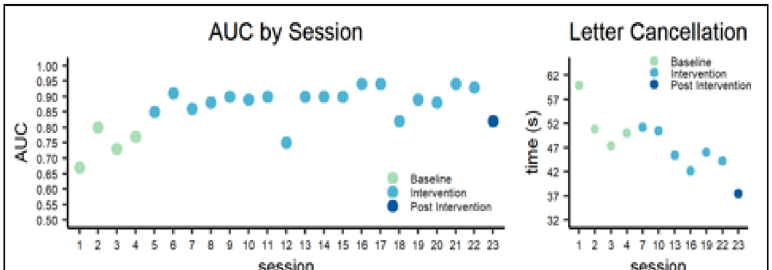

Figure. AUC by session with significant increase in performance compared to baseline on attention-based letter task with introduction of neurofeedback (left). Letter cancellation performance by session with downward trend indicating better performance compared to baseline on selective attention measure (right).

Discussion: We delivered NFB based on posterior alpha rhythm during an RSVP calibration session. Preliminary results demonstrated improvements in AUC and at least some of the cognitive measures underlying reading in select participants. Analyses of the remaining 3 participants will provide more evidence to justify a larger clinical trial of BCI-based NFB to improve reading related visual processing in mild AD.

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BCI-enhanced decision making for realistic environments in teams of humans and AIs

Riccardo Poli, Saugat Bhattacharyya, Caterina Cinel, Luca Citi

Brain Computer Interfaces and Neural Engineering Lab, University of Essex, UK (email: rpoli@essex.ac.uk)

Introduction: In [1] we described collaborative brain-computer interfaces (cBCIs) for decision-making based on the estimate of the decision confidence of individuals from EEG features, which improved decision accuracy. In [2] we showed that BCI-assisted group decisions in a face recognition task can be improved by integrating an artificial agent (AI) that is able to recognise faces as well as assess its own confidence as an extra team member. While group performance was significantly improved, the AI behaved quite differently from the humans, which could potentially lead to teamwork problems (e.g., acceptance, trust). In this study, we have extended this work by testing the possibility of developing and adding (multiple) AIs with different "personalities" (that can potentially present fewer teamwork problems) as team members as well as considering a task of military relevance.

Material, Methods and Results: 10 participants were presented with a sequences of short realistic videos (frame rate=10Hz) that simulated the viewpoint of a user, through a simulated night camera, stationed at a military outpost. In the videos, in each trial a uniformed character appeared from a distance from any direction and walked towards the outpost (Figure 1(left)) [1]. Participants had to decide, within 2.5s, whether the character was wearing a helmet or a cap. Next, participants had to indicate their degree of confidence using an 11-point scale (from 0=not confident, to 100=very confident) within 2s. The experiment was split into 6 blocks of 60 trials. A Biosemi ActiveTwo EEG system was used to record the neural signals from 64 electrode sites. The data were sampled at 2048 Hz, referenced to the mean of the earlobe electrodes, and band-pass filtered between 0.15 to 40 Hz. Decision confidence of humans was estimated by a random-forest classifier using two Common Spatial Patterns applied to decimated (16 Hz) response-locked EEG epochs starting 1s before the response and lasting 1.5s. Our AIs first extract histogram features of each video frame that are then fed into a random forest classifier to make independent decisions and produce a confidence measure (based on the technique developed in [2]). The AIs responds exactly 1000ms after the first appearance of the target. In one AI the confidence measure was modified to confer it a *confident* personality, while we made the other AI *under-confident*. The confidence measures produced by the classifier for both humans and AIs were then used to weigh individual responses when making group decisions. Group accuracies are shown in Figure 1(right). Groups of size 1 to 10 were formed by considering all possible combinations of the ten human participants. Each human group was then augmented with the two AIs. Groups assisted by a combination of humans and artificial agents (BCI-and-AI-assisted groups in green) were significantly better (two-tailed Wilcoxon signed-rank test $p<0.03$) than standard-majority groups (Traditional groups in red) and cBCIs (BCI-assisted groups in blue) for group of up to size 8.

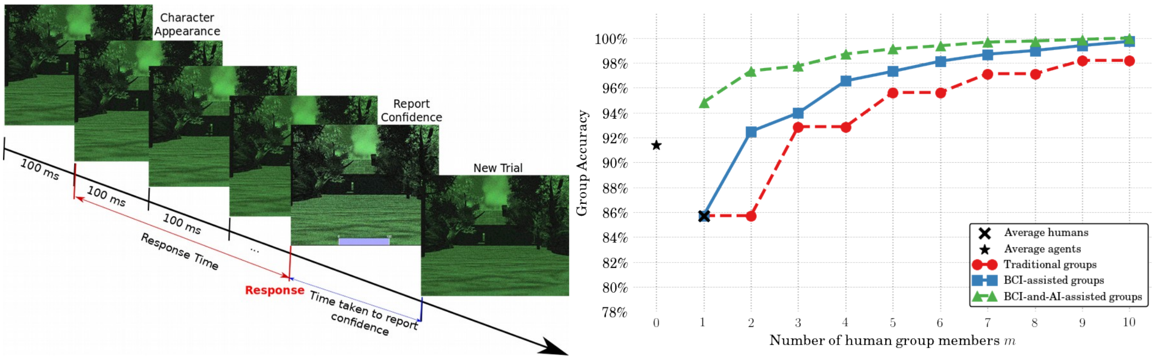

Figure 1. (left) Example of sequence of video frames in a single trial. (right) Group accuracy versus number of human group members. The cross and star represents average performance of humans and virtual humans, respectively.

*Discussion: C*ombining cBCIs with multiple AIs increased the overall performance of decision-making by groups in a realistic environment. We were able to create high-performance AI team members of different personalities.

Significance: Humans are the most expensive commodity in group decisions. So, our approach yields big accuracy improvements at no cost. AI members with human-like personalities are likely more acceptable to human teams.

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Fatigue evaluation in SSVEP-BCIs based on wavelet entropy of EEG

Yufan Peng[1,2], Chi Man Wong[1,2], Ze Wang[1,2], Agostinho Rosa[3], Feng Wan[1,2*], Tzyy-Ping Jung[4]

[1]*Department of Electrical and Computer Engineering, Faculty of Science and Technology, University of Macau, Macau,*

[2]*Centre for Cognitive and Brain Sciences, Institute of Collaborative Innovation, University of Macau, Macau;*

[3]*Dept. of Bioengineering, LaSEEB-System and Robotics Institute, Instituto Superior Tecnico, University of Lisbon, Portugal*

[4]*Swartz Center for Computational Neurosciences, University of California, San Diego, United States*

* Faculty of Science and Technology, University of Macau, Macao, China. E-mail: fwan@um.edu.mo

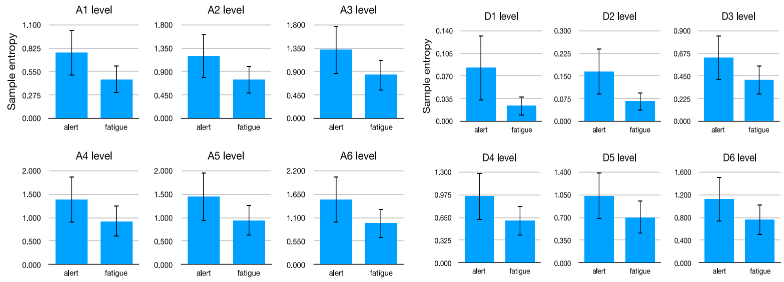
Introduction: The complexity of EEG signals decreases as the subject's fatigue level increases [1], while some EEG spectral powerbands are reported more sensitive to fatigue compared to others [2]. This study compares how the wavelet entropy of EEG signals from different frequency bands performs as fatigue index in an SSVEP-BCI task. Specifically, the new method calculates the complexity of EEG signal in multiple frequency bands using wavelet decomposition to measure the fatigue during the SSVEP-BCI task. The study results showed that the low-frequency components could track fatigue level better than the higher frequency components.

Material, Methods and Results: 11 subjects (normal college students) performed a standard SSVEP based BCI experiment of 30 trials in six blocks. The subjects' fatigue levels were evaluated before and after each block through questionnaires [3]. The fatigue scores before and after experiments indicated significant fatigue increases with $p < 0.001$.

Within each block, the EEG signals at Oz from the first and last 5 trials were used to calculate the fatigue indices corresponding to the "alert" and the "fatigue" stages, respectively. The EEG signals were decomposed into approximations A1 to A6 and details D1 to D6, in which the Daubechies wavelet of order 4 (db4) was chosen. As the sampling frequency is 600Hz, according to the Nyquist's rule, the original EEG signal covers the frequency range 1-300Hz and the estimated frequency ranges of A1 to A6 as well as D1 to D6 are listed below:

A1: 0 - 150 Hz	A2: 0 - 75 Hz	A3: 0 - 37.5 Hz	A4: 0 - 18.75 Hz	A5: 0 - 9.375 Hz	A6: 0 - 4.6875 Hz
D1: 150 - 300Hz	D2: 75 - 150 Hz	D3: 37.5 - 75 Hz	D4: 18.75 - 37.5 Hz	D5: 9.375 - 18.75 Hz	D6: 4.6875 - 9.375 Hz

Sample entropy values of A1 to A6 and D1 to D6 were calculated and referred as wavelet entropy fatigue indices.



Sub-band	Mean difference	Std. Error	P value
A1	0.310	0.069	<0.001
A2	0.459	0.103	<0.001
A3	0.478	0.108	<0.001
A4	0.466	0.112	<0.001
A5	0.508	0.118	<0.001
A6	0.551	0.125	<0.001
D1	0.058	0.014	<0.001
D2	0.099	0.024	<0.001
D3	0.219	0.054	<0.001
D4	0.347	0.080	<0.001
D5	0.327	0.084	<0.001
D6	0.361	0.092	<0.001

Figure 1. The wavelet entropy indices values in alert and fatigue states. ***Table 1. Statistical analysis results in different bands.***

The support vector machine (SVM) and the multi-layer artificial neural network (ANN) were applied to classify the fatigue states based on the proposed fatigue indices. On the individual level, the A6 index as well as the index combination that includes A6 showed better performance compared with those without.

Discussion: Due to large individual differences, the accuracy of fatigue evaluation on the individual level was low in this experiment (85% with A6, around or lower than 80% without A6), despite that the changes of all fatigue indices show a high level of statistical significance. Lower-frequency ranges such as A6 may relate to some physiological variations that are less interfered with by individual differences. As sleep onset or deprivation could induce augmented delta (0-4 Hz) activity and a lower entropy value of EEG signals, this phenomenon suggests that sleepiness may play a major role in the fatigue during the SSVEP-BCI task.

Significance: This study explored the performance of entropy values of EEG in different frequency bands as a fatigue index in the SSVEP-BCIs tasks and found that the entropy values in the lower-frequency bands outperform the entropy values in higher frequency bands at the individual level.

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Using Resting EEG to Improve LDA Classification of ERPs

Jan Sosulski[1], Jan-Philip Kemmer[1], Michael Tangermann[1]*
[1]*Albert-Ludwig-University Freiburg, Freiburg, Germany*

**Zentrum für Neurowissenschaften, Albertstr. 23, 79104 Freiburg, Deutschland. E-mail: michael.tangermann@blbt.uni-freiburg.de*

Introduction: In many BCI applications using event-related potentials (ERP) the classifier is trained in a calibration period prior to the start of the online task. We propose an approach for minimizing this period.

Material, Methods and Results: We use data of an auditory oddball task. For 13 participants between 51 and 67 trials of 90 tones each (75 non-target, 15 target) were recorded for different SOA conditions. Before and after the experiment, two minutes of resting data was recorded.
We employ linear discriminant analysis (LDA) [1] for classification, using mean amplitudes of five ERP time intervals per epoch and channel as features. In LDA, the weights $w = \Sigma^{-1}(\mu_2 - \mu_1)$ are calculated using the class means μ_1 and μ_2 and the covariance matrix Σ. Importantly, Σ is calculated from mean-free data (i.e., any ERP-related information is removed) and does not depend on class labels. Hence, we can process the resting data in the same manner as the ERP data and extract pseudo-epochs to augment the calculation of Σ, but not of the class means. Using only a single trial (i.e. 90 epochs) to train the LDA and perform 5-fold cross-validation, we still obtain an average AUC of 0.701. However, using the task-unrelated resting EEG data improves the performance by more than 4 AUC points. Interestingly, using the covariance matrix calculated **only** on the resting data, also improves considerably over calculating it on the sparse trial data.

Data used for Σ	Only current trial	Current trial + resting	Only resting
Mean AUC	0.701 ± 0.021	0.743 ± 0.024	0.740 ± 0.024

Table 1. *Results on the data of 13 subjects. First, the average of all trials for one subject is calculated. Then, the mean of the 13 averages is reported, with corresponding standard error of the mean.*

Discussion: The estimation of the covariance matrix can be improved by using task-unrelated resting data. This is a promising result for BCI applications, as resting measurements are a common part of many BCI experiments. In future work, we aim to estimate the covariance by oversampling epochs from task related data, and using all EEG data available in an experiment.

Significance: Our findings can be used to improve classification performance / reduce the calibration times of ERP based BCIs that work with small data sets by using all the available data, i.e. also data not related to the task.

Acknowledgments: This work was supported by the Cluster of Excellence BrainLinks-BrainTools funded by the German Research Foundation (DFG), grant number EXC 1086, by the DFG project SuitAble (TA 1258/1-1) and by the state of Baden-Württemberg, Germany, through bwHPC and the German Research Foundation (DFG) through grant no INST 39/963-1 FUGG.

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Does the presence of vibrotactile stimulation produce false positives in the detection of a motor state from EEG?

L. Hehenberger[1], G. R. Müller-Putz[1*]

[1]*Institute of Neural Engineering, Graz University of Technology, Graz, Austria*

*Stremayrgasse 16/IV, 8010 Graz, Austria. E-mail: gernot.mueller@tugraz.at

Introduction: In applications where brain signals are used to control end effectors in order to replace motor functions, it is beneficial to provide artificial somatosensory input. Among non-invasive methods, vibrotactile stimulation [1,2,3,4,5] is a popular modality, since it is versatile, and seldomly perceived as unpleasant. While existing studies dealing with vibrotactile stimulation and control signals derived from electroencephalography (EEG) have shown concern for how the stimulation affects BCI performance [1,2,5], they usually leave aside the concern of false positives evoked by the effect of the afferent input on the signals of interest. Here, we address this aspect with respect to event-related desychnronization/synchronization (ERD/S) [6].

Material, Methods and Results: We analyzed EEG signals recorded in 2 experiments. In experiment 1 [5], participants performed planar center-out hand movements with kinesthetic vibrotactile feedback, without feedback, or received sham feedback without moving. In the vibrotactile conditions, the stimulation was on and stationary for at least 1.5s before the self-paced movement onset (or the onset of the kinesthetic sham feedback). In the movement conditions, we observe μ and β ERD during the movement period, and weaker during the pre-movement period. This ERD is consistent in both conditions. On the other hand, in the non-movement condition, we find ERS in the μ band, and no response in the β band. In experiment 2, participants performed visually guided motor imagery (MI) of the same task as in experiment 1, either with or without additional kinesthetic vibrotactile guidance. Similarly to experiment 1, there was a 2s pre-MI period where in the vibrotactile condition, the stimulation was on and stationary. We find distinct μ and β ERD during the MI period, and faint ERD during the pre-MI period. Again, the ERD profiles are highly similar between the two MI conditions.

Discussion: In both the executed and imagined movement tasks, ERD is unaffected by the vibrotactile feedback/guidance, respectively. In experiment 1, we found considerable ERD before the movement onset, though this cannot be a consequence of the vibrotactile input, since it also occurs in trials without stimulation. More likely, it occurs due to participants' mental preparation for the movement. Moreover, in the non-movement condition in experiment 1, there is no ERD.

Significance: According to our findings, vibrotactile input does not per se elicit ERD-like patterns. This suggests that it can be used as a feedback tool without risking false positives in the detection of a motor state in motor execution or imagery tasks.

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Brain stimulation with pulsed millimetre-radiowaves and gas bubbles

Ivan S. Maksymov*, Andrey Pototsky and Sergey A. Suslov
Swinburne University of Technology, Hawthorn, Victoria 3122, Australia
*Mail H74, PO Box 218, Hawthorn VIC 3122, Australia, E-mail: imaksymov@swin.edu.au

Introduction: We suggest that ultrashort millimetre-wave pulses can be used to stimulate brain via thermoelastic generation of ultrasound waves directly inside the brain. We also show that gas bubbles naturally present in the brain tissues can increase the accuracy of brain stimulation.

Background: A non-invasive brain stimulation technology based on focused ultrasound (US) benefits from its physical property to pass through the skin, bones and brain tissues with little attenuation. However, as with many other types of waves, US cannot be focused beyond a certain beam size due to the fundamental diffraction limit. This makes it technically challenging to use focused US beams for accessing individual neurons in the brain.

Light has a much shorter wavelength than that of US so that laser beams can be used for this purpose without hitting the optical diffraction limit. However, light cannot penetrate through the skull, which prevents its use for a non-invasive brain stimulation. A photoacoustic (PA) method, where laser light is delivered with high precision directly into a brain via an optical fibre and its energy is converted into US waves via thermoelastic effects, offers only a partial solution because it still requires inserting a physical fibre into the scull.

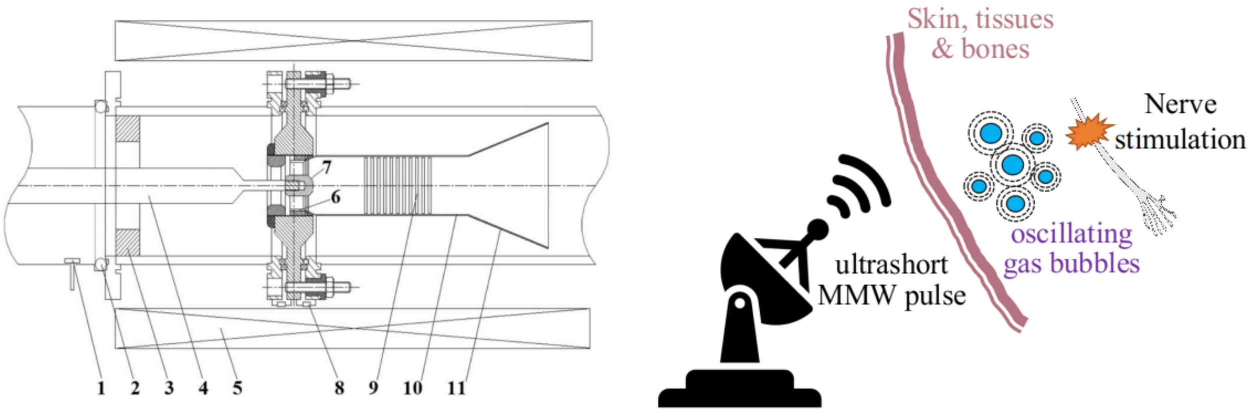

Figure 1. Schematic of an 8-mm (37.5 GHz) relativistic magnetron (with the diffraction output system (parts 9-11) designed by the corresponding author [1]) used as a source of MMW pulses (left) and the proposed brain stimulation method (right). The interaction of MMW pulses with the brain tissues results in the generation of US waves that, in turn, drive nonlinear oscillations of gas bubbles naturally trapped in the brain tissues.

Methods: Here, we propose a novel approach to brain stimulation, where, as with the PA techniques, US waves are generated directly inside the brain, but light is replaced with a different type of non-ionising electromagnetic radiation that can safely pass through the skull (Fig. 1). We theoretically investigate the possibility of using ultrashort millimetre-wave (MMW) electromagnetic pulses for the generation of US waves in the brain tissues. MMWs effectively play the role of short laser pulses used in PA techniques. We also demonstrate via our modelling that the interaction of MMW-generated US waves with gas bubbles that are naturally present in the brain tissue [2] would enable accessing specific zones of the brain with a higher precision. Our relevant results have been published [3, 4] and discussed at specialised meetings [5, 6].

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Electroencephalography recording duration in EEG-based authentication systems.

N. Abo Alzahab[1], M. Baldi[1], L. Scalise[1]*

[1]Marche Polytechnic University, Ancona, Italy

*E-mail: Nibras.Abo.Alzahab@gmail.com

***Introduction**:* The endless race between cybersecurity specialists and hackers requires continuous developing of authentication systems. One well-recognized choice consists in the use of biometrics, which is the use of unique physiological features (signatures) for authentication. A promising biometric signature is based on electroencephalography (EEG) signals [1]. However, there are several design aspects to be addressed before developing a robust EEG-based authentication system. One important design challenge concerns the EEG duration [2,3], which is experimentally studied in this work.

***Materials, methods, and results**:* The STEW (Simultaneous Task EEG Workload) dataset, which includes 48 subjects with 2.5 minutes of recording, was used. It includes resting-state case and mental workload cases. Firstly, an EEG-based authentication system was built using the following pipeline. First, the data was filtered using 1st order Butterworth bandpass filter with a range of 3-40 Hz. Afterwards, the spikes were filtered by replacing the outliers over 97% quantile and below 5% quantile of the average value of the EEG signal. The data was segmented into equal size segments, 75% overlapping. Next, 17 features were extracted including A) Statistical features, B) Power Spectral Density (PSD) Features, Entropy Features, D) Fractional Dimension Features, and E) Detrended Fluctuation Analysis (DFA) Features. The classification stage used 7-layers neural networks with a number of neurons equal to 200, 175, 150, 125, 75, and 48, from input to output.

The EEG signals were segmented 19 times according to the length of the segment. The lengths selected are: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2 ,3, 4, 5, 6, 7, 8, 9, 10 s. Each segment length was used as an input to the EEG-based authentication system where the accuracy of the system was recorded. The training of the system was repeated three times. The values of the average of the three runs and the standard deviation were calculated and are illustrated in Fig 1. It is observed that the two lines represent the same trend since they are correlated with a 0.99 correlation coefficient Results also show correlation coefficients in the range: 0.96 – 0.98 with literature. Hence, these are in line with findings reported in [2 and 3].

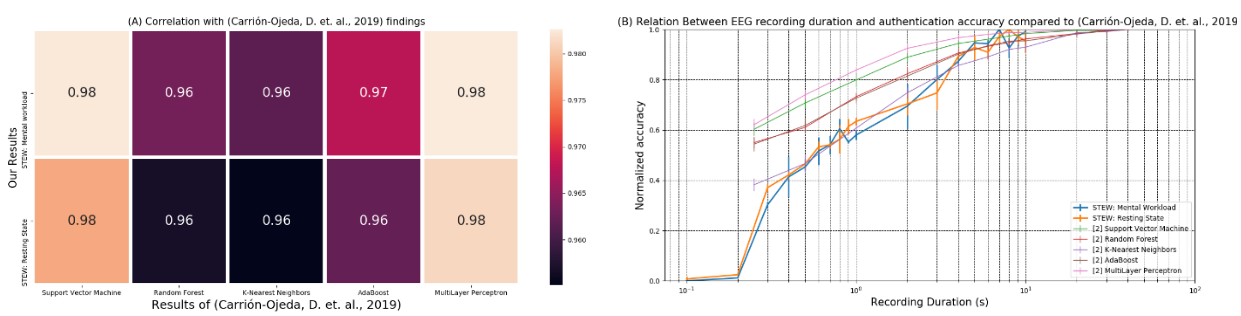

Figure 1. (A) Correlation coefficient between the findings of our work and findings in [2]. (B) Authentication accuracy with standard deviation for each EEG recording duration in the findings of [2] and ours.

***Discussion**:* Fig 1 shows an increasing trend from 0.1 s until 4 s. After 4 s, no significant increase was observed, meaning that 4 s shall be considered as a measure of the minimum recording duration needed for achieving optimal performance. The EEG-based authentication system will be less effective for shorter recordings while the longer time duration does not offer sufficient benefits in terms of performance to justify the corresponding increased requirement of computational and memory resources.

***Significant**:* This work sets a threshold for the EEG recording duration in EEG-based authentication systems. This encourages future researchers to develop pipelines that achieve similar or higher performance with a lower recording duration.

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Assessing a new form of BCI user learning

Khadijeh Sadatnejad[1*], Fabien Lotte[1,2]

[1] *Inria Bordeaux Sud-Ouest, Talence, France;* [2] *LaBRI (CNRS / Univ. Bordeaux / Bordeaux INP), Talence, France*

*200 avenue de la Vieille Tour, 33405 Talence cedex, France. E-mail: seyedehkhadijeh.sadatnejad@inria.fr

Introduction: Optimizing BCI user training requires to understand it and thus to discover various possible user learning forms. The *classDis* metric [1], which aims at quantifying class seperablity, may not capture potential user adaptation to the BCI classifier. Indeed, we suspect that, with BCI training, some users may learn to produce EEG patterns that are not more discriminant, but that become increasingly more similar to what the classifier expect, i.e., training EEG data, thus increasing classification accuracy. Thus, here we aim at studying and quantifying whether users' online (test) EEG data becomes increasingly more similar to the training EEG data with training.

Material, Methods and Results: To do so, we choose some robust landmarks from both the training and test sets and propose a Test-Train Adaptation (TTA) metric. TTA computes the average Riemannian distance, d_R, between these landmarks in the training and test sets: $TTA = (\sum_{ci} d_R\left(\bar{C}_{train}{}^{(ci)}, \bar{C}_{test}{}^{(ci)}\right)/\sigma_{train}{}^{(ci)} + d_R(\bar{C}_{train}, \bar{C}_{test})/\sigma_{train}))/(N_c+1)$, with $\bar{C}_{train}{}^{(ci)}$ the mean and $\sigma_{train}{}^{(ci)}$ the standard deviation of class ci training Spatial Covariance Matrices (SCMs) and N_c the class number [2]. Decreasing TTA values may suggest increasing adaptation of user's test EEG signals to the classifier training set. We assessed user learning on a CYBATHLON dataset [3] (1 user for 10 sessions) and a Mental Tasks (MT) dataset [4] (16 users for 6 sessions each). For both, we reduced between-session non-stationarity using SCMs recentering to the mean of either the baseline or each session first run as in [3,4]. We evaluated BCI users learning using Pearson correlation between run index and Classification Accuracy (CA), *classDis*, or TTA. For the CYBATHLON dataset (Fig. 1.(a)), results revealed significant learning effects using TTA in 8-24 Hz ($\rho = -0.56$, $p = 0.05$) and CA ($\rho = 0.68$, $p = 0.01$) while *classDis* did not show significant learning. On the MT dataset (Fig 1. (b)), 4 users showed significant learning with TTA (mean $\rho = -0.47$, $p = 0.03$), 4 with *classDis* (mean $\rho = 0.56$, $p = 0.04$) and 2 with CA (mean $\rho = 0.51$, $p = 0.03$) in 8-30 Hz. These frequency sub-bands were used in the online experiments. Only one user showed significant learning with all three metrics.

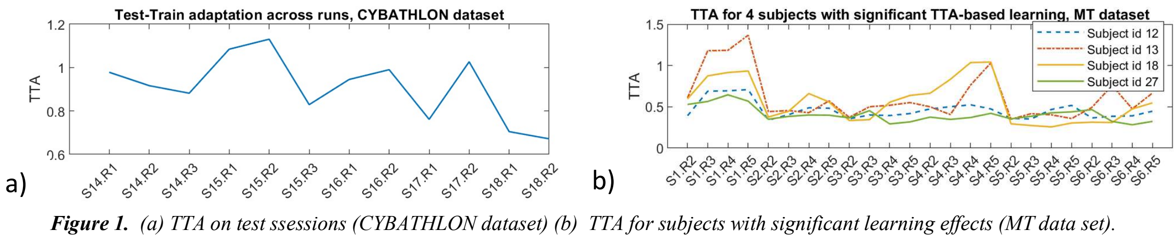

Figure 1. *(a) TTA on test ssessions (CYBATHLON dataset) (b) TTA for subjects with significant learning effects (MT data set).*

Discussion: The observed inconsistencies between learning metrics suggest that there is not a single type of BCI user learning, and that users' adaptation to the classifier is one of them.

Significance: TTA can quantify this new type of learning, and thus may be used in the future to better understand and refine BCI user training to each user learning progress.

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A neurorehabilitation BCI that decodes high-gamma EEG over hemicraniectomy (hEEG) to produce faster, more accurate sensory feedback and to promote learning

R.D. Flint[1], P. Prakash[1], Y. Li[2], D.L. Ripley[3,4], N. Brkic[3,4], A. Do[2], M.W. Slutzky[1,3,4]
[1]Department of Neurology; [3]Physical Medicine and Rehabilitation; Northwestern University, Chicago IL USA.
[2]Department of Neurology, University of California, Irvine, Irvine CA USA. [4]Shirley Ryan AbilityLab, Chicago IL.

Introduction. BCIs discern intent, such as the intent to move one's limbs. BCIs are most famously used to bypass damaged parts of the nervous system and replace lost function (BCI as prosthesis). This can offer hope to individuals who cannot otherwise expect to recover meaningful function in affected part(s) of their body. However, stroke and traumatic brain injury (TBI) are by far the most common causes of paralysis. With these kinds of neurotrauma, BCIs can be used for rehabilitation: for example, by controlling an exoskeleton or functional electrical stimulation of the paralyzed limb, thereby synchronizing motor intent with sensory feedback and driving Hebbian-type plasticity between sensory and motor areas of the brain. To date, such applications have almost exclusively relied on noninvasive recording methods (EEG or MEG) that can reliably obtain only low-frequency (<40 Hz) signals [1-3]. We are currently investigating whether high-gamma signals (HG; 70-200 Hz), which have higher spatial and temporal resolution, can more efficiently drive synchrony between pre- and post-synaptic neurons, therefore inducing greater plasticity. Here, we describe a neurorehabilitation BCI that records EEG from over the site of a hemicraniectomy (hEEG), in people with severe TBI who required the craniectomy to prevent brain herniation. Unlike traditional (skull-intact) EEG, hEEG enables us to measure and decode modulations in HG power [4].

Materials, Methods, and Results. We designed and built a novel BCI to decode intended levels of isometric thumb flexion force, in a behavioral task analogous to object grasp. The BCI provided haptic feedback proportional to intended force level, by applying pressure to the dorsal aspect of the subject's thumb. We recorded hEEG from frontal cortex electrodes, decomposing the signals into their frequency representations using previously reported methods [5]. We built decoders from real (or attempted) force, and the post-TBI participants then employed the resulting decoders to complete the isometric force task using HG modulations in real-time BCI control. Separately, we replicated these experiments in a set of healthy (skull-intact) volunteers, who used the power in μ/β frequencies (7-35 Hz) from frontal EEG to exert BCI control. Both groups were able to successfully control the haptic device sufficiently to complete a random-target force task. An important difference between HG-based BCI control and μ/β BCI control was that HG control delivered haptic feedback to the subject significantly faster: on average, HG control delivered haptic feedback to the user 150 ms faster than μ/β control.

Discussion. HG signals provided more tightly synchronized feedback to the thumb in a BCI task than did μ/β signals. This suggests that HG signals could enable greater driving of plasticity from BCI-controlled haptic feedback. Also, a BCI that delivers sensory feedback within a physiologically realistic time frame will provide a natural-feeling, rather than a delayed haptic sense. Future work will examine the ways BCI training can be used to optimize functional improvement in people with brain injuries.

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Towards passive BCI: Investigating the effect of different tilting directions on Perturbation Evoked Potential (PEP)

Shayan Jalilpour, Gernot Müller-Putz*
Institute of Neural Engineering, Graz University of Technology, Graz, Austria
* Stremayrgasse 16/IV, 8010 Graz, Austria. E-mail: gernot.mueller@tugraz.at

Introduction: Passive brain-computer interfaces (pBCIs) can detect the current mental state of the subjects while they do not have an active control during the experiment. One application of pBCIs is found in perturbation evoked potentials (PEPs). PEPs appear in brain signals when destabilizing events occur for a person [1]. Using pBCI-based on PEP as an assistive technology in driving or aviation scenarios can help to compensate for imbalance situation. In this study, we designed an experiment similar to the aviation scenario in which participants sat in a glider and experience postural instability. We aimed to investigate the influence of two different tilting directions on PEPs.

Material, Methods and Results: Two healthy participants sat in a glider and they were asked to gaze at fixation cross in front of them (Fig. 1). A robot (KUKA KRc1) was used to move the glider to two different directions (left and right) with a tilting angle of 5˚. To make the experiment unpredictable, we considered 6 to 10 small movements with tilting angles of 1.5˚ and -1.5˚ (left and right) between perturbations. Electroencephalography (EEG) signals were recorded by EEGO amplifier (ANT-neuro) with 63 electrodes and sampled at 512 Hz. Also, the Myo armband was mounted on the subject's right arm to detect the onset of perturbations by recording acceleration. Subjects performed 6 runs which included 120 perturbations in total (60 for each direction).

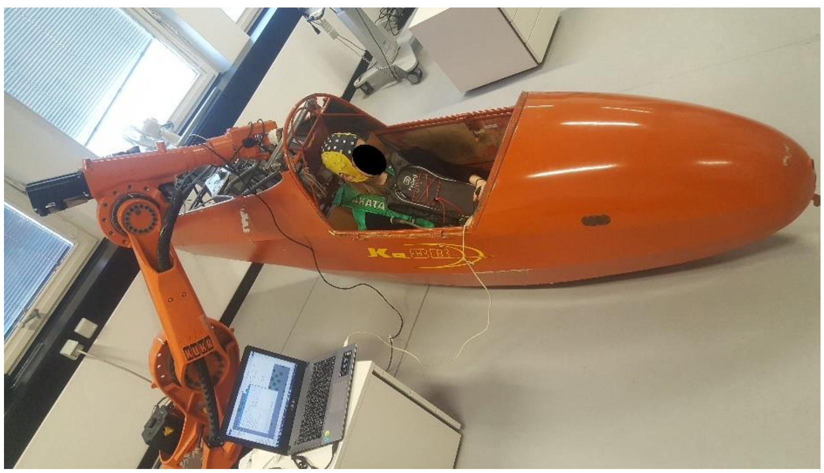

Figure 1. *Experimental setup. KUKA robot was connected to the glider, and tilted it to left and right directions.*

EEG data were filtered between 0.3 and 35 Hz (zero-phase Butter- worth filter, 4th order), and PREP pipeline [2] was applied to remove noisy channels and common referencing. Then, data were epoched from -0.5 s to 1.5 s with respect to the perturbation onset. Noisy trials were excluded by using the three different statistical parameters (amplitude threshold, joint probability, and kurtosis). After that, we filtered data between 0.3 and 10 Hz and resampled it to 60 Hz. 10×10 cross-validation was performed by using a radial basis function kernel (RBF) support vector machine (SVM) classifier and amplitude of the time samples were exploited as features. Left and right perturbations were classified with an average accuracy of 95.36%.

Discussion: The results indicate different tilting directions are discriminated with high accuracy, although we need more data to validate the results. Future research should be done to explore the potential of using asynchronous detection of PEP in online applications.

Significance: With this study, we implemented the experiment similar to aviation by using the glider and KUKA robot. We were able to differentiate left and right perturbations which is of great value to compensate for instability during flight.

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Motor Intention Prediction for Multimodal Upper Limb Stroke Rehabilitation

K. Chugani[1*], A. Rojas[1], A. Soria-Frisch[1]

[1]*Starlab Barcelona SL*

Avenida Tibidabo 47 bis, 08035, Barcelona, Spain. E-mail: karan.chugani@starlab.es

Introduction: FEXO is a novel upper limb stroke rehabilitation platform that provides a multimodal approach to be used for clinical applications, combining an upper limb exoskeleton, serious gaming, functional electrical muscle stimulation, and transcranial electrical stimulation. Motor intention detection using Electroencephalography (EEG) allows the actuator systems to synchronize with patient engagement. The work described herein, presents the design of motor intention module, which can detect the moment when the patient intends to initiate a movement and send a command to the multimodal system for it to assist the patient's movement.

Material, Methods and Results: The experimental pilot study, performed on 3 healthy subjects, was based on self-paced upper limb movements as described in [1], with 4 EEG channels and 1 Electromyography channel recording biceps activity of the subjects, which served as ground truth. Training was divided into two sections. The first section, which consisted of 40 trials, was used to train a classifier. After a small rest the subjects performed a second section of 30 trials, which was used to test the system. As in [2], each of the trials in was divided in 1 second length windows with an overlap of 0.2s. For each window, Event Related Desynchronization in the alpha and beta bands was extracted. These features were fed into a Linear Discriminant Analysis classifier, which predicted if the subject had initiated a movement for a window. To evaluate the performance of the system two metrics were used. The detection rate measured the % of trials in which motor intention was successfully detected and the false positive rate measured the % of trials where the classifier output motor intention when the subject was at rest. The final performance of the system was a detection rate of 50.37% and false positive rate of 32.13%. This was achieved using just 7 minutes and 20 seconds of training time, significantly shorter than other similar studies.

Discussion: This study aimed to develop a practical multimodal stroke rehabilitation system to be used in clinical settings. Current State of the Art systems [1,2,3] require high-density EEG montages and a large number of training trials to achieve high performances. Given the time scarcity in clinical settings, and the difficulty for patients to perform a long training session due to their reduced stamina, the translational value of such systems is reduced. In contrast, the system proposed, although having plenty of room for improvement in terms of accuracy, provides a time effective solution for upper limb stroke rehabilitation.

Significance: The work done in this project is an important first step bridging the gap between academic research and practical applications of motor imagery BCIs for stroke rehabilitation. It combines a multimodal approach with a time effective solution for motor intention detection. This kind of system presents clear advantages in a clinical context.

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MI-BCI Performances correlate with subject-specific frequency band characteristics

C. Benaroch[1*], C. Jeunet[2], F. Lotte[1]

[1]*Inria and LaBRI (University of Bordeaux, CNRS, Bordeaux INP), France;*
[2]*CLLE (CNRS, Univ. Toulouse Jean Jaurès), France*

* E-mail: camille.benaroch@inria.fr

Introduction: Motor Imagery (MI) tasks modulate EEG activity, notably in the α and β frequency bands (8-30 Hz). During BCI calibration, data driven methods are often used to select features in those bands, with little consideration for the resulting human performances. Can this approach reach optimal performances? To answer this question, this study investigated the relationship between the characteristics of subject-specific frequency bands selected by machine learning (mean frequency (FB-Mean) and length (FB-Length)) and online BCI users' performances.

Material, Methods and Results: We analysed the data of 59 healthy MI-BCI naïve subjects from the dataset presented in [1]. Each subject was trained to perform two MI-tasks - imagining right- and left-hand movements - during one MI-BCI session (6 runs of 20 trials/MI-task: 2 calibration runs and 4 feedback runs). From the calibration runs, we selected the most discriminant frequency band in the α-β range using the algorithm introduced in [2]. MI-BCI performance was assessed as the classification accuracy (CA) averaged over all feedback epochs during the feedback runs.

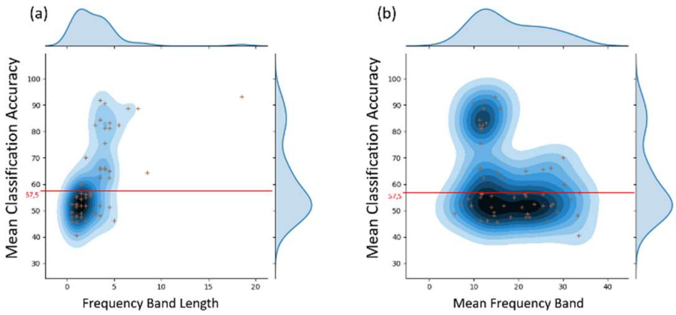

Figure 1. *Bivariate distribution of the frequency band length (a) and the mean frequency of the band (b) with the mean classification accuracy. In red, the chance level for 2-classes, 80 trials per class and α=5%*

We then studied how the FB-mean and FB-length obtained using machine learning were related to online CA, by studying their correlation and distribution. The results showed a significant Pearson correlation between mean CA and both FB-Length ($r = 0.67$, $p<0.001$) and FB-Mean ($r = -0.34$, $p<0.01$) (see also Fig. 1).

Discussion: The characteristics of the frequency band selected by machine learning correlated with online CA. Subjects with the highest CA were the ones for whom the selected frequency bands were narrow (FB-Length: ~[2-6] Hz) and centered in α-lowβ (FB_Mean: ~[11-20] Hz).

Significance: Our study suggests that online MI-BCI performances correlate with the characteristics of the frequency band, selected using machine learning. This raises questions regarding the causality link direction: could we use this frequency band to predict online performances? Could we improve machine learning algorithms with constraints on the band to be selected? Is this correlation due to a covert confounding factor (e.g., mental strategy)?

Acknowledgements: This work was supported by the European Research Council with project BrainConquest (grant ERC-2016-STG-714567).

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Transfer Learning in Motor Imagery with Large Data

J. Lee, D. Gwon, H. Kim and M. Ahn*

Information and Communication Engineering, Handong Global University, Pohang-Si, Republic of Korea

*E-mail: minkyuahn@handong.edu

Introduction: Due to individual difference in brain signals, traditional BCI systems have required calibration session where data is collected to train machine learning classifiers. Attempts to eliminate this process is called 'zero-training', which allows users to use BCI system without any preparation. Zero-training has been studied with various types of brain signals and paradigms. In this research, we attempt to see if zero-training can be achieved in motor imagery, using only a traditional classifier and a set of large dataset from other subjects. Such transfer learning has been used in various researches with some degree of adaptation[1]. Here, we focus on the amount of data and its impact in zero-training performance.

Methods and Results: We used publicly available motor imagery dataset acquired from 52 subjects[2]. Each dataset contains 100 or 120 trials per condition (left and right imagery) respectively, and each sample contains electroencephalogram (EEG) signals from 64 channels. We used conventional common spatial pattern (CSP) filter along with Fisher's Linear Discriminant Analysis (LDA) for analysis[3]. We first calculated classification (left or right) accuracy of 52 subjects using only the subject's own data. This within-trained method, which is the conventional method, resulted in classification accuracy of 67.42% in 10-fold cross validation. For the zero-trained method, we randomly selected N number of subjects' data to calculate covariance matrix and train the classifier for each subject. Rest of the process was same as in [3], and the testing subject's data was excluded from the training dataset. We increased the size N and measured the change in accuracy. The result is shown in Figure 1A. When using maximum number of subjects given in the dataset (N = 51 in this case), mean transfer learning accuracy was 63.53%, which was still lower than that of within-trained accuracy ($p<0.05$ from paired t-test). Within-trained accuracy along with transfer learning accuracy for 52 subjects is plotted in Figure 1B.

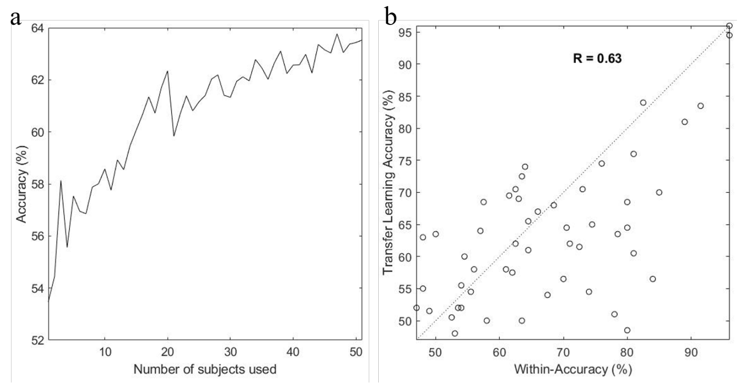

Figure 1. (A) Classification accuracy as N (Number of subjects used) increases (B) Within-trained accuracy compared with transfer learning accuracy in all 52 subjects

Discussion: This study examined the changes in transfer learning accuracy in large scale motor imagery dataset. Although the result indicates there is room for improvement when compared to within-trained accuracy, the result gives us some insight into how previous data collected from multiple subjects can be valuable for better BCI performance. It is also worth noting that some low performing subjects' accuracy increased when using transfer learning. Large scale data cleaning as well as adaptation is to be studied in future studies.

Acknowledgements: This work was supported by the National Research Foundation of Korea (2017R1C1B5017593) and the Institute of Information &Communications Technology Planning & Evaluation (2017-0-00451) funded by the Korea government.

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Motor imagery BCI performance prediction using eyes-open and eyes-closed resting states

M. Kwon[1], H. Cho[2], K. Won[3], M. Ahn[3], S.C. Jun[1*]

[1]Gwangju Institute of Science and Technology, Gwangju, South Korea; [2]National Center for Adaptive Neurotechnologies, Albany, NY, USA; [3]Handong Global University, Pohang, South Korea

*61005, Gwangju, South Korea. E-mail: scjun@gist.ac.kr

Introduction: Motor imagery (MI) BCI is one of the popular paradigms to manipulate external machines using brain activities that includes user's intention. However, it was reported that about 15 – 30% of subjects failed to use the MI BCI system; the MI task was required to lengthy training time as well as users might feel frustration from the results. Therefore, for the prescreening purpose, some researchers studied MI performance predictors using resting states [1,2,3], but these predictors were suggested from only one resting state, that is, eyes-open or eyes-closed states. In this study, we proposed a stiffened predictor using combination of eyes-open and eyes-closed data which may be more robust to subject variability.

Material, Methods and Results: A total of 41-session data from 15 subjects were collected using 64 channel-EEG system (BioSemi ActiveTwo) in the experiment. Participants were instructed to imagine three kinds of movements (left hand, right hand or both feet, 40 trials/class) at offline task, and a pair of movements (classes) yielding the highest classification accuracy were selected for online feedback task (75 trials/class) per subject. iCSSP [4] and FLDA were applied to online data. In addition, relative band powers of eyes-open and eyes-closed resting states at two channels (among C3, C4, or Cz channels) depending on movement pair of online task were estimated to compare between high (acc. > 70%) and low (acc. < 60 %) performance groups. From the results, we proposed a predictor that is slightly modified version of PP factor [2] as shown below:

$$\text{Proposed MI predictor} = {(\propto_{eo} + \theta_{ec} + \alpha_{ec})}\big/{(\theta_{eo} + \beta_{eo} + \beta_{ec})}. \tag{1}$$

Here relative band powers are estimated from spectral bands such as theta (ϑ; 4 – 8 Hz), alpha (α; 8 – 13 Hz), and beta (β; 13 – 30 Hz) during eyes-open (*eo*) or eyes-closed (*ec*) state. We observed that the classification accuracies from online feedback task quite varied from 44.0% to 99.3%, and our proposed predictor yielded a correlation value of $r = 0.5239$ ($p < 0.001$), which is quite higher than $r = 0.1999$ ($p > 0.1$) estimated by PP factor [2].

Discussion: Blankertz *et al.* [1] addressed that some subjects failed to predict MI performance although they have larger alpha power, because their signals have similar behaviors between two classes. Our proposed predictor using eyes-open and eyes-closed resting data may compensate subject-specific band powers and may be more robust to subject variability than existing predictors.

Significance: We suggested MI performance predictor using two kinds of resting state data to reduce subject-specific band powers.

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Learning Informative Representation for EEG-based BCI

Wonjun Ko[1], Eunjin Jeon[1], Seungwoo Jeong[2], Heung-Il Suk[1, 2*]

[1]*Department of Brain and Cognitive Engineering, Seoul, Republic of Korea;*

[2]*Department of Artificial Intelligence, Seoul, Republic of Korea*

*145 Anam-ro, Seongbuk-gu, Seoul, Republic of Korea, E-mail: hisuk@korea.ac.kr

Introduction: Recent advances in deep learning-based brain-computer interfaces (BCIs) have been making methodological and practical impacts on BCI fields. On the other hand, owing to its high variability and endogeny in signals, decoding motor imagery (MI) EEG is still a challenging problem [1]. More specifically, the MI is caused by a user's internal cognitive process, thus it becomes hard to have a complete trust about a *reliability* to the acquired EEG [2]. In this work, we introduce our recent work of inferring to the MI-related sub-parts in each EEG trial and thus can improve the decoding performance without sacrificing the degree of freedom of BCI models.

Material, Methods and Results: In our work, we used the *big motor imagery dataset* [1], which is acquired from 54 subjects during 2 sessions with 62 electrode channels. In our proposed framework, we mainly exploit three modules for the *informative representation learning*: (i) an encoder network to extract *spatio-spectral-temporal* features of MI EEG; (ii) a 'blocker' network that determines a blocking mask to pass only informative (or MI-related) features; (iii) a classifier. In the blocker, a *multi-head attention* [3] is used for deciding what is important information in the given features. By multiplying the blocking mask from the blocker and the features, a classifier focuses on task-related signals in the given EEG trial. For quantitative analysis, we measured classification accuracies of deep learning methods trained with and without our blocking module. As a preliminary experiment, we considered subject-dependent classification to ensure the effectiveness of the proposed algorithm and achieved an accuracy improvement by about 5% on average over 54 subjects on compared to the conventional training strategy. Furthermore, we interpret our methods by visualizing a pair of the learned blocking mask and spectrogram of each subject.

Discussion: We proposed a novel framework for informative representation learning and its use for MI-based BCI. Even though this study mainly focused on MI decoding, the proposed methods can also be applicable to other types of endogenous BCIs, thus it would be our forthcoming research direction.

Significance: The proposed algorithm learned to estimate MI-related sub-parts ability to represent task-relative information from input temporal EEG signals. In our framework, any existing or novel deep learning-based BCI method can be used for the encoder and classifier, thus the algorithm is not dependent on the model.

Acknowledgements: This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (No. 2017-0-00451; Development of BCI based Brain and Cognitive Computing Technology for Recognizing User's Intentions using Deep Learning).

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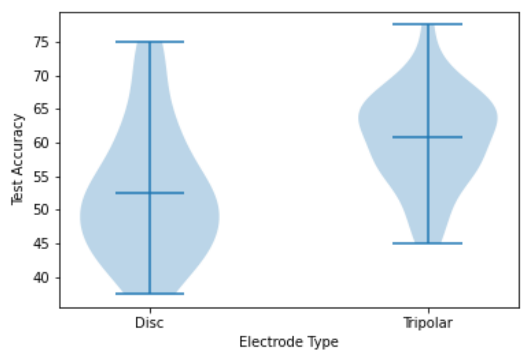
Classification of EEG from Disc versus Tripolar Electrodes for Language Mapping Task

Paras Q. Memon[1*], Chuck Anderson[1], Walter Besio[2]
[1]*Department of Computer Science, Colorado State University*
[2]*Electrical, Computer & Biomedical Engineering, The University of Rhode Island*
[*]Fort Collins, CO, USA 80523. Email: paras.memon@colostate.edu

Introduction: Speech production can occur covertly and overtly in spoken language. Little information is known about the covert and overt language mapping and how these behaviors are processed differently and what mechanisms are used [1]. Classification of covert versus overt speech was compared using conventional disc versus new tripolar EEG electrodes [2].

Material, Methods and Results: EEG signals from conventional disc and tri-polar electrodes at 32 locations were recorded from one participant as they were shown pictures and asked to name the pictures overtly as well as covertly. Convolutional neural networks were trained to classify the conventional overt versus covert samples using either disc or tripolar electrodes. Results suggest that tripolar electrodes perform better compared to disc electrodes with accuracies, averaged over 30 different partitions of data into 80% training and 20% testing partitions, of 52.5% and 60.8%, respectively, as shown in the below figure.



Discussion: For one subject, EEG data from tripolar electrodes resulted in an increase in average test set accuracy of about 8%. Experiments are on-going for an additional 15 subjects. Analysis of the trained networks will be conducted to identify discriminative features.

Significance: Speech could play a significant role in future BCI applications, but the accuracy of classification of speech from EEG must first be increased. Our results suggest that the new tripolar EEG electrode design might contribute to this.

Acknowledgements: This work was partially supported by a U.S. Fulbright Student Fellowship and NIH Grant 1R43NS105267-01A1.

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Silent Speech BCI Classification Using Deep Learning with Noise Assist Multivariate Empirical Mode Decomposition

Hyeong-jun Park[1] and Boreom Lee[1*]

[1] *Department of Biomedical Science and Engineering, Gwangju Institute of Science and Technology (GIST), Gwangju, Republic of Korea*

[*] 423, Dasan, 123, Cheomdangwagi-ro, Buk-gu, Gwangju, Republic of Korea. E-mail: phyeong106@gist.ac.kr

Introduction: The purpose of this study is to propose a method to classify silent speech electroencephalogram (EEG) using noise assist multivariate empirical mode decomposition (NA-MEMD) with 1D deep convolutional neural network (CNN).

Material, Methods and Results: The experimental paradigm was designed by e-Prime 2.0 software (Psychology Software Tools, Inc., Sharpsburg, PA, USA) and silent speech EEG was measured at a sampling rate of 1000 Hz through a HydroCel Geodesic Sensor Net with 64 channels and Net Amps 300 amplifiers (Electrical Geodesics, Inc., Eugene, OR, USA). The sensors were located according to the international 10-20 system and measured EEG when imagining five vowels /a/, /e/, /i/, /o/, /u/, and rest state for three seconds from five healthy subjects. Subjects perform 5 sessions, and each session contains 10 trials of each task. For preprocessing, we applied an IIR 4^{th} order Butterworth band-pass filter with bandwidth 0.5 to 250 Hz and band-stop filter to remove the power noise. After preprocessing, we divided each trial into 5 segments with a 1 s length and 0.5 s overlap [1]. We applied 10-fold cross-validation to separate the data into training set and test set. Then, NA-MEMD which can address the effect of non-stationarity characteristics and the mode mixing problem of EEG was applied to extract eight intrinsic mode functions (IMFs) [2]. Six statistical features were extracted from each channel in each IMF to construct 1D feature vectors which utilized as inputs for 1D deep CNN. Support vector machine (SVM) using rbf kernel (SVM_{rbf}), SVM using linear kernel (SVM_{lin}), linear discriminant analysis (LDA), and 1D shallow CNN were used for comparison. As a result, the classification accuracy of 1D deep CNN was higher than that of other classifiers.

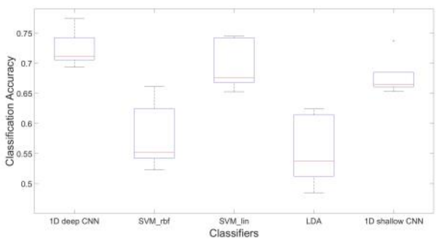

Figure 1 *Classification accuracy for each classifiers*

Discussion: When we compared 1D deep CNN with other classifiers through paired t-test, it was found that there was a statistically significant difference ($p<0.05$) with the classification accuracy of all classifiers except SVM_{lin}. From the result, we found that NA-MEMD based feature extraction and classification using 1D deep CNN can enhance the performance of silent speech based BCI system.

Significance: We proposed 1D deep CNN framework with NA-MEMD based filter-bank feature extraction in this work. The average classification accuracy of 1D deep CNN was higher than other classifiers used for comparison, and there was a statistically significant difference from that of other classifiers except SVM_{lin}.

Acknowlegements: This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (No.2017R1A2B4009068).

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Enhancing the head model by eyes, neck and face muscles

Nils Harmening[a,c], Daniel Miklody[a], Marius Klug[b], Klaus Gramann[b]
[a]*Neurotechnology, Technische Universität Berlin, Berlin, Germany*
[b]*Biological Psychology and Neuroergonomics, Technische Universität Berlin, Berlin, Germany*
[c]*Sekr. MAR 4-3, Marchstr. 23, 10587 Berlin, Germany. E-mail:* `nils.harmening@tu-berlin.de`

Introduction EEG data are often heavily artefact polluted by eye movements and blinks (EOG) and face and neck muscle activity (EMG). Researchers usually try to overcome artefacts with methods operating in sensor space (e.g. filtering, substracting signals from additional eye or neck electrodes) or offline removal of automatically or even manually identified independent components (ICs). When source localization techniques are applied, the data was commonly cleaned (if cleaned) before the actual data analysis.
However, this chronological procedure leads to distorted EEG time series and introduces a bias into the subsequent source localization.
Therefore, we propose adding potential artefact sources to the head model in a similar way, as it is done for cortex sources. Treating muscles and eyes as proper contributors to EEG potentials allows them to be identified, ignored or excluded automatically during the source localization process without distorting the original EEG signals.

Material, Methods and Results We developed a fitting routine to warp the open source muscle atlas MIDA [1], that had been obtained by segmenting high-resolution MRI scans, into the scalp mesh of a Boundary Element Model (BEM). Evenly spaced grids were constructed in every muscle mesh, that form the artefact sourcemodel. According to the propagation direction of muscular action potentials, the source's pole orientations were aligned with the muscle's fiber directions. Horizontal and vertical dipoles were placed in the retina and cornea of both eyeballs to model EOG signals. Besides mimicking EMG signal sources with dipoles as done for EOG and EEG, tripoles were used in a second approach in order to more realistically mimic motor unit action potentials (MUAPs).
For every cortical, muscular and ocular source, a leadfield was calculated by using the extended BEM.
This extended BEM model was validated by a detailed Finite Element Model (FEM).
The performance of the different sourcemodel approaches was tested on an EEG data set, that were collected from subjects doing full-body rotations in virtual reality (VR) in the Berlin Mobile Brain/Body Imaging Lab (BeMoBIL), thus containing many artefacts from head and eye movements. As exemplarily shown in fig. 1, source localization (comparing subspace correlations of the data's ICs and the sourcemodel's leadfields, measured by their residual variance (rv)) successfully identified cortical, muscular and ocular ICs during physical rotations, that can be associated to the actual muscles in use.

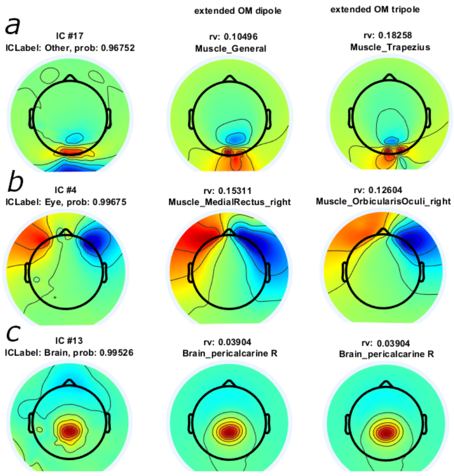

Fig. 1: 17th (a), 4th (b), 13th IC (c) showed lowest rv with dipolar (middle) / tripolar (right) leadfields of neck muscles (a), eye muscles (b), cortical source (c), respectively.

Discussion and Significance As validated by the preliminary results, our extended head model has the potential to be used as a future standard head model. Even subject-specific head models gained from MRI or specific cortex sourcemodels can easily be enriched by adding our artefact sourcemodel due to the developed warping routine.

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Towards Person-Independent Classification of Internal and External Attention from EEG Data

Lisa-Marie Vortmann[1*], Felix Putze[1]

[1]*Cognitive Systems Lab, University of Bremen, Bremen, Germany*

*Enrique-Schmidt-Straße 5, 28359 Bremen, Germany. Email: vortmann@uni-bremen.de

Introduction: For many years, Brain-Computer Interfaces (BCIs) have been used to decode electroencephalographic (EEG) data to extract information about the current spatial location that a user's attention is directed at. However, the spatial location of attention is not the only interesting information encoded in EEG data. Human attention is a complex concept with several possible levels of differentiation [1]. In this work, we concentrated on the automatic classification of internally and externally directed attention. Internal attention refers to a focus on stimuli produced by one's own mind, whereas external attention describes a focus on surrounding stimuli [1]. Putze et al. [2] showed that it was possible to classify single trial EEG data into these two categories. Our future aim is to go from person-dependent classifier training to a person-independent classifier that excludes the need for time-consuming training trails ahead of the actual usage of the BCI. This analysis is a first step.

Methods and Data: The data used for this analysis was collected in [4]. During an Augmented Reality task with an internal and an external condition, the EEG data of 14 participants was recorded. The preprocessing in this analysis was identical to [4]. The data of all subjects was pooled and treated as if collected from a single subject to gain insight about the similarity and generalizability of brain activity patterns during internal and external attention. We posed two research questions: (1) What epoch length is necessary for a reliable classification result? (2) Which classifier is suited for the analysis? The first question is especially relevant for real-time decoding systems because the data used for the current state estimation should be rather short as switches between the two states can occur frequently. We compared 13, 7, 4, 2, and 1 second epoch length by cutting the epochs into non-overlapping shorter epochs. Additionally, we compared two classification algorithms. The first classifier was identical to the classifier used in [4] (Linear Discriminant Analysis, LDA). The second classifier was the shallow convolutional Neural Network (ShallowConvNN) that extracts the Filter Bank Common Spatial Patterns (FBCSP) that was suggested by Schirrmeister et al. [3].

Results: Each combination of classifier and epoch length was trained and tested 100 times to account for slight variations due to random choices during the training of the classifiers and random splitting of the data (50% Training, 25% Validation, 25% Test). We calculated the 95%-confidence interval of the classification accuracy.

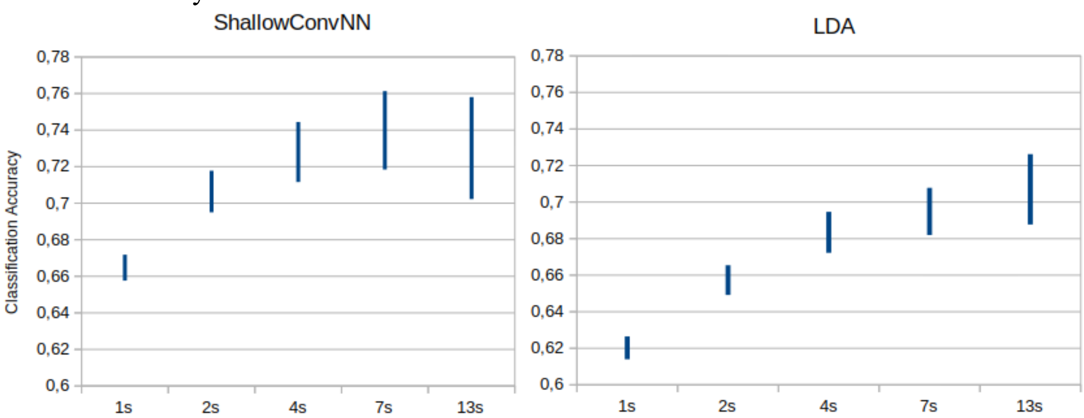

Figure 1: The 95%-confidence intervals calculated from 100 training and testing runs of all epoch lengths (x-axis) for the two classifier.

Discussion: We showed that the Neural Network outperforms the LDA for a person-independent dataset. The classification results of the ShallowConvNN are best for 7 second epoch lengths with a 95% probability of reaching between 72% and 76% classification accuracy. Even shorter epochs of 4 seconds can be classified reliably (71% to 74.5% classification accuracy, 50% chance).

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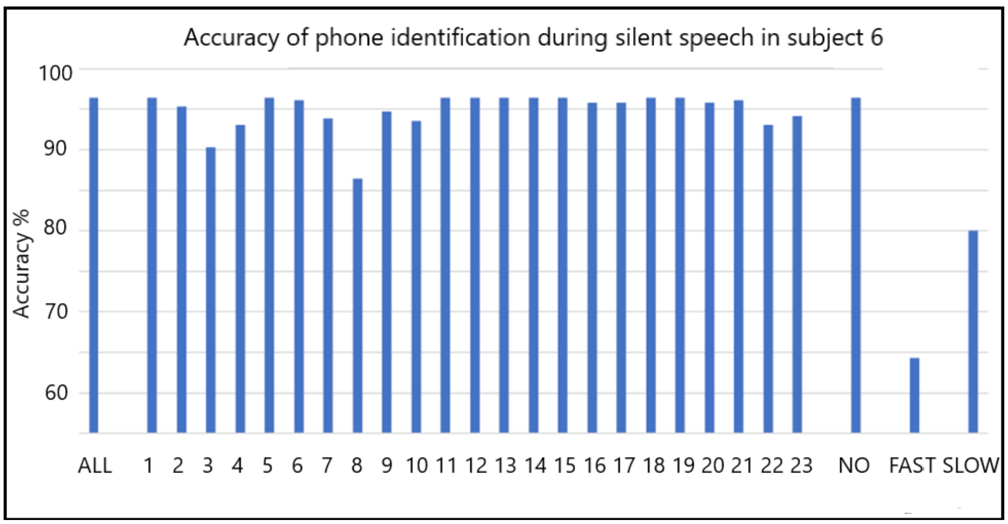
Slow firing single units are essential for optimal decoding of silent speech.

A. Ganesh[1.] A.J. Cervantes[2.], and P.R. Kennedy[1.]

[1.] A. Ganesh and P.R. Kennedy, Neural Signals Inc, Neural Prostheses Laboratory, 3400 McClure Bridge Road, Suite D402, Duluth, GA 30096, USA. Phil@neuralsignals.com
[2.] A.J.Cervantes, MD, Belize International Institute of Neuroscience, 4760 University Heights, West Landivar, Belize City, Belize.

Introduction: The development of a speech prosthetic for those who are locked-in (paralyzed and mute) requires decoding patterns of individual single units during *silent* speech[1,2]. The aim of this abstract is to provide evidence that fast and slow single units recorded from the speech motor cortex of locked-in and intact subjects *speaking silently* are both important in decoding. Slow firing units are essential for *optimal decoding accuracy.*

Materials, Methods and Results: The speech motor cortices in two human subjects were implanted with Neurotrophic Electrodes. In both subjects, single units were decoded during silent speaking of phones. The decoding was performed using a Classification paradigm (Matlab). The results indicate that even though fast firing units are important to maintain accuracy, slow firing units contribute to decoding accuracy because when they are removed from the analysis, the accuracy drops from 96.7% to 80%.



Legend: The accuracy of phone identification during silent speech in subject 6 is 96.7% when ALL UNITS are included (left bar ALL). Excluding each unit (1-23) in sequence may change the accuracy. When the non-firing units (NO) are excluded the accuracy remains the same. When FAST firing units are excluded the accuracy drops to about 64%. When slow firing units are excluded the accuracy drops to 80%.

Discussion: The slow firing units are important, though not as important as the fast firing units as can be evidenced from the decreases in accuracy shown in the figure. The data is essentially the same for the other subject. The figure above indicates 23 single units recorded from one electrode. Histological analysis after implantation for 13 years indicates copious numbers of myelinated axons, and no scarring[3] with no loss of functionality[2]. These findings are unique to this electrode.

Significance: Slow firing units cannot be omitted from analysis as evidenced by these data. Accuracy of decoding is paramount. These data also indicate just 23 single units can successfully decode phones.

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Correlation-based channel selection and regularized feature optimization for MI-based BCI

Yangyang Miao, Cili Zuo, Shurui Li, Chang Liu, Hao Sun, Jing Jin*

Key Laboratory of Advanced Control and Optimization for Chemical Processes, Ministry of Education, East China University of Science and Technology, Shanghai, China

*P.O. Box 200237, Shanghai, China. E-mail: jinjingat@gmail.com

Introduction: Multi-channel EEG data are usually necessary for spatial pattern identification in motor imagery (MI)-based brain computer interfaces (BCIs). To some extent, signals from some channels containing redundant information and noise may degrade BCI performance.

Material, Methods and Results: We assume that the channels related to MI should contain common information when participants are executing the MI tasks. Based on this hypothesis, a correlation-based channel selection (CCS) method is proposed to select the channels that contained more correlated information. Furthermore, a novel regularized common spatial pattern (RCSP) method is used to extract effective features. Finally, a support vector machine (SVM) classifier with the Radial Basis Function (RBF) kernel is trained to accurately identify the MI tasks. An experimental study is implemented on three public EEG datasets (BCI competition IV dataset 1, BCI competition III dataset IVa and BCI competition III dataset IIIa) to validate the effectiveness of the proposed methods. The results show that the CCS algorithm obtained superior classification accuracy (78% versus 56.4% for dataset1, 86.6% versus 76.5% for dataset 2 and 91.3% versus 85.1% for dataset 3) compared to the algorithm using all channels (AC), when CSP is used to extract the features. Furthermore, RCSP could further improve the classification accuracy (81.6% for dataset1, 87.4% for dataset2 and 91.9% for dataset 3), when CCS is used to select the channels.

Discussion: This study provides an efficient way to select channels based on correlation analysis. The correlation-based channel selection (CCS) algorithm that requires less channels can both improve the performance of MI-based BCI and greatly benefit an application with disabled end-users potentially for long-term use. On the other hand, this work also paves the way for MI feature optimization research. The proposed RCSP algorithm performed the regularization by using only one subject’s data. From a practical perspective, this approach can minimize the time needed for data acquisition.

Significance: The proposed approach is a promising candidate for performance improvement of MI-based BCI.

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Decoding Spoken English Phonemes from Dorsal Motor Cortex

G. Wilson[1*†], S. Stavisky[1†], F. Willett[1], D. Avansino[1], L. Hochberg[2], J. Henderson[1‡], S. Druckmann[1‡], K. Shenoy[1‡]

[1]*Stanford University, USA;* [2]Providence VA Medical Center, Brown University, Massachusetts General Hospital, & Harvard Medical School

[†]*co-lead,* [‡]*co-senior*; * 318 Campus Drive West, W100-A Clark Center, Stanford, CA 94305. E-mail: ghwilson@stanford.edu

Introduction: Restoring speech through a brain-computer interface (BCI) is a promising therapeutic approach for patients with neurological disorders such as stroke and ALS. Prototype speech BCIs have used electrocorticography (ECoG) measurements from distributed populations across the cortex [1, 2]. In this work, we explored a complementary approach: accessing higher spatial resolution neural activity using two microelectrode arrays in "hand knob" area of human motor cortex. This dorsal area was previously shown to modulate during speech and face movements, enabling classification between ten words or syllables [3]. Here, we decode a comprehensive set of English phonemes from a rich spoken words dataset.

Methods: A BrainGate2 clinical trial (NCT00912041) participant ('T5') spoke 420 different words in an instructed delay task. Phoneme onset times were manually labeled offline. Neural signals were collected from two 96-channel silicon microelectrode arrays placed in T5's left 'hand knob' area of motor cortex. These signals were bandpass-filtered using a 3rd order Butterworth causal filter from 125 to 5000 Hz to extract high-frequency signals capturing spike-band power. We extracted a 500 ms neural activity window centered around each phoneme's onset. For each such window, we averaged activity within ten 50 millisecond bins, z-score normalized, and compressed the resulting feature set using principal components analysis (75% variance retained).

Results: When training with 14 minutes of speech data, we observed 29% cross-validated classification accuracy across 39 phonemes (Fig. 1; prior-informed chance was 6%) using a logistic regression model. Performance did not saturate with increasing dataset size or channel count, indicating room for further improvement. Classifier confusions were higher between phonemes of the same articulatory group (shuffle test, $p < 0.002$). Using only pre-audio onset neural activity to predict the first phoneme, we observed 35% accuracy across 18 distinct classes ($p < 0.002$).

Discussion: The measured performance indicates that local neural signals can drive phoneme decoding, and suggest that higher performance can be expected with more training data, more electrodes, and targeting cortical areas with stronger speech-related activity. Latent phonetic structure in classification errors – as well as pre-voice onset decoding – indicate that these signals likely reflect a motoric representation.

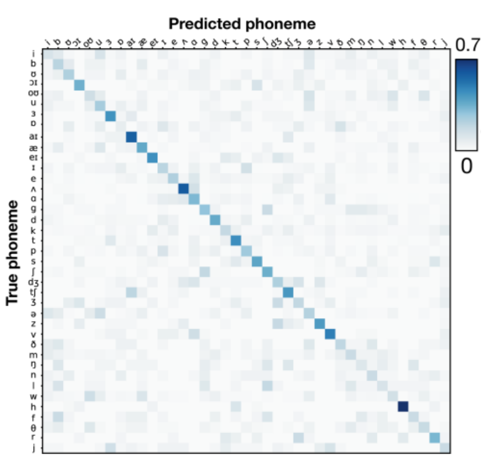

Figure 1. Cross-validated phoneme classification

Significance: Our results suggest that intracortical recordings can provide a large amount of speech-related information despite limited spatial coverage. We believe that better performance could be obtained from arrays implanted in ventral speech cortex, motivating future work in participants who cannot speak.

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Phase Amplitude Coupling in motor imagery Brain-Computer Interface

D. Gwon, J. Lee, H. Kim and M. Ahn*

Dept. of Information and Communication Engineering, Handong Global University, Pohang-Si, South Korea

*E-mail: minkyuahn@handong.edu

Introduction: Performing certain movements involves complex processes in human brain. Interestingly motor imagery shows similar brain pattern (so called even-related desynchronization) to that of motor execution. This is a key feature that most motor imagery BCI (MI-BCI) use [1]. However, this is not only the change by motor imagery, but also the other complex process happens. Recently Phase-Amplitude Coupling (PAC) in motor execution was reported [2]. This indicates the PAC may be also observable during motor imagery. We investigated PAC in motor imagery and evaluated for potential feature for MI-BCI.

Methods and Results: We used publicly available electroencephalogram dataset recorded from 52 healthy subjects [3]; each subject conducted 100 or 120 motor imagery trials for left and right hand respectively, and an additional resting state (eye-open) for 60 seconds was acquired. For this study, we divided all recordings into 3 states: (1) rest (resting state with eye-open), (2) ready (two seconds before motor imagery cue), and (3) motor imagery (0.5~2.5s after cue). With all epochs, PACs from low frequency (Mu: 8 to 14Hz, and Beta: 20 to 28Hz with 4Hz step) to high frequency (60 to 110Hz with 20Hz step) were calculated based on Tort's method [4]. For statistical tests, student's t-test was used for three and two states comparison respectively.

Summed PAC per each subject and distribution across states are presented in Figure1. Relatively PAC increases during ready state and decreases during imagery state. In Beta-to-Gamma PAC, we observed significant difference in 'rest' versus 'ready' (33 subjects at C4 and 29 at C3, $p < 0.05$) and 'ready' versus 'imagery' (42 subjects at C4 and 43 subjects at C3, $p < 0.05$). However, only 23 (C3) and 16 (C4) subjects showed significant difference in 'rest' versus 'imagery'. In Mu-to-Gamma PAC, statistical test revealed significant difference in 'rest' versus 'ready' (22 subjects at C4 and 24 at C3, $p < 0.05$) and 'ready' versus 'imagery' (36 subjects at C4 and 35 at C3, $p < 0.05$). However, the PACs for 'rest' versus 'imagery' were significantly different ($p < 0.05$) only in four subjects at C3 and three subjects at C4.

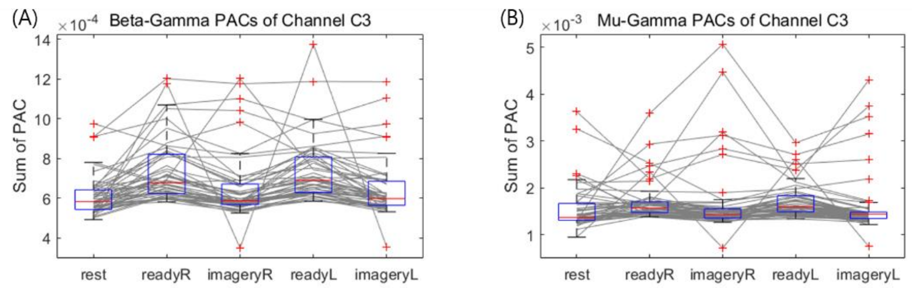

Figure 1. Sum of PAC for each subject's state. PAC was computed for beta (20-28Hz), Mu (8-14Hz) and gamma (60-110Hz) band.

Discussion: This study demonstrates that the changes of PACs are also observable in EEG, just as in the intracerebral sites [2]. The results seem related to ERD pattern that power of Mu rhythm decreases during imagery process. As seen in Figure 1(B), PAC also decreases during imagery process. In the future, we will further investigate the accuracy gain by adding PAC to the conventional Power spectrum feature in MI-BCI. In addition, the subject specific PAC pattern will be also studied.

Acknowledgements: This work was supported by the National Research Foundation of Korea (2017R1C1B5017593) and the Institute of Information &Communications Technology Planning & Evaluation (2017-0-00451) funded by the Korea government.

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Real-time-compatible decoding of articulatory and acoustic speech features from intracranial brain signals

G. Le Godais[1,2,3*], X. Ran[1,4*], P. Roussel[1,2], F. Bocquelet[1,2], T. Hueber[3], M. Aubert[1,2], D. D'Almeida[1,5], P. Kahane[6], S. Chabardès[5], B. Yvert[1,2]

[1]Inserm, Braintech Lab U1205, Grenoble, France; [2]Univ Grenoble Alpes, Braintech Lab U1205, Grenoble, France; [3]CNRS, Gipsa-Lab, Grenoble, France; [4]Zhejiang University, Qiushi Academy for Advanced Studies, Hangzhou, China; [5]CHU Grenoble Alpes, Department of Neurosurgery, Grenoble, France; [6]CHU Grenoble Alpes, Department of Neurology, Grenoble, France;

*Braintech Lab U1205, UFR Chimie Biologie, Bât. Biologie B, 2280 rue de la piscine, 38610 Gières, France.
E-mail: gael.le-godais@grenoble-inp.fr, ran.xingchen@qq.com

Introduction: Speech BCIs consist in decoding neural activity in real time to control an artificial speech synthesizer [1]. Different strategies can be considered [2], including the direct prediction of the acoustic content of speech [3][4][5] or the indirect prediction of articulatory movements [6] that can further be converted into an acoustic signal [7]. Efficient decoding has been obtained using bLSTM artificial neural networks [6], but these architectures do not allow real-time synthesis as they process full sentences at once. Here, we designed a decoding scheme combining linear model and deep neural networks compatible with real-time speech synthesis from brain signals.

Material, Methods and Results: Two patients with ECoG grids read short sentences aloud. The signal power amplitudes in 10-Hz frequency bands between 0 and 200 Hz that were significantly modulated by speech production, were considered as features, and their dimensionality further reduced by PCA. Speech signals were decomposed into 25 Mel-Cepstrum coefficients using SPTK. Linear and Kalman-filter models were built to predict either directly these coefficients from neural features, or indirectly articulatory (EMA) trajectories further converted to Mel coefficients using a feed-forward DNN. Two strategies were found to improve speech synthesis: 1) transfer learning of the articulatory-to-acoustic DNN, and 2) autoencoder-based post-correction of the EMA trajectories and Mel coefficients predicted by linear/Kalman regression. Median correlations between actual and predicted Mel coefficients reached 0.44±0.13 and 0.29±0.13 for direct and indirect predictions, respectively.

Discussion: This study proposes a new decoding scheme compatible with real-time prediction of speech from ongoing intracranial brain signals.

Acknowledgements: This work was supported by the FRM Foundation under grant No DBS20140930785, the French National Research Agency under Grant Agreement No. ANR-16-CE19-0005-01 (Brainspeak), and by the European Union's Horizon 2020 research and innovation program under Grant Agreements No. 732032 (BrainCom).

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MindOpen-Prototyping Real-time BCI for Designers in Virtual Reality based on Self-chosen Motor Imagery

Qi Yang[1*], Jesus G. Cruz-Garza[1], Saleh Kalantari[1]

[1] *Cornell University, Ithaca, NY*

[*] E-mail: qy244@cornell.edu

Introduction: Active non-invasive brain-computer interfaces (BCIs) have the potential to map natural design intention to machine commands and enable intuitive control of design elements, therefore opening the possibility for design-oriented BCI applications. Testing BCI performance with discrete, motor-imagery linked, and design-oriented tasks is critical for understanding the capabilities of BCI in design scenarios.

Materials, Methods, and Results: We developed a BCI design tool that enabled users to change the position, size, and shape of a window by self-chosen motor imagery in real-time immersive VR environment. Users were asked to devise motor imagery that matched the design task desired: move window left, right, up, down, or expand/compress shape vertically, horizontally, and change form altogether between a rectangle and circle. The brain to window design interface pipeline connected a 128 channel Biosemi EEG device, Openvibe, Matlab, and Unreal Engine. We evaluate preliminary results on a case study with 9 designers, and assessing the BCI performance through test set classification accuracy, user experience, and attitudes toward BCI. Each class has 5 trials and 50 seconds in total. Figure1 shows two out of 9 binary classification schemes. The EEG data was recorded at 256 Hz, band pass filtered (1~40 Hz), and pre-processed with ASR. We selected 48 best band power features and cross-validated our classifier iteratively using 4 motor imagery trials to train a Linear SVM classifier and 1 trial as the test set.

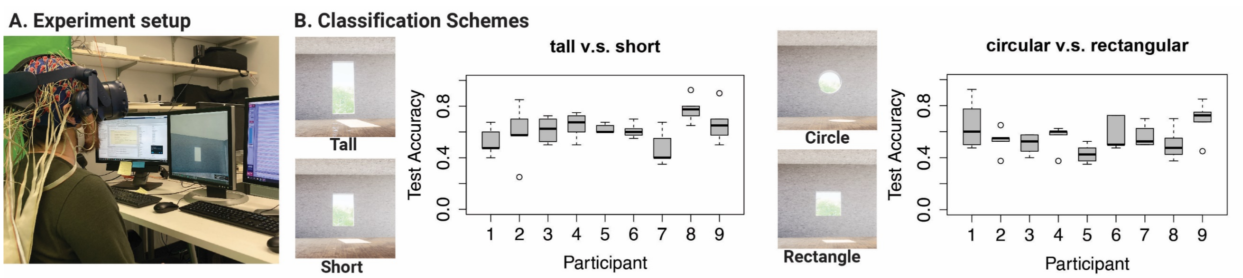

Figure1.Experiment flowchart and test-accuracy for different ML models.

Our BCI-enabled design tool achieved around a mean accuracy of 61% (sd = 14%, n = 9) off-line test accuracy, with a range of 25%-93%. Most users were designers, and first-time BCI users. The "Changing shape" task was regarded as the most "interesting" and "inventive" in User Experience Questionnaire (UEQ).

Discussion: Test accuracy or task-completion time have been the dominant metric to evaluate BCI performance [1]. However, in some design scenarios, we found that deviated outcomes or mistakes in the BCI experience can possibly trigger inspiration. Thus, it encourages us to conceive BCI that embraces the plasticity and uncertain nature of the thinking processes [2], which makes BCI unique from other modalities. The study advocates that more measures should be developed to measure the significance of BCI, including user experience and self-report attitudes [3].

Significance: The study experimented with the feasibility and performance of BCI as a tool for interior design, based on self-chosen motor imagery in high-fidelity immersive virtual environment. The study exposed questions such as to measure for success and feedback of error through hybrid paradigms [4].

Acknowledgements: The authors thank Tong Xu, James Dalton Rounds, and Yingyi Shu.

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Towards a framework for BCI assessment, and multisession BCI performance using a switch-scanning augmentative and alternative communication device by individuals with ALS

J. S. Brumberg[1*], K. Pitt[2]

[1]*Department of Speech-Language-Hearing, University of Kansas, Lawrence, KS, USA,* [2]*Department of Special Education and Communication Disorders, University of Nebraska-Lincoln, Lincoln, NE, USA*

**Dole Human Development Center, Room 3001, 1000 Sunyside Ave, Lawrence, KS, USA. E-mail: brumberg@ku.edu*

Introduction: Augmentative and alternative communication (AAC) techniques can provide access to communication for individuals with severe physical impairments due to diagnosis such as amyotrophic lateral sclerosis (ALS) and locked in syndrome (LIS) (e.g., [1]). An array of options exist which may allow an individual to make communication interface selections such as eye gaze and switches, with clinical feature matching procedures being used to identify the best AAC option for an individual (e.g., [2]). BCI may serve alongside existing AAC access methods to provide communication device control for those with severe physical impairments across the life span. However, current BCI software largely utilizes custom made software and displays that are unfamiliar to AAC stakeholders [3,4]. Further, there is limited information available exploring the heterogenous profiles of individuals who may use BCI (e.g., [2,5]). Therefore, we aimed to evaluate how individuals learned to control a motor-based BCI switch to a clinically utilized row-column AAC scanning pattern, and factors associated with BCI performance and user satisfaction were related to performance. These results are then interpreted against feature matching-based BCI screening and assessment framework [5] designed to help clinicians select the most appropriate combination of BCI features for each individual.

Materials/Methods: Four individuals with ALS completed 12 BCI training sessions either in a lab setting (N=2) or at home (N=2), while neurotypical control participants completed 3 sessions in a lab setting (all approximately 1-2 hours in length). In addition to BCI training, participants with ALS completed a comprehensive BCI assessment [5] for screening sensory, cognitive and motor (imagery) skills likely important for successful BCI performance. In addition, user feedback on fatigue, satisfaction, frustration, and motivation were collected during each training session. Participants completed an average of 300 BCI trials per session, copy spelling words via a 28-item matrix containing letters A-Z, space, and backspace. Keyboard items were selected using an auto-advancing switch scanning interface using a sensorimotor rhythm paradigm from 62 active EEG electrodes collected at 256 Hz (g.HIAmp, g.tec) and processed using regularized common spatial patterns [6] and linear discriminant analysis.

Results: BCI performance (e.g., $r_s(10) = .715$, $p < .05$ for participant A3) and frustration (e.g., $r_s(10) = -.702$, $p < .05$ for participant A4) levels influenced satisfaction, with performance being variable and largely tracked by symptom severity for those with ALS. Participants without ALS also varied in their performance, though all were able to control the device at levels above those with ALS.

Discussion: BCI-based control of a commercial AAC scanning paradigm is feasible for those with ALS. Obtaining user feedback during BCI trials is crucial as factors influencing satisfaction may vary. Future work is necessary to optimize BCI performance, and standardize and revise BCI assessment procedures [2,5].

Significance: Increasing consistency between clinical and BCI practices may facilitate BCI translation and communication success and social participation by engaging AAC stakeholders (clinicians, clients, and commercial partners) in a familiar framework.

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Modelling the Acceptance of BCI-based Stroke Rehabilitation Procedures: Heading for Efficiently Personalised Therapies

C. Jeunet[1*], K. Forge[1], F. Amadieu[1], J. Py[1], D. Gasq[2]

[1]CLLE, CNRS – Univ. Toulouse Jean Jaurès, France; [2]ToNIC, INSERM – Univ. Toulouse 3, France

*Maison de la Recherche, 5 Allées Antonio Machado, 31058 Toulouse. E-mail: camille.jeunet@univ-tlse2.fr

Introduction: BCI-based stroke rehabilitation procedures (BCI-SRPs) have demonstrated their efficiency to improve patients' motor and cognitive abilities [1]. In the coming years, they are expected to substantially improve stroke patients' quality of life. Still, BCI efficiency is known to be modulated by several factors, including the so-called *technology acceptance* [2]: the patients' levels of agency, anxiety or mastery confidence (inter alia) will most likely influence the BCI-SRP efficiency. Yet, until now, this dimension of technology acceptance has mostly been neglected. We hypothesise that optimising BCI acceptance by personalising BCI-SRPs will increase patients' engagement and consequently enhance the efficiency of these procedures. In order to design such personalised BCI-SRPs, we have to determine what factors influence BCI acceptance, to estimate how much they influence BCI acceptance and to uncover how they interact with one another. As a first step towards this objective, we introduce a model of BCI acceptance that is based on the Technology Acceptance Model 3 (TAM3) [3].

BCI acceptance model: According to the TAM3, BCI-SRP acceptance is determined by both the *perceived usefulness* and *ease-of-use* of the technology. These two parameters modulate the patients' *behavioural intention* and consequently their *use behaviour*. Four dimensions would influence this BCI-SRP acceptance: system characteristics, facilitating conditions, individual differences and social factors. This influence has been suggested to be altered by the patients' levels of *experience* and *voluntariness* in the use of the technology. The Fig.1 provides a schematic representation of our model.

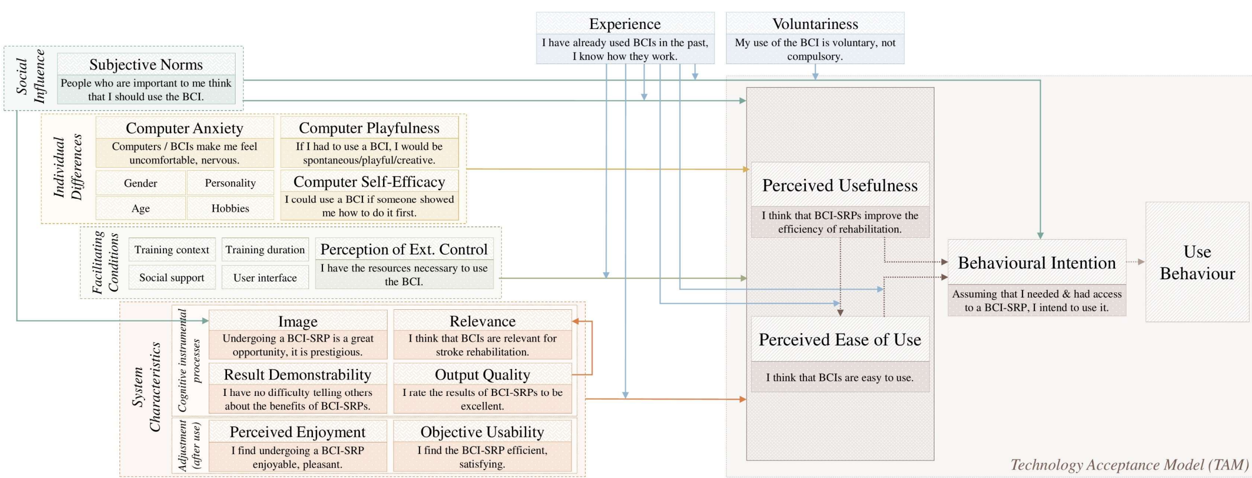

Figure 1. *Schematic representation of the BCI-SRP acceptance model in the context of stroke rehabilitation procedures. Each factor of the model is associated with an illustrative item that will be used in our online questionnaire to build a probabilistic model of BCI-SRP acceptance.*

Future work: We are currently implementing an online questionnaire that will be circulated to a representative sample of the population, including both healthy subjects and stroke patients. Each factor of the model will be assessed through at least three items, examples of which are provided in Fig. 1. Based on this model architecture and on the scores allocated to each factor by the people who completed the questionnaire, we will use a reinforcement learning approach to train a probabilistic model that will enable us to estimate how much each factor influences BCI-SRP acceptance, and how these different factors influence each other.

Significance: Thanks to this model, it will be possible to adapt BCI-SRPs to each patient, based on their profiles. We expect this approach not only to improve BCI-SRP acceptance, but also to enhance the efficiency of these procedures, which remains to be verified through a prospective randomised controlled trial.

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Including participants with speech and physical impairments in BCI research: Challenges and lessons learned

B. Peters*, B. Eddy, M. Kinsella, D. Klee, D. McLaughlin, T. Memmott, B. Oken, M. Fried-Oken, on behalf of the Consortium for Accessible Multimodal Brain-Body Interfaces (CAMBI)
Oregon Health & Science University, Portland, OR, USA;

*707 SW Gaines St #1290, Portland, OR, 97239. E-mail: petersbe@ohsu.edu

Introduction: Many BCIs are designed for use by people with severe speech and physical impairments (SSPI), but including these individuals as study participants is challenging. We present lessons learned from two recent studies of non-invasive EEG-based BCI communication systems, and recommendations for including participants with disabilities and ensuring effective and ecologically valid data collection.

Material, Methods and Results: Study 1 included two people with ALS, vision impairments, and minimal volitional movement, who attempted five copy-spelling sessions with an SSVEP-based BCI during weekly visits [1]. Study 2 involved up to five sequential calibrations of a P300-based BCI on a single day by 12 people with SSPI resulting from a variety of conditions [unpublished data]. We faced challenges related to participant characteristics and performance, experimental design, data collection, and equipment.
Low calibration accuracy: In Study 2, three of 11 participants had AUCs ≤ .70 in all calibration sessions, and another three had at least one session with an AUC ≤ .70. Participants demonstrated variable calibration accuracy (AUC) in repeated sessions on the same day. SD values ranged from 0.03 to 0.08 and differences between highest and lowest scores for the same participant measured up to 0.22.
Variable typing performance: Each participant in Study 1 had typing accuracies ≤ 50% in two of five weekly sessions. Typing accuracy varied considerably across weekly visits, with lows of 0% for each participant and highs of 88% and 100%, and may have been affected by participant illness or fatigue.
Unsuitable performance measures: Typing accuracy was the primary dependent variable in Study 1. Due to the variable number of queries needed for character selection, participants made three to 12 selections in copy-spelling sessions of the same duration, making it difficult to compare sessions.
Difficulty collecting data on subjective measures: In Study 1, an adapted 17-item UX questionnaire was originally administered for each session. Due to the time and effort required for yes/no responses, this inventory was discontinued entirely for one participant and shortened to five items for the other.
Poor data quality: Post-experiment offline review of EEG recordings revealed significant artifacts, both persistent and intermittent, related to external electrical noise and bad channel connections. While the artifacts themselves did not exclude participants, several sessions were unusable for planned analyses.
Hardware-related discomfort: Data collection was discontinued early for four of 12 participants in Study 2 due to pain and discomfort from wearing a dry electrode cap.

Discussion: We recommend that research teams: 1) consider study designs with multiple data collection sessions per participant, such as single-case designs; 2) ensure that dependent variables adequately measure performance under experimental conditions; 3) minimize the effort required for participants to complete UX measures; 4) use online signal viewing to facilitate real-time artifact identification and minimization; 5) consult electrode cap manufacturers for advice on optimizing user comfort and signal quality; and 6) ask frequent yes/no questions about pain or discomfort when working with participants with communication impairments, and watch for signs of discomfort such as changes in facial expression.

Significance: These recommendations may support the effective inclusion of people with SSPI in BCI research, which is crucial to the development of BCI systems that work for their intended populations.

Acknowledgements: This work was supported by NIH 2R01DC009834 and NIDILRR 90RE5017.

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Detection of imagined words segments for asynchronous BCI

T. Hernández-Del-Toro*, C.A. Reyes-García, L. Villaseñor-Pineda
Biosignal Processing and Medical Computing Lab,
Instituto Nacional de Astrofísica, Óptica y Electrónica, Mexico

*E-mail: tonahdz@inaoep.mx

Introduction: An asynchronous BCI [1] based on imagined speech [2], allows the control of an external device in the moment the user desires to, by decoding from brain signals, imagined speech. In order to build this type of asynchronous BCI, we must be able to detect from a continuous signal, when does the subject starts and finishes to imagine a syllable, word, or phrase. In this work, we present a system that automatizes the detection of imagined words segments from continuous EEG signals. This results show promising for future implementations of a BCI based on imagined words related to directions that can be applied as controlling a pointer in a navigation system that can help impaired people.

Material, Methods and Results: In order to achieve the detection of imagined words segments, feature sets based on the Discrete Wavelet Transform, Empirical Mode Decomposition, Wavelet energies, Higuchi Fractal Dimension, Katz Fractal Dimension, and Generalized Hurst Exponent are used. Three datasets containing recordings of trials (A continuous signal containing an idle state, followed by an imagined word segment, followed by another idle state) of subjects are used to test the method. The datasets and feature sets are described in [3,4] For each subject 75% of trials are used as training set, and the rest 25% are used as test set. The classifiers that have achieved higher F1 scores in the three datasets were Random Forest, and Logistic Regression. Results are shown in Table. 1.

Dataset	Classifier	F1 score	Precision	Recall
1	RF	0.73 ± 0.07	0.66 ± 0.08	0.87 ± 0.9
2	RF	0.79 ± 0.04	0.70 ± 0.04	0.93 ± 0.06
3	LR	0.68 ± 0.04	0.65 ± 0.06	0.83 ± 0.04

Table 1. *Higher f1-scores, precision, and recall, obtained for each of the three datasets, and the classifiers used in each dataset. Although an independent classifier was trained for each subject. The results shown are the mean and standard deviation over all the subjects for each dataset.*

Discussion: The results obtained, can be implemented as a pre-processing part of a general BCI that takes continuous EEG signals as input and after recognizing the onset and ending of an imagined word, then the classification of the word can be made in order to give an action related to the BCI. A system that can take this use is a pointer in a navigation system that offers apps as writing messages, moving a wheelchair, or some entertainment system.

Significance: With this work we prove the feasibility of detecting the onset and ending of imagined words. This task is indispensable to develop asynchronous BCI that are based on imagined speech.

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Feature-based spatial attention reliably controls a gaze-independent BCI

C. Reichert[1,2,3*], S. Dürschmid[1,4], I. F. Tellez Ceja[5], H. Hinrichs[1,2,3,4]

[1]Leibniz-Institute for Neurobiology, Magdeburg, Germany; [2]Center for Behavioral Brain Sciences, Magdeburg, Germany, [3]Forschungscampus STIMULATE, Magdeburg, Germany, [4]University Medical Center, Magdeburg, Germany, [5]Otto-von-Guericke University, Magdeburg, Germany;

*Leibniz-Institute for Neurobiology, Brenneckestr. 6, 39118 Magdeburg, Germany. E-mail: christoph.reichert@lin-magdeburg.de

Introduction: BCI systems intended for communication often rely on visual stimuli with the requirement that the user has to direct gaze to the target. However, potential users might not be able to move their eyes and may suffer from low visual acuity. Using displays presenting annotated selectable targets is therefore not suited for such users. We developed a BCI system that stimulates the left and right visual hemifields with different colors using light-emitting diodes (LEDs), to which participants can shift attention without moving their eyes. Directing attention to one of the lateralized color stimuli evokes a component known as N2pc, which indicates spatial attention shifts [1]. These hemispheric differences we decoded to generate the BCI command.

Material and Methods: We recorded the EEG from 14 parietal-occipital active electrodes (BrainProducts) and the EOG while subjects (N=7) directed attention to one of two colors, stimulated with LEDs, which illuminated two 3cm wide rear projection areas located 11cm left and right from a printed fixation cross, 70cm in front of the subject. Subjects had to decide whether an acoustically presented number was even or odd by attending to stimuli of the corresponding color while fixating a cross. The LEDs simultaneously illuminated the color red on one side and green on the other side, changing sides in a random order and flashing ten times with an SOA of 850ms, a jitter of 250ms and with duration 250ms. Afterwards, the feedback was presented acoustically by a female computer voice and subjects had to evaluate the correctness of the feedback by pressing a button. Classification was based on canonical correlation analysis, similar to the approach described in [2].

Results: On average, the BCI decoded the subjects' intentions correctly in 93.0% (std: 4.5%) of the 120 trials. In four of the subjects only 5 or less false classifications occurred.

Discussion: We developed a novel gaze-independent BCI, intended to communicate binary information. Since no visual details had to be recognized and only the appearance of the feature *color* must be spatially located in the left or right visual hemifield, it has the potential to be used by people with low visual acuity. The decoding algorithm we used is data-driven, autonomously weighting contributing electrodes highly and noisy electrodes lowly and thus it is robust and easy to handle. The results demonstrate that the algorithm is highly efficient in decoding the visual hemifield, in which the presentation of an attended color occurred, from hemispheric differences in the EEG, specifically the N2pc component.

Significance: The system we developed has the potential to serve as a technically simple realizable communication device for severely paralyzed people who even cannot move their eyes (who are locked-in), enabling them to respond to acoustically asked questions, permitting two reply options.

Acknowledgements: Funded by the federal state of Saxony-Anhalt and the „European Regional Developement Fund" (ERDF 2014-2020), Vorhaben: CBBS, FKZ: ZS/2016/04/78120.

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ECoG-based Control in 3D Space via Stable Discrete Commands

S. Seko[1,2*], N. Natraj[1,2], R. Abiri[1,2], Y. Graham[1,2], N.F. Hardy[1,2], E.F. Chang[1], K. Ganguly[1,2]

[1]University of California-San Francisco, San Francisco, CA, [2]San Francisco Veterans Affairs Medical Center, San Francisco, CA.

*1700 Owens St., San Francisco, CA. E-mail: sarah.seko@ucsf.edu

Introduction: For individuals with paralysis, Brain Computer Interfaces (BCIs) have the potential to restore lost function through the control of external assistive devices. Despite successful demonstrations, there remain translational challenges to real-world BCI-based control. Notably, signal instability results in the need for daily decoder recalibration. This is problematic for complex control tasks which require continuous high-dimensional neural input, such as the control of a 3D robotic arm performing functional upper-limb tasks. Recently, we demonstrated that stable "plug-and-play" control of a 2D cursor, with the ability to stack multiple discrete control dimensions, is possible by leveraging the stability of electrocorticography (ECoG) and long-term closed-loop decoder adaptation [1]. Here, we show that multiple stable and stacked control dimensions via ECoG enable a novel framework for continuous, real-time control of a robotic arm operating in a virtual 3D Cartesian action space.

Materials, Methods, and Results: A subject with severe spastic tetraparesis was implanted with a 128-channel chronic ECoG array over sensory and motor cortices as shown in Fig. 1A [1]. To initialize discrete control commands, the subject was instructed to imagine movements related to separate body parts (right hand, head, left hand, feet, tongue) and mimed words ("up"). A multilayer perceptron was used to classify discrete actions from the extracted neural features (delta (0.5-4 Hz), beta (12-30 Hz), and high-gamma (70-150 Hz) power) at 8 Hz. Six discrete commands were mapped to 2D Cartesian directions to perform a center-out discrete selection and cursor control task (with two sets of commands mapped to up/down). Stable control was achieved via closed-loop batch updates of the decoder over a few sessions of online training. This decoding framework was then mapped to control a robotic arm end-effector in a 3D simulation environment (Fig. 1B). The subject was able to transfer the control signals from 2D and immediately control the device to perform a 3D center-out task (Fig. 1C). Furthermore, the subject was able to complete diagonal trajectories to off-axis targets by alternating discrete inputs (Fig 1D). This continuous motion was achieved by imposing virtual mass-damper dynamics.

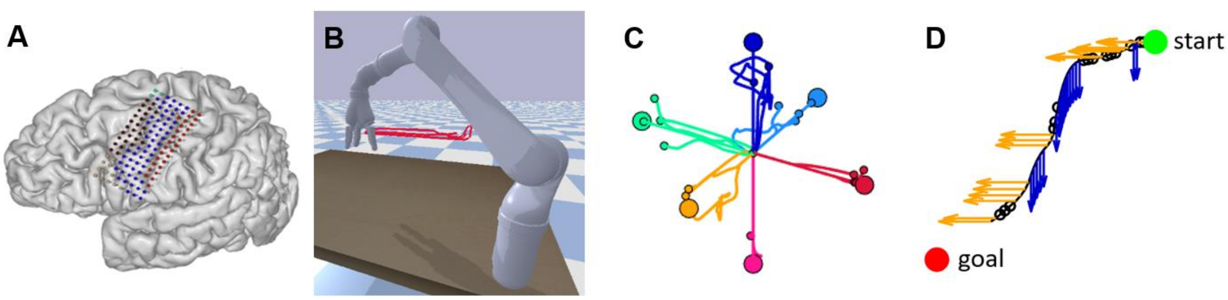

Figure 1. *A. ECoG implantation. B. Pybullet simulation environment with Kinova Jaco robotic arm. C. Trajectories from the 3D center-out task showing the position of the robot end-effector. D. Representative off-axis trajectory with the discrete selection shown as a blue or yellow arrow.*

Discussion: These results suggest that robust discrete commands can be used as the input to be a "universal joystick" for neuroprosthetic control which can be mapped to different action spaces and coordinate frames, providing a novel framework for continuous real-time control of an upper limb 3D robot.

Significance: This approach provides a framework for the development of long-term reliable control of devices which operate in high-dimensional spaces.

Acknowledgements: This work was funded by the National Institutes of Health through the NIH Director's New Innovator Award Program, grant number [1 DP2 HD087955] and support from the Weill Institute for Neuroscience, UCSF.

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Decoding transient neural signals related to grasp: Applications for cursor click

Brian M Dekleva[1,3], Jeffrey M Weiss[1], Jennifer L Collinger[1-4*]

Depts. of [1]Physical Medicine & Rehabilitation and [2]Bioengineering, University of Pittsburgh, Pittsburgh, PA, USA; [3]Center for the Neural Basis of Cognition, Pittsburgh, PA, USA; [4]Dept. of Veterans Affairs, Pittsburgh, PA, USA

[*]3520 Fifth Ave, Suite 300, Pittsburgh, PA, USA, 15213. E-mail: collinger@pitt.edu

Introduction: Intracortical brain-computer interfaces (iBCI) commonly use neural activity during imagined upper limb actions to control an end effector. For example, activity related to arm or hand translation can be mapped to the movement of a mouse cursor, and activity related to hand grasp can be mapped to mouse click. This approach allows for an intuitive user strategy, and has proved successful for point-and-click control [1]. However, the use of grasp imagery for reliable, sustained click during translation (i.e. click-and-drag) has yet to be demonstrated.

Material, Methods and Results: We recorded from chronic microelectrode arrays in the motor cortex of a human participant with tetraplegia as he performed covert (attempted) arm and grasp actions. The participant observed 2D movement of a cursor between targets, interleaved with instructions to either "click" or "release", visualized as change in cursor radius. The participant attempted to mimic the movement of the cursor with covert arm translation, and the change in click state with covert hand grasp (squeeze for click, release for un-click; Fig. 1 *top*).

From the neural activity recorded during this training period, we created two click decoders. The first, based on previous approaches [1], used a linear discriminant analysis (LDA) classifier to separate activity during "clicked" periods from "unclicked" periods (output probability shown in green, Fig. 1 *middle*). The second approach used two separate LDA classifiers to instead identify activity related to click state *transitions* (click onset and click release; output probabilities in blue and orange, Fig. 1 *middle*). We found that the classification of static click state had low signal-to-noise ratio and was unreliable as a control signal (green trace, Fig. 1 *bottom*), but grasp onset and offset events were marked by highly salient neural transients, which could be reliably detected and used to provide nearly perfect click performance (purple trace, Fig. 1 *bottom*), regardless of click duration or concurrent cursor movement.

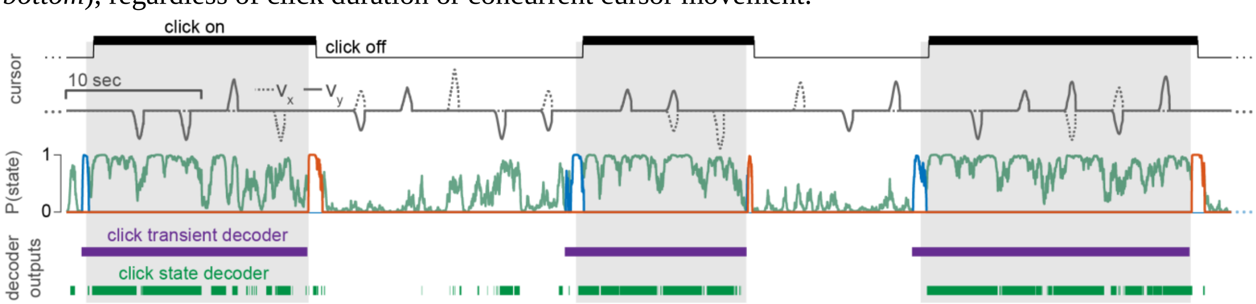

Figure 1. Click decoder performance during click-and-drag. ***top:*** *Target click trace and [x, y] cursor velocity.* ***middle:*** *LDA probability outputs for click onset (blue), offset (orange), and state (green).* ***bottom:*** *Decoder outputs from the transient-based (purple) and state-based (green) approaches.*

Discussion: The use of grasp imagery for iBCI control is complicated by an apparent suppression of grasp-related activity during arm translation [2]. Across many tasks incorporating concurrent grasp and translation, we find neural activity related to grasp and grasp force to be unreliable and context-dependent. In contrast, transient neural components at grasp onset and offset appear to be more salient and generalizable.

Significance: Intuitive control schemes are vital for motor iBCI technology, and using grasp imagery for click or robotic hand closure is a prominent and sensible approach. A decoding approach based on transient features of neural activity related to grasp provides reliable and generalizable control.

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Auto-adaptive BCI using labels inferred from an ECoG-based continuous cognitive state signal

V. Rouanne[1*], T. Costecalde[1], A. L. Benabid[1,2], T. Aksenova[1]
[1]*Univ. Grenoble Alpes, CEA, LETI, Clinatec, F-38000 Grenoble, France*
[2]*CHU Grenoble Alpes, Grenoble, France*
[*]E-mail: vincent.rouanne@cea.fr

Introduction: One of the major drawbacks of BCIs is associated with the necessity to train the decoders that convert neural data into control signals for effectors. With classical supervised training, the user cannot freely decide which actions to perform when acquiring labelled data. Conversely, neural data is not labelled when the user freely controls the BCI. This translates into long periods of downtime for the BCI, during the initial training of the decoders and their updates. In the paper, we report an approach to label neural data during free BCI control. Data is labelled using a newly reported cognitive state signal detected with ECoG from the user's motor cortex neural data. This cognitive state signal being correlated to the user's perceived correctness of the actions performed by the BCI's effectors. We subsequently show the capabilities of auto-adaptive BCIs to train from scratch their control decoders using this cognitive state signal.

Materials, Methods and Results: The dataset used in this offline simulation of online use consisted of ECoG neural data collected with one subject in the scope of a long-term clinical trial "BCI and Tetraplegia" (NCT02550522). The subject used motor imagery to control a human avatar displayed on a computer screen, in 13 sessions spaced over 141 days. The avatar walked forward when the subject performed leg motor imagery and stayed idle when no motor imagery was performed. The control decoder used to actuate the avatar was purposely trained on small amount of data to ensure that some error occurred. The cognitive state decoder was trained on one third of the data, one third was used to train a control decoder from scratch using the auto-adaptive BCI and the last third was used to evaluate the performances of the newly trained decoder. Performances were assessed using the mean area under the receiver operating characteristic curve (AUC) for the control decoder.

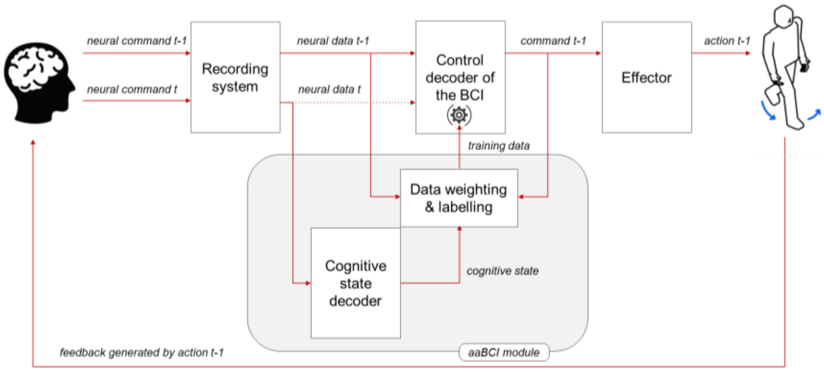

Figure 1. *Schematic of the auto-adaptive BCI loop and of how the cognitive state decoder is added in the classical BCI closed loop*

The mean AUC for the control decoder was 0.735 when trained with the auto-adaptive BCI. When the output of the cognitive decoder was randomly shuffled prior to the training of the control decoder, the mean AUC was 0.494. Comparatively, if the control decoder was trained classically with the knowledge of the real labels for the control decoder, the AUC was 0.913.

Discussion and Significance: The supervised performances were expected to be higher than the auto-adaptive ones, considering the associated additional constraints described above. The auto-adaptive BCI with shuffled labels performed randomly, while the non-shuffled one performed in-between. There is uncertainty in the labels inferred using the cognitive state signal, explaining the performances of the auto-adaptive BCI. It would require more training data to compensate, what will naturally occur as the BCI is used. The possibility to train control decoders during free use of a BCI would alleviate one of their major drawbacks. These findings should be replicated, as this cognitive state detection and proof of concept of an auto-adaptive BCI for motor control were performed with one subject only. Additionally, future studies should investigate the performances of auto-adaptive BCIs for more complex effectors, and specifically effectors with multiple continuous degrees of freedom.

A Generalized CNN Architecture for Real-time Continuous Feedback in Motor Imagery based BCI

Sujit Roy[1]*, Anirban Chowdhury[2], Karl McCreadie[3], Girijesh Prasad[4]
*Ulster University, Magee Campus, UK. E-mail: Roy-s2@ulster.ac.uk

Introduction: The use of convolutional neural networks (CNNs) is slowly catching momentum in classifying brain-signals for different brain-computer interface (BCI) applications. A major challenge that CNN could address is the generalisability of the classifier across different subjects [2]. Although limited success has been achieved, the applicability of a generalised CNN to providing continuous feedback is not reported so far.

Material & Methods: To this end, we have used adaptive training algorithms such as stochastic gradient descent with momentum (SGDM), and adaptive momentum (Adam) with automatic parameter optimisation for training a generalized deep convolutional neural network (CNN) for continuous feedback and showed its performance in the cases of intra- and inter-subject learning based on a left vs. right hand motor imagery paradigm. Figure 1 shows the construction of input image for CNN using BCI Competition IV 2b Dataset [1]. For continuous prediction, 11 trial segments were generated from a single trial [2].

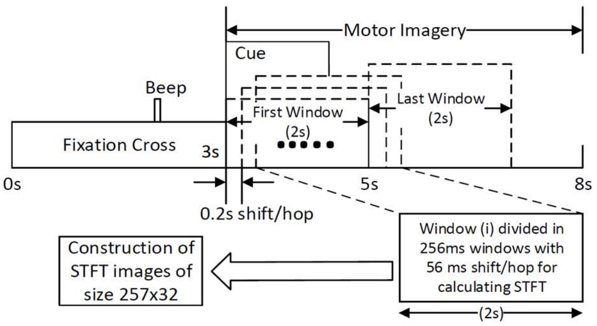

Figure 1: Construction of STFT images by sliding window of the size 2 s with a shift/hop of 200 ms is divided into 256 ms sub-windows (with 56 ms shift/hop) for calculating STFT the motor-imagery period within the trial.

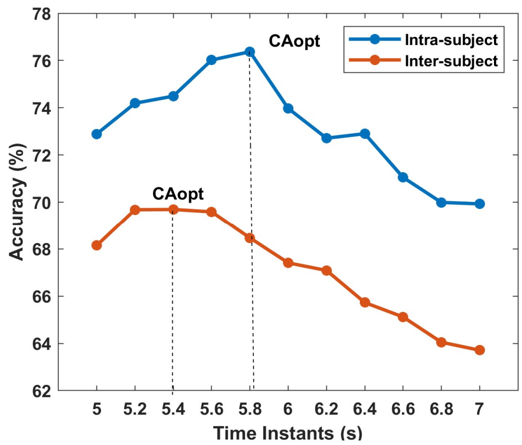

Figure 2: The average accuracy across the subjects for each time instant is shown for intra and inter-subject learning. The vertical lines show the time-point where accuracy is maximum for intra and inter-subject learning.

Results: The results, obtained on the publicly available BCI competition IV-2b datasets, yield average accuracies of 72.63% (k=0.45) and 73.13% (k=0.46) for Adam and SGDM respectively for intra-subject continuous prediction. Similarly, for inter-subject continuous prediction accuracies were 71.49% (k =0.42) and 70.84% (k =0.42) for Adam and SGDM respectively for 7 out of 9 subjects. There is no reported accuracy for the continuous classification of the EEG dataset for real-time BCI. However, Lawhern et al.[3] in their EEGNet model argued that a single CNN can perform well over multiple EEG-BCI paradigms such as P300, ERN, MRCP, and SMR, although EEGNet didn't perform significantly better than conventional FBCSP approach. Additionally, DeepConvNet is not shown to have performed significantly better than FBCSP whereas our model performed as good as FBCSP and further we showed its validity for inter-subject learning. Figure 2 shows the average accuracy across 9 subjects for time instants for intra and inter subject classification and its variability across time. **Significance**: Thus the applicability of a generalised CNN architecture with automatic parameter optimisation has been shown for the first time for continuous feedback generation which is an essential feature for practical applications of real-time BCI.

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The BCI Publication Database: A comprehensive, categorized, open-access catalog of articles on brain-computer interfaces

W. A. Schmitt[1,2*], P. Emery[3], E. Greenberg[1], T. M. Vaughan[1,4], J. R. Wolpaw[1,4], J. J. S. Norton[1,4]
[1]National Center for Adaptive Neurotechnologies, Wadsworth Center, NYS Department of Health, Albany, NY, USA; [2]Center for Addiction Medicine, Massachusetts General Hospital, Boston, MA, USA; [3]Department of Computer Science and Engineering, University of South Florida, Tampa, FL, USA; [4]Stratton VAMC, Albany, NY, USA
*120 New Scotland Ave, Room 2085, Albany, NY 12208. Email: schmitt@neurotechcenter.org

Introduction: Here we introduce the BCI Publication Database, a comprehensive, categorized, open-access catalog of articles on brain-computer interfaces (BCIs) for bibliometric analysis of the BCI field.

Materials, Methods and Results: The articles included in the BCI Publication Database were sourced from PubMed. All publications that contained the terms "brain computer interface", "brain machine interface", or "direct brain interface" in the title or abstract were downloaded and considered for inclusion. To date, the database includes 2611 publications (up to December 2016). Each publication was categorized in terms of publication type (e.g., original research, review article), data type (e.g., original data, data set), populations studied (e.g., human (healthy), animal (primate)), application (e.g., enhance function, replace function), recording method (e.g., electrical, metabolic), recording technologies used (e.g., EEG, fMRI), brain signals analyzed (e.g., auditory, motor), experimental paradigm (e.g., motor imagery), purpose (e.g., communication, robotic control), and contribution (e.g., signal processing technique). Using these categories, we find that the BCI field is mainly comprised of publications that use healthy human subject populations (n=1098, 42%), record brain activity using EEG (n=1459, 56%), and investigate motor brain signals (n=933, 34%). It is notable that studies investigating clinical human subject populations, invasive recording technologies (e.g., ECoG and intracortical), and visual brain signals have grown over five-fold from 2006 to 2016.

Significance: This work enables researchers to quickly identify BCI publications that are relevant to their research and provides a means to perform bibliometric reviews on specific subfields of the BCI literature. Furthermore, it encapsulates the current state of the BCI field. Refining and expediting the classification process and including publications after 2016 is underway.

Acknowledgements: This work was supported by the National Institute of Biomedical Imaging and Bioengineering of the NIH (Grant P41EB018783 (JRW)) and by the Veterans Administration (Merit Award I01BX002550 (JRW)).

Parallel Spelling using P300 and Feedback Response

A. D'Amico[1*], M. Mousavi[1], V. R. de Sa[1]

[1]*UC San Diego, California, USA*

*9500 Gilman Dr, La Jolla, CA, USA, 92093-0515. E-mail: adamico@ucsd.edu

Introduction: P300-based spellers using a grid of characters have been available for decades [1]. However, they require users to foveate making them inaccessible to completely locked-in patients. We have developed a paradigm which allows users to spell without eye movements by presenting stimuli in a fixed location. Rather than serially presenting complete characters, we instead show users segments in order to probe for multiple letters in parallel [2]. Since the chosen stimulus will be displayed to participants, it may be possible to use the feedback-related event related potential (ERP) to increase the system's performance [3].

Materials, Methods and Results: 64 channels of EEG were collected from participants (n=5) using the standard BrainVision actiCHamp system with reference electrode Cz. Participants completed an offline task where they were assigned a target letter and completed a total of 30 trials where they would see their target and non-target letters along with associated segments. Targets were shown 30% of the time and participants were instructed to count the number of targets they viewed. All stimuli were presented for 390 ms with 180 ms between trials and a 5 second break between blocks of 10 trials. Every 10 trials, the participants were given sham feedback on what letter they were 'thinking' of with an accuracy of 50%.

EEG data were processed offline in Python by re-referencing to the average of the mastoid electrodes and bandpass filtered with a non-causal 4th-order Butterworth filter between 1 and 20 Hz. Epochs were extracted for the P300 and feedback ERPs at -250 ms and 1000 ms around stimulus onset. Features were extracted using windowed means between 300 and 800 ms for the P300 and 200 and 800ms for the feedback ERP. Linear discriminant analysis was used to train classifiers using leave one trial out cross validation.

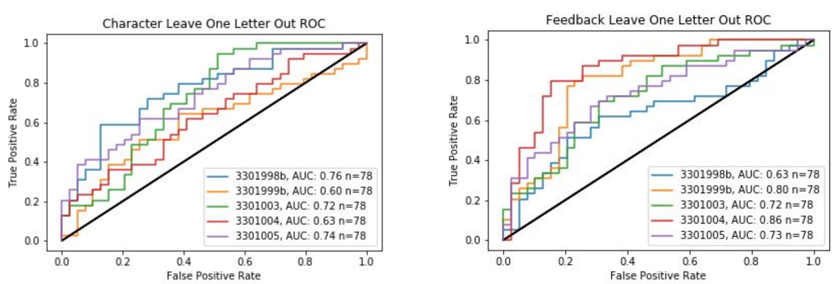

Figure 1. *Receiver operating characteristics (ROC) curve for leave one trial out for each participant. Trials were balanced for the characters to match the number of feedback trials. The area under the curve (AUC) is also provided for each ROC.*

Discussion: It is possible to use a combination of classifiers trained on the P300 and feedback responses in order to adjust the confidence of the probabilistically selected character. Confidence in the P300 and feedback classifiers can be tuned to accommodate specific users.

Acknowledgments: This work was supported by NSF IIS 1528214, and 1817226.

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TAG, you're it: Calibrating the Wadsworth BCI Home System

K. Fitzpatrick[1], V. Gupta[1], C.S. Carmack[1,2], G. Townsend[3], K. A. Gosmanova[1]; D. Goldberg[1], J.R. Wolpaw[1,2], T.M. Vaughan[1,2*].

[1]National Ctr for Adaptive Neurotechnologies, Wadsworth Ctr, Albany, NY, USA; [2]Stratton VA Med Ctr, Albany, NY, USA, [3]Algoma Univ, Sault Ste. Marie, ON, Canada

*120 New Scotland Avenue,Albany, New York. E-mail: vaughan@neurotechcenter.org

Introduction: Individuals with amyotrophic lateral sclerosis have used the Wadsworth Home System–a P300-based visual brain-computer interface (BCI)–independently as their only means of computer-assisted communication over weeks and months [1]. Currently, successful use of the Home System relies on subject-specific predictor variables determined with a stepwise linear discriminant analysis (SWLDA) [3]. The training set used to determine these variables is a series of trials where the system and the user have a prior knowledge of the correct answer (i.e., the target). Once chosen, these variables are verified and used to calibrate the system. This study tests the effectiveness of an alternative calibration routine that uses data that are tagged for the correct answer post hoc. This alternative calibration routine (TAG) can be used with off-the-shelf software and could assist clinicians and consumers by simplifying use and reducing evaluation time. This could increase the number of individuals who might benefit from a BCI.

Material, Methods and Results: Four participants without neurological diagnosis completed two sessions each with the BCI Home System. Each session comprised 25 selections divided into 5 five-letter English words. Each selection required the participant to count up to eight faces as the faces flashed over the target character in a 4X7 (28 item) matrix. The Conventional Method (CM) used the BCI2000 P300 Spelling Application with all English letters arranged alphabetically. The Alternate Method (TAG) used TOBII Dynavox Communicator5™ software with a similarly arranged virtual keyboard. Using all eight sequences, accuracy for the four subjects did not differ significantly between the CM and the TAG (99.6 ± 0.4 and 88.0 ± 20.0, respectively; $p > 0.1$ by t-test). We are seeking to improve the reliability of the classification produced by the TAG program. Next steps include: adding additional subjects; and testing the impact of stimulus rate, sequence number, and the size and arrangement of target relative to the nontarget.

Discussion: These preliminary analyses suggest there is promise in developing an automated calibration routine for independent use of the Wadsworth BCI Home System. Such a system would simplify use and save time, thereby removing significant roadblocks to clinical use.

Significance: Ease of use and reliability are the hallmarks of BCI translation. Integrating an automated routine for calibration would improve both aspects of BCI usability.

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Binocular Visual stimulation for Robust and Comfortable SSVEP-Based BCIs in Head-Mounted Display Headsets

Kuan-Jung Chiang[1*], Masaki Nakanishi[1], Tzyy-Ping Jung[1]
[1]*Swartz of Computational Neural Science, University of California San Diego, La Jolla, USA*
*P.O. Box 9500, Gilman Drive #0559, La Jolla, CA, USA. E-mail: kuchiang@eng.ucsd.edu

Introduction: Steady-state visual evoked potential (SSVEP)-based brain-computer Interfaces (BCIs) have been successfully integrated with emerging technologies such as wearable sensing and virtual/augmented reality (VR/AR) in recent years [1], showing great potentials to bridge the gap between laboratory-based experiments and its real-world applications. However, SSVEP-based BCIs still suffer from visual discomfort and fatigue, which greatly hinders their widespread and routine use in the real world. Studies have shown that stimulating users with higher frequency can reduce the discomfort at the expense of lower SNR [2]. That is, it is a trade-off between the performance and usability of SSVEP-based BCIs. This work proposes a new stimulation method that takes advantage of binocular head-mounted VR/AR displays (HMDs) to reduce discomfort but maintain the discriminability of SSVEPs.

Material, Methods and Results: The proposed stimulation technique presents different images (i.e., visual stimuli) at the same position on each binocular screen so that each of user's eyes can be stimulated by different stimuli at the same time. In this work, we propose six stimulation schemes: A) present low-frequency stimuli (8, 9, 10, and 11 Hz) to the dominant eye and high-frequency ones (24, 27, 30, and 33 Hz) to the non-dominant one, B) the reverse of the scheme A (i.e. high-band to the dominant eye and low-band to the non-dominant one), C) high-frequency stimuli to both eyes, D) low-frequency stimuli to both eyes, E) low-frequency stimuli to the dominant eye and a static image to the other, and F) the reverse of the scheme E. The stimulation program was implemented in Unity with the Windows Mixed Reality package. The HMD used in the experiment was Samsung Odyssey with the refresh rate ninety frames per second.

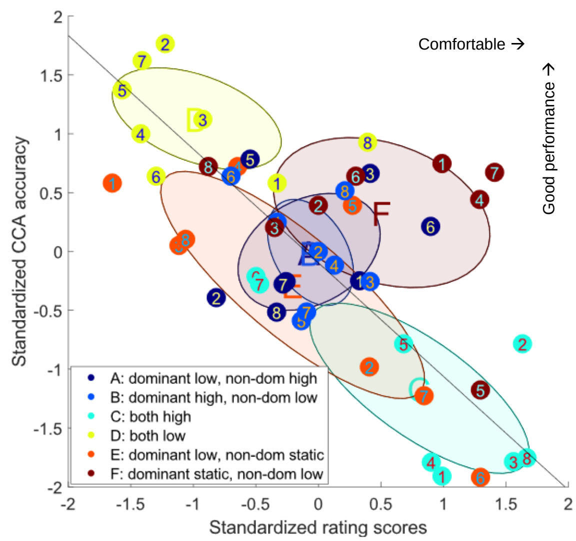

Figure 1. CCA decoding accuracy versus the rating scores of eight subjects in each scheme. The numbers on the dots indicate the subject id. The ellipsoids present the generative Gaussian distribution.

We collected SSVEPs from eight participants (subjects), each went through four (targets) x nine (trials per target) x six (schemes) total trials. The participants were asked to rate how comfortable they felt to the stimuli (from 1-least comfortable to 10-most comfortable) for every three trials. Fig. 1 shows the scatter plot of the decoding accuracy obtained by canonical correlation analysis (CCA)-based algorithm versus the rating scores of all subjects in each scheme. Both the accuracy and rating scores were standardized to zero-mean and unit-variance within each subject.

Discussion: The schemes C and D shown in Fig. 1 are the conventional SSVEP stimulation method, used as baseline schemes in this study. The result clearly showed the trade-off between the rating scores and the decoding accuracy. The schemes A and B still lay near the trade-off line between the schemes C and D. The scheme F is located mostly in the upper right area, which implies this scheme can reduce discomfort but still induce good-quality SSVEP.

Significance: The pilot results showed that the proposed stimulation schemes, which leverage the binocular display in HMDs, could lead to stable SSVEPs with less visual discomfort.

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Wearable Sensor-Driven Responsive Deep Brain Stimulation for the Improved Treatment of Essential Tremor

S. Cernera[1*], J. Alcantara[1], E. Opri[2], J. Cagle[1], K.D. Foote[1], M.S. Okun[1], A. Gunduz[1]

[1]*University of Florida, Gainesville, FL, USA;* [2]*Emory University, Atlanta, GA, USA*

*1275 Center Drive, Gainesville, FL. E-mail: scernera@ufl.edu

Introduction: Essential tremor (ET) is the most prevalent adult-onset tremor disorder [1]. ET patients unresponsive to medication may consider deep brain stimulation (DBS) [2]. However, DBS operates continuously, constituting limitations to the battery life of the implanted neurostimulator (INS) and to the therapeutic window of DBS, often leading to adverse effects [3]. We hypothesize that wearable sensor signals, specifically the electromyogram (EMG), are capable of detecting movement that can act as the control signal for a responsive DBS (R-DBS) system, which can provide targeted and personalized therapy.

Material, Methods and Results: EMG data were recorded using Trigno Acquisition Unit (Delsys, Inc, Natick, MA) sensors from ten subjects with ET. Feasibility of R-DBS using wearable sensors was evaluated using Nexus-D, which is a Medtronic investigational system able to titrate stimulation parameters by communicating with the subject's INS. For R-DBS, two separate paradigms were tested. The first focused on a linear detector using a calibrated threshold with a single sensor (Fig. 1), while the second was a multi-sensor paradigm using a support vector machine. The feature used in both paradigms was the power within the subject's tremor frequency band (±2 Hz) (Fig. 1B). To clinically validate R-DBS, we used the Fahn-Tolosa-Marin Tremor Rating Scale (TRS). Across subjects and R-DBS paradigms, R-DBS decreased tremor power by 40.48±28.87% within the contralateral extensor EMG during the TRS compared to DBS off. Furthermore, both standard DBS and R-DBS resulted in significantly lower scores on the contralateral TRS (i.e. less severe tremor) compared to DBS off ($p<0.001$). Continuous DBS and R-DBS provided statistically equivalent contralateral TRS scores ($p<0.01$), calculated using a two-one sided test. Finally, R-DBS decreased the total electrical energy delivered (TEED) by 55.97±13.45% across TRS trials.

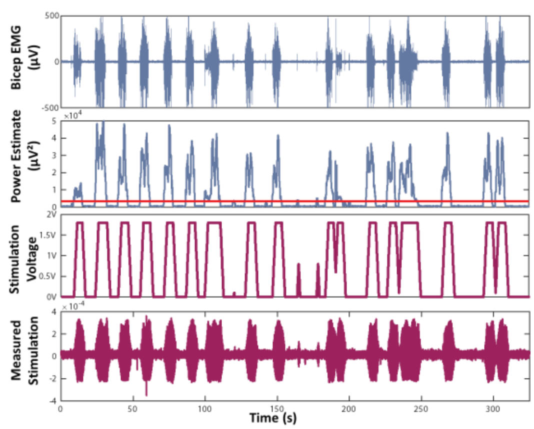

Figure 1. A. *Raw EMG recorded from subject 8's left bicep while performing a cup reaching task.* ***B.*** *The mean EMG power within the subject's tremor frequency band (6±2Hz). The red line is a calibrated threshold extracted from a receiver operating characteristic curve.* ***C.*** *The stimulation voltage calculated within the responsive stimulation code. Every instance that the power exceeds the calibrated threshold in* ***B****, stimulation increased at a rate of 0.8 V/s with a sensitivity of 92.8% and specificity of 87.6%.* ***D.*** *Estimated stimulation from an EMG placed over the DBS extension wire to prove Nexus-D is modulating stimulation. TEED was decreased by 53.52% in R-DBS compared to continuous DBS.*

Discussion: From these results, we have proven the feasibility of an R-DBS paradigm, which provided statistically equivalent clinical benefit, while delivering less total electrical energy.

Significance: R-DBS is expected to improve treatment by only providing stimulation when necessary, by minimizing undesirable side effects related to continuous DBS, and by prolonging battery life of the INS, subsequently improving the therapeutic window of DBS and the quality of life for patients with ET.

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THE INFLUENCE OF GRAPHICAL PRESENTATION ON MOTION ONSET VISUAL EVOKED POTENTIAL FOR BRAIN COMPUTER INTERFACE

Tao Lyu[1], Aleksandra Vuckovic[1], Tiejun Liu[2]

[1] School of Engineering, University of Glasgow, Glasgow, United Kingdom
[2]School of Life Science and Technology, University of Electronic Science and Technology of China, Sichuan, China
E-mail: t.lv.1@research.gla.ac.uk, aleksandra.vuckovic@glasgow.ac.uk, liutiejun@uestc.edu.cn

INTRODUCTION: Introducing gaming element in Brain Computer Interfacing (BCI) makes it more interesting and entertaining for the users [1]. Visual evoked potential (VEP) is popular BCI paradigm because it does not require learning and enables relatively fast detection. Traditional flash or pattern reversal VEP-based BCI is often accompanied with visual fatigue. Motion-onset visual evoked potential (mVEP) is elicited by the motion of an object and is therefore more comfortable for a long term use. Some research indicates that colors of the objects and background may affect performances of BCI systems based on VEP, such as P300 [2]. In this study we investigated the influence of color and size of targets on performance of mVEP-BCIs.

MATERIALS AND METHODS: Ten subjects (aged 24 $\pm$ 3 years old, 7 males) sit 50 cm from a computer screen and looked at the moving target line in one of the four rectangles corresponding to the number in the central panel (Fig 1). The size of central panel was 7cm*15cm and the size of targets was 1.5cm*1cm. EEG was recorded with eight electrodes (CP3, CPz, CP4, P3, Pz, P4, O1, O2) using usbAmp (Guger Technologies, Austria) with sampling frequency 256 samples/s, subsequently down-sampled to 20 samples/s. The recorded EEG data were saved in 4 groups according to the numbers of the targets. The duration for the line to cross each target rectangle was 140 ms and 60 ms to cross between two rectangles. There were 250 trails for each rectangle. Four out of 8 electrodes with strongest mVEP were selected individually for each participant. EEG was filter between 0.5Hz-10Hz and period 0-900ms was used for analysis. Three successive trails of target data were averaged and classified against non-target data with 10-fold cross-validation using Linear Discriminant Analysis classifier. Six User Interfaces (UI) were tested: UI A (Fig 1), B and C had red, blue and green target line respectively and the same geometry, UI D was the same size and color of target line as A but whole background was gray, UI E had same color and same size of central panel as A but twice smaller target panels, UI F has same color and size of target panels as A but twice bigger central panel (target panels were further apart).

RESULTS: The classification result of UI A(Fig.1), B, C with red, blue or green target line were 76.78$\pm$5.90%, 79.15$\pm$6.15% and 78.32$\pm$6.45% respectively. UI D classification was 79.79$\pm$5.86%, UI E was 76.92$\pm$4.95% and UI F was 80.41$\pm$3.43%. There were no statistically significant differences between different mVEP UIs($p<0.05$, Kruskal Wallis test).

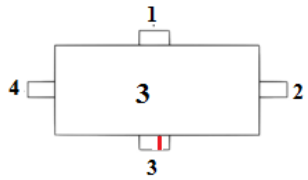

Fig.1. UI A with red target line and standard size of rectangles. User is instructed to look at target 3

DISCUSSION: Our results show that the colour and size of UI have no influence on mVEP performance.

SIGNFICANCE: Using mVEP BCI allows great flexibility in creating UI that could be embedded in computer games.

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Neural Speech Decoding Prior to Speech Onset

Debadatta Dash[1], Paul Ferrari[1], Jun Wang[1*]

[1]*The University of Texas at Austin, Austin, TX 78712, USA*

*CMA 4.112,2504A Whitis Ave, Austin, TX 78712, USA. E-mail: jun.wang@austin.utexas.edu

Introduction: Current neural decoding studies of overt speech typically parse the neural signal data based on the acoustic onset and offset for brain-computer interface (BCI) applications. However, for application to patients with limited or no motoric ability, decoding on speech intention or imagination is necessary. To this end, we investigated neural speech decoding prior to, during, and following speech production, in addition to a preparation/imagination segment.

Material, Methods and Results: We used Magnetoencephalography (MEG) to record the neuromagnetic signals from eight subjects corresponding to five short phrases (e.g. I need help) during speech preparation (imagination) and production. We parsed the production stage of the recorded neural signals into three segments as pre-speech (cue of articulation to acoustic onset), speech (acoustic onset to acoustic offset) and post-speech (acoustic offset +500 ms). We trained a support vector machine on the root mean square features of neural signals with 5-fold cross-validation to classify the five phrases during each of the stages (Imagination, Pre-speech, Speech, and Post-speech) and their combination. All segments were decoded above chance level (20%).

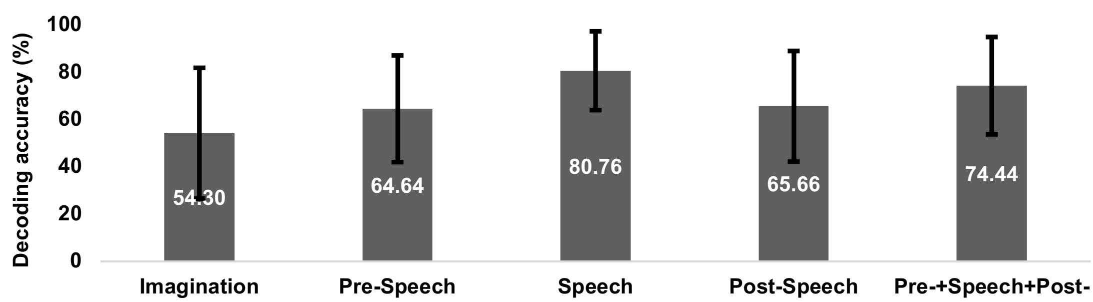

Figure 1. *Average classification accuracy of eight subjects during different stages (error bar: standard deviation)*

Discussion: As expected the overt speech stage was decoded with the highest accuracy (80.76%). However, both pre- and post-speech data provided about 65% accuracy, providing evidence for decoding phrases prior to speech onset. Motor preparation/onset and auditory feedback may have contributed to the accuracies for pre- and post-speech decoding, respectively. Interestingly the combination of speech and peri-speech data decreased accuracy (74.44%). This may indicate that peri-speech data introduced non-specific information, or more likely that the overt-speech segment contained spurious movement-related artifact that inflated the accuracy.

Significance: The above chance accuracy for pre-speech decoding suggests the possibility for a fast, possibly real-time brain-to-text BCI application for locked-in patients. Future studies are aimed at investigating source level decoding at specific spatial-temporal and -spectral signatures.

ESN-Based Primary Hand Movement Decoding from EEG Signals under Both Hand Movement

Jiarong Wang[1], Luzheng Bi[1*]

[1]*Beijing Institute of Technology, Beijing, China;* E-mail: bhxblz@bit.edu.cn

Introduction: Compared with motor imagination-based or evoked potentials-based BCIs, decoding hand movement can provide intuitive control and is of high application value. However, existing studies are restricted under the condition that only single-hand movement is allowed at a time [1, 2, 3]. In practice, both hands' cooperation is common. Thus, the problems arise: 1) how to decode primary hand movement under both-hand movement? 2) what are effects of the opposite hand movement on the decoding? In this paper, we proposed a novel echo state network (ESN)-based decoding model of hand movement direction.

Methods: Eight healthy subjects participated in the experiment. The standard center-out paradigm was adopted with both hand movement in orthotropic directions. EEG signals were acquired from 24 selected channels and down-sampled to 100 Hz. Baseline correction, common average reference, and a four-order [0.01-6] Hz band-pass Butterworth filter were applied. ESN was used for feature extraction. Principle component analysis was applied to reduce the feature dimension. Linear discrimination analysis (LDA) was performed for classification.

Results and Discussion: Movement related cortical potential (MRCP) is shown in Fig.1 (a). The continuous decoding performance of the primary hand movement direction given two conditions by LDA and ESN-LDA models is shown in Fig. 1 (b) and (c). *1)* During the preparation period [-1.5 0] s, the decoding performance of both models was steady. During the movement period [0 1.5] s, the decoding performance gradually increased and peaked at 1s and 0.9 s for models *LDA* and *ESN+LDA*, respectively. The decoding performance was both above chance level (50%), because movement preparation information and movement execution information were involved in EEG signals in the two periods, respectively. *2)* Overall, the ESN-LDA model showed better performance, which may attribute to that ESN could capture the nonlinear dynamics of brain activity. *3)* Given the opposite hand movement, both models showed better decoding performance of the primary hand movement decoding.

Significance: This work is the first to focus on the primary hand movement decoding under both-hand movement, and also the first to apply ESN for feature extraction in hand movement decoding from EEG.

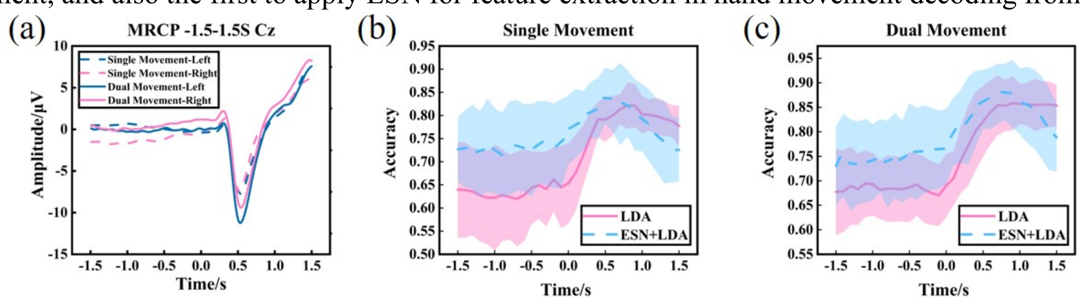

Figure 1. *(a) Averaged MRCP at Cz channel from -1.5s to 1.5s. (b) Continuous decoding performance of single movement. Note that [-1.5 0] s is the preparation period after the class-cue. [0 1.5] s is the movement period after the go-cue. Time 0 is the onset of go-cue. The shadow part represents the standard deviation. (c) Continuous decoding performance given both-hand movement.*

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Moving Closer to Application: ALS Patients Control a Virtual Wheelchair Using a Tactile Brain-Computer Interface

M. Eidel*[1], P. Ziebell[1], N. Mrachacz-Kersting[2], A. Kübler[1]

[1] *Institute of Psychology, Department of Psychology I, University of Würzburg, Würzburg, Germany;*
[2] *Faculty of Information Technology, Fachhochschule Dortmund, Dortmund, Germany*
**Marcusstraße 9-11, 97070 Würzburg, Germany, E-mail: matthias.eidel@uni-wuerzburg.de*

Introduction: Brain-Computer Interfaces (BCI) can be used to assist the severely disabled, for instance patients suffering from amyotrophic lateral sclerosis (ALS). Many paradigms, however, rely on intact vision and gaze control to work efficiently [1], and these are often affected in later stages of ALS [2]. Because of this limitation, alternative modalities that instead use auditory or tactile channels are in the focus of recent research. We implemented a tactile P300 BCI for wheelchair control [3, 4] and tested the system with potential end-users with ALS.

Material, Methods and Results: Four directional wheelchair commands were selectable by concentrating on short vibrations, applied by small, computer-controlled devices (Tactors) on body positions corresponding with the desired movement directions.

Figure 1: Left: Tactor positions. Right: Virtual environment from the perspective of the user.

Twelve ALS patients were invited to train with the system on three sessions with three months in between, to confirm the feasibility of the paradigm among potential end-users and to assess the impact of both training and disease progression on event-related potentials (ERP) and BCI performance. Every session, patients first performed three calibration runs to define classifier weights, then a guided BCI copy task with feedback of the most recent classification result, and finally a semi-free wheelchair navigation task in a virtual 3D apartment (Fig. 1). Preliminary results indicate that tactile P300 ERPs can be elicited and that effective wheelchair control above 70% accuracy [5] can be achieved by some of the participants.

Discussion and Significance: We describe data from ALS patients in various stages of the disease in the rarely considered use-case of wheelchair control and demonstrate that this tactile paradigm is feasible for some end-users. As the study continues, we hope to collect valuable data of BCI training effects among ALS users.

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Affect and ambient auditory effect on movement-related cortical potential

L. Yao[1*], Y. Hao[2]

[1]*Cornell University, Ithaca, USA,* [2]*University of Pennsylvania, Philadelphia, USA;*

*Phillips Hall, Ithaca, NY, USA. E-mail: ly329@cornell.edu

Introduction: A non-invasive brain switch based on movement-related cortical potential (MRCP) has shown a promising advantage of detecting movement intention, 300 ms before the movement onset [1]. Movement speed and force can directly influence the MRCP waveform and detection accuracy [2]; however, cognitive/affective conditions during BCI usage was less investigated and could potentially influence MRCP. Towards a robust brain-switch construction, we investigate the negative and neutral emotional state and ambient auditory effect on the MRCP waveform in this preliminary study.

Material, Methods and Results: Participants were 43 healthy and right-handed college students. They were asked to press the space bar when the affective image appears and ignore the repeated background (ambient) sound. The background sound involved two conditions: pitch decrease (1400 Hz – 600 Hz) and pitch increase (600 Hz – 1400 Hz), each lasting 2 minutes at 55 dBA [3]. Both conditions appeared three runs, randomly presented. In each run, 10 negative and 10 neutral images randomly appeared for 4.5 s, which was interleaved by a cross sign lasting about 1~2 s. EEG was recorded from a 128- channel BioSemi EEG device with a digital sampling rate at 512 Hz. The EEG signal was Laplace spatial filtered around the C3 channel in the left motor cortex, and bandpass filtered from 0.5 to 3 Hz. The EEG signal was epoched at the keypress time point, with 1.5 s before and 1.5 s after the keypress. Fig. 1 shows the MRCP signal between neutral and negative images response, under pitch decrease (Fig. 1a) and increase condition (Fig. 1b). There was a significant rebound ([157 177] ms) difference between neutral and negative images response in pitch decrease condition, $p = 0.009$; the waveforms ([460 500] ms) were different between neutral and negative images in pitch condition increase, $p = 0.038$.

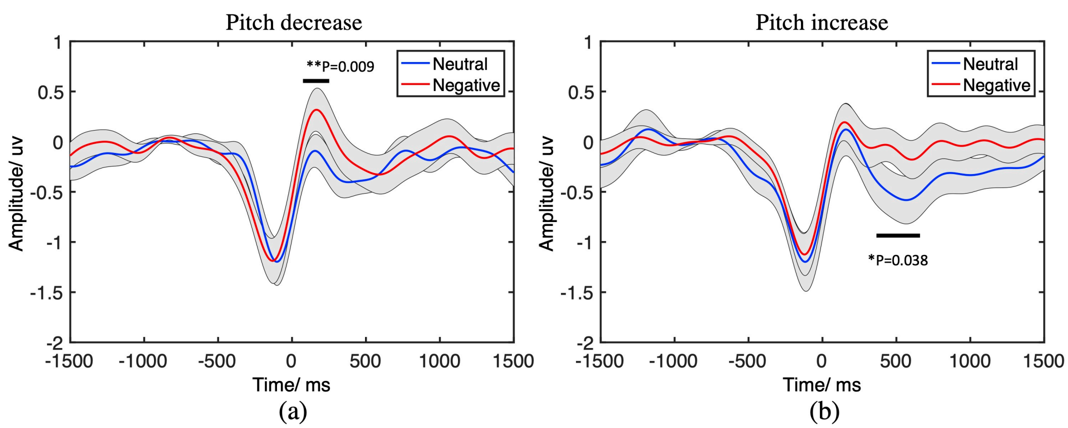

Figure 1. *Influences of MRCP signal by the affect and ambient sound. The zero represents when the key was pressed. (a) The MRCP induced by keypress after neutral or negative images during the repeated pitch decrease condition; (b) The MRCP in pitch increase condition.*

Discussion and Significance: Our study demonstrated that movement induced brain signal is not only related to conscious behaviors, but also unconscious cognitive/affective states and stressful environmental conditions. Towards a robust brain-switch based on MRCP, subject's affective state and ambient environmental should be considered, as it would influence the MRCP signal.

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Brain-Computer Interfaces for Optimal Human-Machine Collaboration

Davide Valeriani[1,2,3*], Alexis Worthley[1,2], Lena C. O'Flynn[1,2], Azadeh Hamzehei Sichani[1,2], Kristina Simonyan[1,2,3]

[1] *Massachusetts Eye and Ear, Boston, MA, USA;* [2] *Massachusetts General Hospital, Boston, MA, USA;* [3] *Harvard Medical School, Boston, MA, USA*

*243 Charles St, Suite 421, Boston, MA 02114, USA. E-mail: davide_valeriani@meei.harvard.edu

Introduction: Previous research has shown that brain-computer interfaces (BCIs) could be used to estimate the decision confidence of single users and improve group decision-making in visual tasks for human [1, 2] and human-machine teams [3]. While receiving advice from others is beneficial when we doubt [4], in other contexts, advice could negatively affect our performance [1]. Here, we investigate the neural correlates of openness to advice in a realistic decision-making task, with the aim of developing BCIs that could adaptively control the advice for maximizing group performance.

Material, Methods and Results: Ten healthy participants (6 females/4 males, age = 42.5 ± 13.8 years) took part in an EEG experiment split into six blocks of 30 trials. In each trial (Fig. 1A), participants were first shown a fictional geographical map of two regions for a duration of 500 ms, which was then overlaid with dots representing endemic cases, with the color of each dot indicating the endemic severity, for another 500 ms. They were asked to decide which region was most in danger (1 or 2) and to indicate their degree of confidence (1 to 4) using a keypad. Next, they were shown a feedback display with their decision and confidence as well as the decision and confidence of an artificial agent, and asked to make a final decision. Neural data were recorded at 512 Hz using a 128-channel EGI EEG system, band-pass filtered between 1 and 40 Hz, and downsampled to 50 Hz. Trials with EEG amplitude higher than 5 mV were discarded. EEG epochs were extracted starting from the feedback display and lasting 500 ms, and baseline corrected by subtracting the mean voltage recorded in 100 ms preceding the feedback display. For each participant, we computed the average EEG signal in (a) trials where participants changed their mind after receiving a disagreeing feedback from the artificial agent (trust), and (b) trials where they did not change their mind after disagreement (distrust). Statistical analysis was conducted by comparing the average EEG signals in trust and distrust trials using the Wilcoxon signed-rank test at $p \leq 0.05$.
We found significant differences in parietal and occipital cortices between trust and distrust trials around 100 ms and 400 ms after receiving feedback (Fig. 1B). Scalp maps showed stronger activation of these regions in trust than in distrust trials, which could be used to predict the final decision of the participant.

Discussion: Neural patterns of openness to advice were found in the occipital-parietal region. These results suggest the presence of biases that could be associated with trust and inform whether receiving feedback would be beneficial, hence enabling the development of optimally-collaborating machines.

Significance: EEG-based neural markers may inform the willingness to receive and consider external advice during realistic decision-making. This opens the possibility of developing BCIs to monitor the mental states of participants and adaptively decide whether it is worth to provide advice for optimal group performance in human and human-machine teams.

Acknowledgements: We acknowledge support from the US DOD BARI program (W911NF1810434).

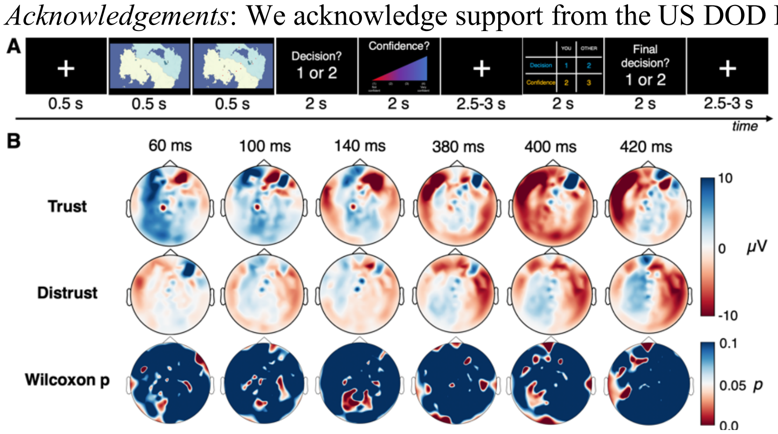

Figure 1. (A) Experimental protocol. (B) Grand average scalp maps comparing trust vs. distrust trials, and corresponding Wilcoxon signed-rank test p values.

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Neural Correlates and Prediction of Decision Confidence

J. Fernandez-Vargas*, C. Tremmel, C. Cinel, L. Citi, R. Poli

Brain Computer Interfaces and Neural Engineering Laboratory, School of Computer Science and Electrical Engineering, University of Essex, Colchester, United Kingdom.

**Email: {j.fernandez-vargas, christoph.tremmel, ccinel, lciti, rpoli}@essex.ac.uk*

Introduction: Confidence is highly correlated with decision accuracy [1] and decision reaction times [2]. In previous research [3,4,5] we predicted users' confidence in each decision using Brain Computer Interfaces (BCIs) trained to extract confidence-related features from EEG and physiological signals for each specific user. Here we explore the possibility of finding neural correlates and obtaining BCI-based predictions of confidence which apply to *all* participants in each of 3 experiments: "Faces", "Visual 2" and "Visual 3" detailed in [3,4,5], respectively.

Materials and methods: Feedback and stimulation in each of experiment were very different, but in all participants had to make a forced binary decision (e.g., target/non-target) on a rapidly presented visual stimulus and to report their confidence (range 0 to 1).

<u>Spatial correlates of decision confidence</u>: To study the differences in P300 amplitude for different confidence levels, we grouped the data into 4 groups – Low (confidence=0.1-0.3), Medium (confidence=0.4-0.6), High (confidence=0.7-0.9), Sure (confidence=1) – and calculated the mean EEG voltage from 250 to 750ms after stimulus presentation for each electrode across trials.

<u>Confidence prediction</u>: We trained a BCI using features extracted from response-locked epochs to predict the confidence reported by participants in each trial. We compared the accuracy of this prediction to the mean confidence (Baseline), testing two training strategies: (a) creating a model for each subject (Subject Training, ST), and (b) creating a model with all the data from each experiment (Experiment Training, ET). ET would be equivalent to a zero-training approach. For both ST and ET we used cross-validation.

Results: Figure 1 shows scalp maps of the P300 amplitude for each experiment and confidence level. Red colours indicate higher amplitude, while blue colours indicate lower amplitude. Regarding confidence prediction, the Mean Absolute Errors (MAE) are presented in the table in Figure 1. Two Wilcoxon rank analyses comparing the ST and ET showed significant differences in all three experiments.

Conclusions: The spatial correlates show that there is a direct relationship between the ERP amplitude and the reported confidence, which is constant in sign and location across different experiments. The confidence prediction results show that the prediction of the confidence using only EEG is possible, not only for single subject prediction, but for a zero-training approach as well.

Acknowledgement: We acknowledge support of the UK Defence Science and Technology Laboratory (Dstl) and Engineering and Physical Research Council (EPSRC) under grand EP/P009204/1. This is a part of the collaboration between US DOD, UK MOD and UK EPSRC under the Multidisciplinary University Research Initiative.

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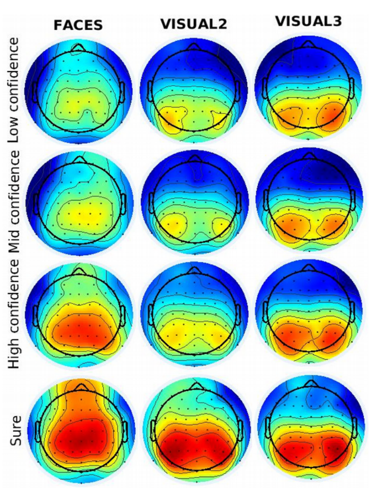


Experiment - Method	EEG	Baseline
Faces - ST	0.211	0.217
Visual 2 - ST	0.172	0.181
Visual 3 - ST	0.167	0.172
Faces - ET	0.270	0.285
Visual 2 - ET	0.221	0.236
Visual 3 - ET	0.202	0.205

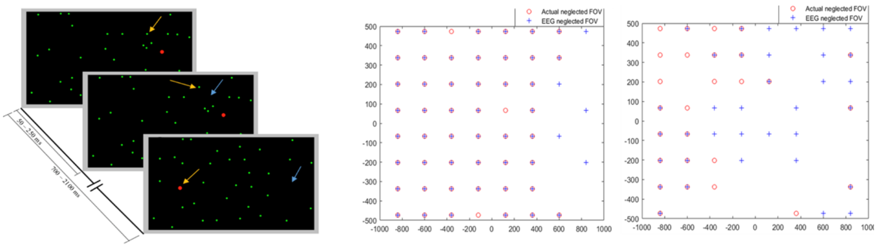
***Figure 1**: (Left) ERP amplitude for three experiments and four confidence levels. (Right) Error of the confidence prediction.*

An EEG-based BCI for Visual Spatial Neglect Detection and Assessment

Murat Akcakaya[1]*, Deniz Kocaanaogullari[1], Aya Khalaf[1], Jessica Kersey[1], Jennifer Mak[1], Xiaofei Huang[2], Sarah Ostadabbas[2], George Wittenberg[1] and Elizabeth Skidmore[1]
[1] University of Pittsburgh, Pittsburgh, PA, USA; [2] Northeastern University, Boston, MA, USA
∗1238 Benedum Hall, 3700 O'Hara St, Pittsburgh, PA, USA 15213 Email: akcakaya@pitt.edu

1. Introduction: Spatial neglect (SN) is observed in 28.6% of the stroke population, it is a strong predictor of disability and it is associated with longer hospital stays [1]. There is a critical need for a detection method that can map the extent of visual SN and that is sensitive to changes in the SN condition. The current gold standard for visual SN detection/assessment, Behavioral Inattention Test (BIT) including 6 pen and paper tasks, does not satisfy this need [2].

2.Material, Methods and Results: 11 stroke patients, 6 with SN (failed at least in one BIT task) and 5 without SN (6 Males and 5 Females, mean age 65.55), participated in EEG data collection under IRB number PRO15020115. Using the Starry Night paradigm, as shown in Figure 1 (a), with 256 Hz sampling rate, EEG was collected from 16 electrodes placed over frontal, parietal, central, and occipital lobes. A keyboard version of the same paradigm without EEG collection was used to learn the ground truth of neglected and non-neglected targets.



(a) (b)

Figure 1: (a) In the Starry Night Paradigm targets are presented as red dots at random locations (every 700-2100ms), and the green dots are the distractors (appearing and disappearing at random locations every 50ms). (b) Best (left) and worst (right) FOV estimation. x and y axes are the screen dimensions in pixels.

After filtering, features are extracted from 500 ms of EEG data time-locked to the presented visual stimuli. First, linear discriminant analysis (LDA) was used to classify neglected targets from the non-neglected ones for each participant with SN with overall accuracy of 70% (60% sensitivity and 71% specificity) and field of view (FOV) for each SN patient was estimated, see Figure 1 (b). Then, Deep Neural Networks with convolutional layers were used to distinguish SN patients from patients without SN, and overall accuracy and F1 score of neglect identification both in the training and test sets were observed as 85%.

3.Discussion: Our results indicate that the proposed BCI based on the Starry Night paradigm and EEG can be used both to detect neglect and to assess the extent of neglect with high accuracy. The future work will focus on clinical trial of the proposed BCI with acute stroke patients.

4.Significance: Such a BCI could be used in neglect rehabilitation to monitor the changes in the SN severity over time and potentially decrease hospital stays and improve independence.

5. Acknowledgement: This work is supported by the NSF through IIS-1915083 and IIS-1915065.

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Semantic Dissimilarity as a Feature for Auditory Attention Decoding

K. Dijkstra[1,*], J. Farquhar[1,2], P. Desain[1,2]

[1]*Radboud University, Donders Institute for Brain, Cognition and Behaviour*

[2]*MindAffect, Nijmegen, the Netherlands*

* E-mail: k.dijkstra@donders.ru.nl

Introduction: The purpose of auditory attention decoding is to determine which speaker a user attends to when presented with multiple speakers simultaneously. The common approach is to extract features from speech that the brain is known to respond to (e.g., the speech envelope), and fit a regression model to predict this feature from EEG data [1]. A recent publication introduces a measure of comprehension based on a semantic dissimilarity feature of narrative speech (a value for the degree of dissimilarity to the previous context, tagged to the onsets of content words) that could be used similarly [2](fig. 1a). Here, we investigate if this dissimilarity feature can be used to identify the attended speech, and whether it can be combined with the speech envelope to improve decoding accuracy over the envelope model alone. Additionally, we investigate the added value of the dissimilarity information over the word onsets that this information is tagged to, by comparing the dissimilarity feature to a pure word onset feature.

Material, Methods and Results: We re-analyse the data from the 'Cocktail Party' experiment from [2]. In this study 33 subjects attended to one of two concurrent audiobooks. We extract the features of interest from the presented speech signals (fig. 1a), and train a regularized regression model to estimate the features of the attended speech from EEG. We transform the weights from this (backward) model into brain activation patterns [3] (fig. 1b). We use the trained models to predict the attended speaker on test trials (nested crossvalidation). The accuracy of these predictions, across three test-segment lengths (15s, 30s and 60s), can be found in fig. 1c. A randomization test is used to determine the significance of the difference between the accuracy of the *envelope* and *combined* (*envelope + dissimilarity)* models, and the *dissimilarity* and *onsets* models ($p = 0.001$ and $p = 0.73$, respectively).

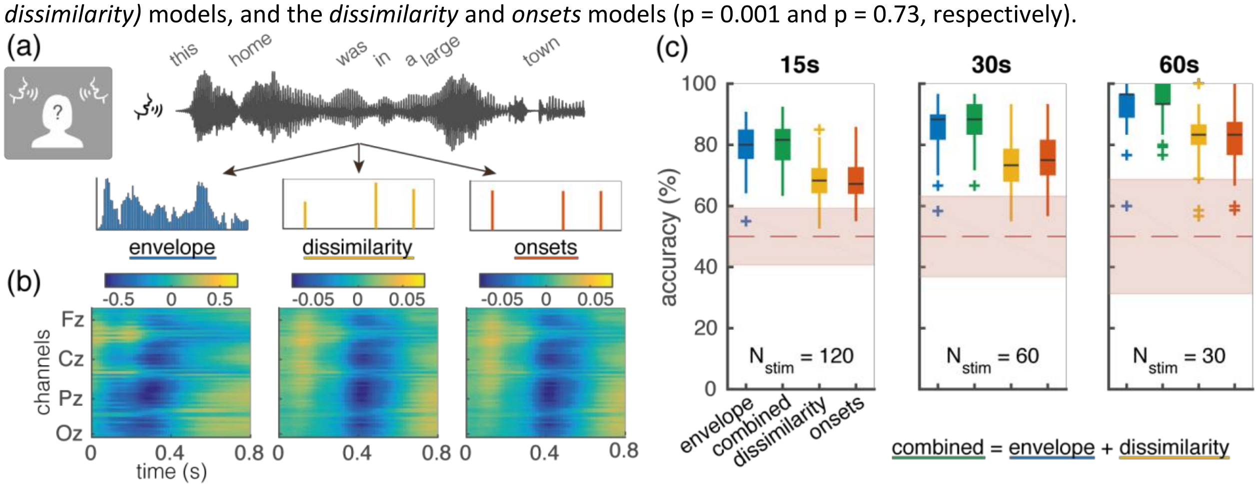

Figure 1. *(a), Features extracted from the speech signals. (b), Brain activation patterns (channels by time, in arbitrary units) estimated from regression weights. (c), Accuracy of identifying the attended speech, for the three features and a model combining the envelope and dissimilarity information. In red, a 95% binomial confidence interval of chance accuracy, based on the respective number of segments.*

Discussion: The addition of the dissimilarity feature significantly improves accuracy over using the speech envelope alone, but only marginally so (a 1.17% increase on average). Furthermore, the dissimilarity model and the word onset model result in similar activation patterns and comparable prediction performance, suggesting that the dissimilarity information is not needed to obtain the measure of comprehension as introduced by [2].

Significance: Adding a semantic dissimilarity feature to an envelope-based attention decoding approach provides only limited value. Furthermore, the results suggest that if one is interested in using a measure of comprehension as described in [2], using only the onsets of the content words is as effective as tagging these with dissimilarity values.

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Adaptive Changes in the Unaffected Hand of Stroke Survivors Using a Bimodal BCI Intervention Design

A.B. Remsik[1*], L. Williams[1], C. Rivera[1], P. van Kan[1], J.C. Wiliams[1], V. Nair[1], K. Caldera[1], & V. Prabhakaran[1],

[1]*University of Wisconsin Madison, Madison, WI, USA*

*1111 Highland Avenue, Madison, WI, USA. E-mail: aremsik@wisc.edu

Introduction*:* Stroke lesions create, among other things, contralateral motor impairment and an interhemispheric imbalance in the brain characterized by hyperexcitability of the contralesional hemisphere [2]. During recovery of motor function following stroke, neuronal reorganization may occur in both the ipsilesional and contralesional hemispheres [1]. Bilateral hemispheric activation has been observed during recovery with BCI devices and may be associated with functional changes in the unimpaired extremity as well as the, targeted, impaired extremity [3]. ***Material****:* Objective behavioral measures of upper extremity motor function (Arm Reach Action Test (ARAT), Nine Hole Peg Test, and Hand Grip Strength) at the baseline, midpoint, completion, and one-month post BCI intervention (i.e. one month follow-up) were used to track changes of the unaffected extremity of stroke survivors participating in a cursor and target BCI intervention for upper extremity motor recovery. ***Methods****:* 34 stroke survivors with varying levels of impairment, time since stroke, and lesion location participated in up to 30 hours of closed-loop, bimodal BCI intervention. ***Results****:* These data suggest that use of a bimodal BCI intervention design may have beneficial effects on the functional capacity of the unaffected upper extremity. Outcome measure Nine Hole Peg Test and Hand Grip Strength, – as seen in Figures 2 & 3 - were observed to demonstrate adaptive changes in the unaffected extremity over time with participation in closed-loop, target and cursor BCI intervention.

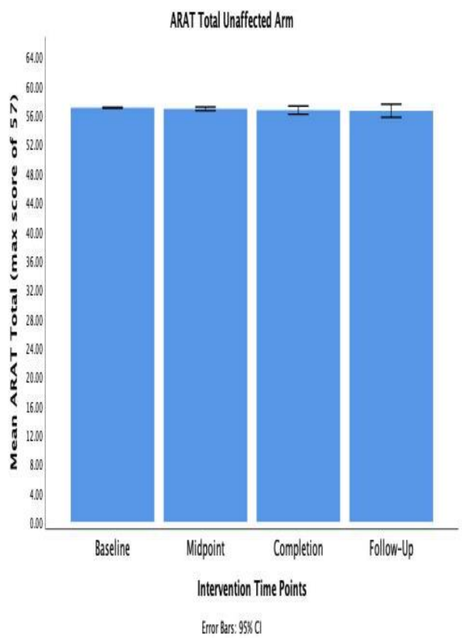

Figure 1. Sample (n=34) mean ARAT scores at each measurement timepoint, error bars denote standard error with a 95% confidence interval.

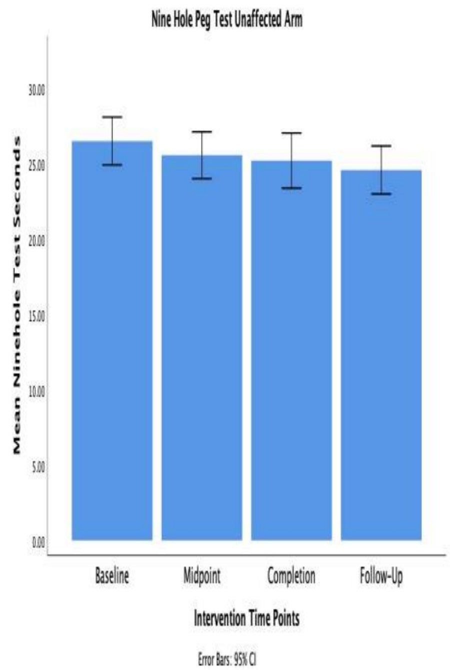

Figure 2. Sample (n=34) mean Nine Hole Peg Test times, in seconds, at each measurement timepoint, error bars denote standard error with a 95% confidence interval. Mean difference Baseline to Follow-Up p = 0.086.

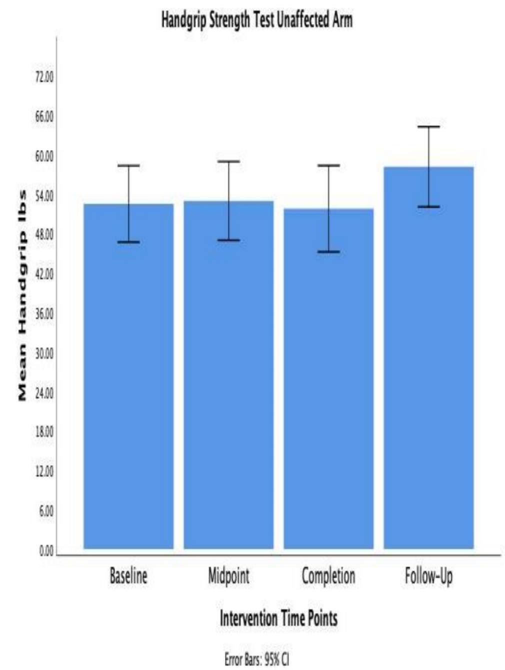

Figure 3. Sample (n=34) mean Hand Grip Strength values at each measurement timepoint, error bars denote standard error with a 95% confidence interval. Mean difference Baseline to Follow-Up p = 0.22.

Discussion & Significance*:* These findings suggest that bimodal BCI task designs may offer additional functional benefits to stroke survivors by involving both lesion and nonlesioned hemispheres during intervention task participation.

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Nahaul: BCI-AI driven Interactive art

Akshay Sujatha Ravindran[1*], Eric Todd[1], Geraldina Interiano Wise[1], Jose L Contreras-Vidal[1]
[1]NSF IUCRC BRAIN, University of Houston, Houston, TX, USA

**4800 Calhoun Drive, Engineering Building 2 E409, Houston, TX 77006. E-mail: asujatharavindran@uh.edu

Introduction: Understanding the creative brain 'in action and in context' is one of the grand challenges in human neuroscience. The *Nahaul* project (a multimedia art performance and experimental approach) was developed to address this knowledge gap while investigating the neural basis of creativity. It combines live interactive artwork driven by closed loop Brain-Computer Interface (BCI) and Artificial Intelligence (AI). The goal is to train an AI model to learn artist-specific representations which explain both the neural and visual signature of the artist's creativity.

Material, Methods and Results: A total of 160 images of the artist's prior work were initially randomly cropped to multiple 512 px resolution images to increase the sample size to a total of 16,000 for training the generative model. StyleGAN was used to model the artist's painting style [1]. Instead of generating the images from gaussian noise typically done in Generative Adversarial Network (GAN), we condition it on the artist's brain activity acquired with scalp electroencephalography (EEG) while she observed and/or created those works. The data was denoised to remove drifts and large bursts using Artifact Subspace Reconstruction [2]. The EEG was mapped into a latent space using the mapping network which was then used to train the generator. Here we present early finding from this long-term ongoing study. Figure 1A shows a concept diagram summarizing the project and 1B shows some of the images that were generated by the model comparing it with the original images from the artists that share resemblance.

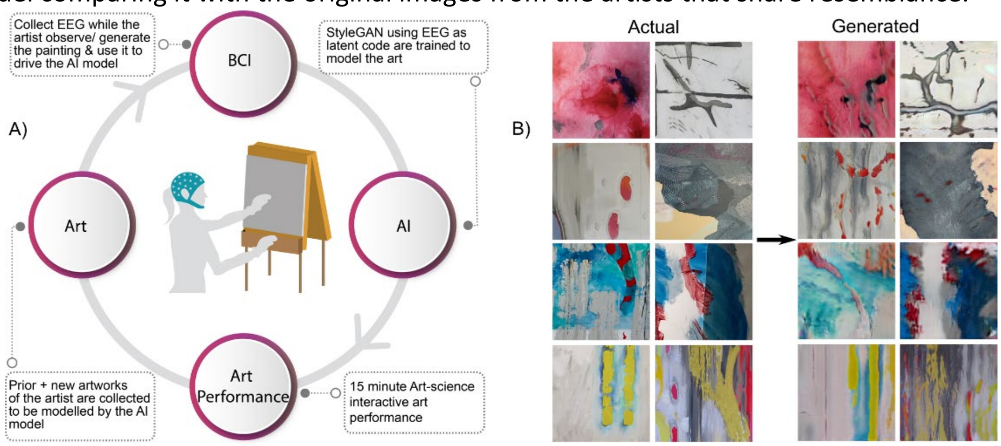

Figure 1 *A) project concept diagram B) Generated vs actual images from the model after training for 5 days*

Discussion: Early findings suggest the AI model is able to model the color and stroke combinations typically used by the artist. Results from functional connectivity, deep network connectivity and spectral analyses will show neural interaction during the art creation, and the features learnt by the GAN.

Significance: The project is projected to have an impact in the study of the brain in action, closed-loop neuromodulation, and new forms of interactive multimedia art. The project also encompasses an art-science performance that integrates BCI, AI and performance art in public settings. This offers a unique STEAM outreach possibility bridging the fields of AI, arts, neurotechnology and neuroscience.

Acknowledgements: The authors thank the NSF IUCRC BRAIN Center, Blaffer Art Museum and the Glassell School of Arts at the MFA-Houston for supporting the study.

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Freedom! Making a case for more options for users during training in BCI

Smeety Pramij[1], Aline Roc[1]*, Fabien Lotte[1]
[1] Inria Bordeaux Sud-Ouest, LaBRI (CNRS, Univ. Bordeaux, BORDEAUX INP), Talence, France
*aline.roc@inria.fr

Introduction: Mental Task-based Brain Computer Interfaces (MT-BCI) are still highly unreliable [1], in part due to suboptimal user training [2,3]. It has been suggested that one possible improvement could be to include more self-paced sequences into MT-BCI user training protocols [1] i.e., allowing the user to train on their own terms, thus adapting the mental exercise to their own needs and preferences. Like many user-centered approaches, providing choice is not a widespread practice on BCI research [3]. This is sometimes done by letting learners choose to train with some MT out of different motor and cognitive possible task options [4] and has been experimented on to some extent, in a long-time self-paced training of a patient [5]. However, a large body of evidence leans towards its beneficial effects in BCI user training procedures.

Material and method: As it is not common practice, experimental evidence is lacking as to how, when or why introducing user choices in BCI training would be effective with experienced or novice users. In the wake of a future experiment, we conducted a literature review to investigate the possible influences of user choice in different research fields - adult education, cognitive science and instructional design. We also classified the possible choices by subcategory: self-paced, self-guided, self-configured.

Results: In the reviewed literature, many learning principles rely on offering options to the learner, e.g. flow/zone of proximal development [6], goal-oriented learning [7], deliberate practice [8], self-paced training [9], autonomy [10], inductive reasoning [11], self-directed learning [12]. Accordingly, suitable learning-related user states in BCI, like intrinsic motivation and sense of agency amongst others, could be induced by offering choices to the user throughout the training protocol. An overview of possible user choices and their influence on training is shown in Fig. 1. For example, users could be provided with the possibility to train the mental task they want either at their own pace or during window-of-opportunity self-paced trials [13]. At a larger level, users might be provided with the possibility to co-design an exercise (e.g. the feedback or the skill trained) with the option to skip a task or to redo a task.

Discussion: Including more leeway in training protocols might induce suitable learning-related states to ultimately improve performances. Future work will formally test some of the presented aspects.

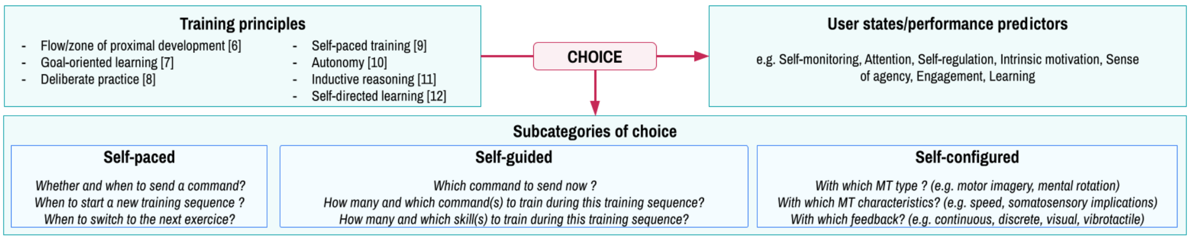

Figure 1: As showcased in the boxes on top, training principles based on learning literature provide a framework in which the user state can be leveraged to improve training outcomes through making choices for themselves. As depicted on the bottom boxes, future research should evaluate the effect of the presence/quantity/frequency of these different subcategories in the outcomes of BCI training programs.

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Improving P300 Speller Performance by Time-Variant Linear Discriminant Analysis

J. Gruenwald[1,2]*, M. Walchshofer[1], Ngadhnjim Sutaj[1,3], C. Kapeller[1], and C. Guger[1]
[1]*g.tec medical engineering GmbH, Schiedlberg, Austria;* [2]*Johannes Kepler University Linz, Linz, Austria;*
[3]*Technical University Vienna, Vienna, Austria*

*g.tec medical engineering GmbH, Sierningstrasse 14, 4521 Schiedlberg, Austria. E-mail: gruenwald@gtec.at

Introduction: A popular brain-computer interface (BCI) application is the P300 speller [1], which relies on the well-known P300 brain wave in the electroencephalogram (EEG). We here present evaluation results from a P300 speller that employs the recently published time-variant linear discriminant analysis (TVLDA) as a classifier [3]. We compare our results to the ones obtained from standard linear discriminant analysis (LDA).

Material, Methods and Results: Five subjects participated in this study. We used the *Unicorn Brain Interface* (g.tec neurotechnology GmbH, Schiedlberg, Austria), providing wirelessly acquired EEG for 8 channels at 250 Hz, and the *Unicorn Speller* for stimulus presentation and data recording. The Unicorn Brain Interface features hybrid electrodes, so we conducted the spelling experiment with dry and wet electrodes. A training run consisted of five characters with 30 row/column flashes each. The training set consisted of 150 targets and 1050 non-targets. We performed power-based artifact rejection and extracted the P300 waves via bandpass filtering from 0.5 Hz to 30 Hz and decimation by a factor of 12. Trial windows were set to 0.1 s pre- and 0.7 s post-trigger, yielding 15 samples per trial and channel. No trigger feedback was used. We compared standard LDA with vectorized features (120-dimensional, see also [2]), and TVLDA as described in [3]. We also added a whitening stage before classification, which further improved performance. We evaluated the performance with respect to the number of training trials and test trial averages. To this end, we performed 200 repetitions of a randomized cross-validation for each scenario and determined the spelling accuracy. As shown in Figure 1, TVLDA at the same time dramatically decreases the training effort while outperforming standard LDA. Furthermore, no substantial difference between dry and wet electrodes were observed.

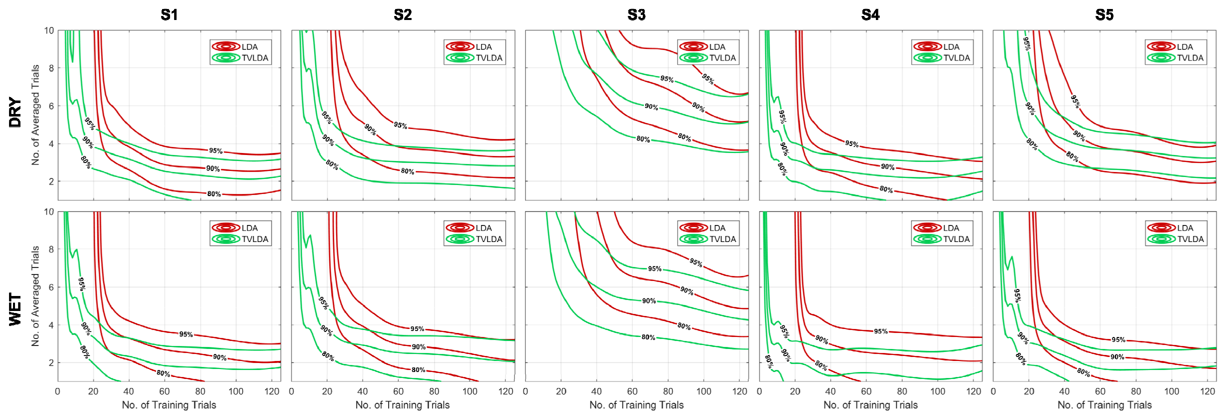

Figure 1. *Cross-validated spelling accuracy ISO lines (80%, 90%, 95%) with respect to training effort and number of averaged trials.*

Discussion: Our preliminary results have shown that TVLDA may be a powerful alternative for standard LDA for P300 spellers. For "good" subjects (S1, S2, S4, S5), as few as 20 training trials and three averages during test can be enough to reach accuracies around 90% and beyond. This dramatically reduces training and spelling time. There is no indication that wet electrodes should be preferred over dry electrodes.

Significance: Our results indicate that there is substantial room for improvement for P300 classifiers. With TVLDA, a simple extension of LDA is available that might become a standard classifier for future P300 spellers.

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Hybrid Brain Computer Interface to access digital technologies for people with Multiple Sclerosis

V. Galiotta[1*], A. Riccio[1], F. Schettini[1], E. Giraldi[1], F. Di Domenico[1], M.G. Grasso[1], F. Cincotti[1,2], D. Mattia[1]

[1]Fondazione Santa Lucia IRCCS, Rome, Italy; [2]Dept. Of Computer, Control and Management Engineering, Sapienza University of Rome, Rome, Italy

*Via Ardeatina, 306, 00179 Rome Italy. E-mail: v.galiotta@hsantalucia.it

Introduction: Multiple Sclerosis (MS) is a chronic neuroinflammatory disease leading to loss of motor and sensory function, thus entailing severe and complex impairments of communication and abilities to interact with digital technologies. Patients suffering from MS experience severe fatigue that can worsen motor disability [1]. Several Assistive Technology (AT) solutions are available for end-users to improve accessibility to technologies. Aim of the present study is the integration of brain computer interface (BCI) with existing assistive or mainstream technologies, resulting in a hybrid BCI-based (h-BCI) communication device [2].

Material, Methods and Results: We developed a h-BCI system interfacing with the commercial AT software GRID3 (Smartbox Assistive Technology) and combining P300-ERP and AT input devices. GRID3 is accessible via all commercial muscular based AT input devices (switches, head-tracker, etc.) and it allows the customization of user interface based on patients' motor/sensory abilities to operate Personal Computer applications. Evaluation protocol consisted of two parts: *i)* multidisciplinary needs assessment and *ii)* h-BCI usability evaluation. Multidisciplinary needs assessment was conducted with 13 end-users with progressive MS who were admitted to the AT-center SARA-t (Fondazione Santa Lucia, Rome) because of their limitation in (at least) one aspect related to interpersonal communication and/or interaction with digital technologies. Most frequent needs reported were PC access (N=8/13), mobile phone access (N=7/13). Eight out of thirteen end-users took part in the system (Fig.1) usability evaluation, in terms of effectiveness, efficiency and satisfaction [2]. Effectiveness: Five out of eight end-users were able to control the system (online acc (%): 83.3 ± 14.6). Efficiency: time per correct selection was 41.0s (± 16.2s); the mean perceived workload (NASA-tlx [3], 0-100) was 24.4 ± 21.0. Satisfaction: mean SUS score (*System Usability Scale* [4], 0-100) was 78 ± 14.9 (Results are referred to participants that controlled the system).

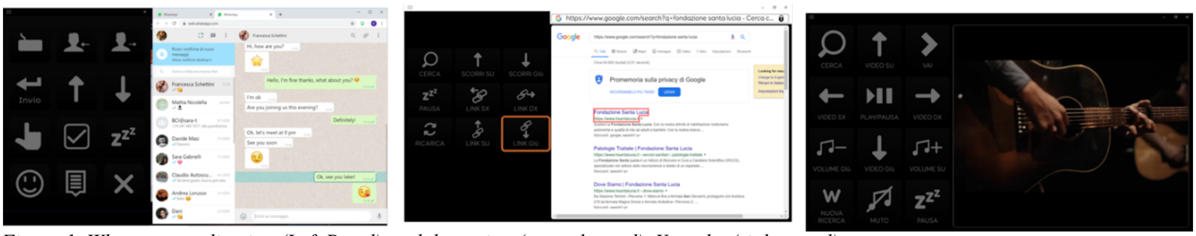

Figure 1. Whatsapp application (Left Panel), web browsing (central panel), Youtube (right panel)

Discussion: The evolution of digital technologies changed the concept of communication: it is not limited to verbal communication, but it includes independent access to digital devices. The system presented here would allow patients with MS to switch to a BCI-access channel according to their level of muscular fatigue or as complementary channel. 62.5% of the end-users were able to control the system with good performance, low perceived workload and high satisfaction about the system functionalities.

Significance: We consider this as an important step to integrate BCI with commercial AT devices and to promote the introduction of personalized h-BCI device into AT centers to support end-users communication.

Acknowledgements: This work is partially supported by Merck - Merck Price in Neurology 2019 awarded to "h-ADDrESS: Hybrid BCI to Access Digital DEviceS for people with multiple Sclerosis" project.

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Learning effects in 2D trajectory inference from low-frequency EEG signals over multiple feedback sessions

Hannah S. Pulferer[1], Brynja Ásgeirsdóttir, Valeria Mondini[1], Andreea I. Sburlea[1], Gernot R. Müller-Putz[1*]

[1]*Institute of Neural Engineering, Graz University of Technology, Graz, Austria*

Stremayrgasse 16/IV, 8010 Graz, Austria. *E-mail:gernot.mueller@tugraz.at

Introduction: Recent research has shown that non-invasive continuous online decoding of executed movement from low-frequency brain signals is feasible [1]. In order to cater the setup to actual end users, we proposed a new paradigm based on attempted movement [2] and, after conducting a pilot study, we believe that user control in this setup may be improved by learning effects over multiple sessions.

Material, Methods and Results: Electroencephalographic (EEG) signals of three participants have been recorded three times each using 64 electrodes, first and last session separated by a maximum of five days to keep the experience fresh in the participant's mind. For each session, the participant sat in front of a TV screen with his/her dominant hand (handedness test) strapped to the chair to mimic attempted movement. Two different paradigms were presented – *snakeruns* [1, 2] and *freeruns* [2]. For both cases, the participant was instructed to follow the target with the eyes and additionally attempt to move the strapped limb as if following the target with a cursor. After eye artifact removal (SGEYESUB, see [3]) and lowpass-filtering (3Hz, 2nd order Butterworth, similarly to [1]), calibration snakeruns (48 trials, trial length 23s) were performed for fitting the decoder, using partial least squares regression and an unscented Kalman filter [1]. Fake feedback in form of a dot on the screen associated to a delayed snake was given from the beginning, and gradually switched to first 50% (three snakeruns, 36 trials) and finally 100% EEG decoded signal (three snakeruns, three freeruns; 36 trials each). The recorded data of all sessions were analyzed offline and the average correlations of snake and decoded trajectories over all trials and feedback conditions of the snakeruns were calculated, as depicted in Fig. 1. The explained variances of the first two principal components (PCs) of the online freerun trajectories were evaluated, too.

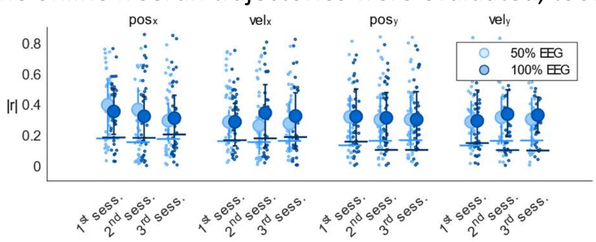

Figure 1. *Correlations for all trials with mean (big dots), 25th and 75th percentile (whiskers) and chance levels (horizontal lines, see [1]) for each directional movement parameter pos_x, vel_x, pos_y, vel_y, session and feedback condition in one subject. For all prerequisites, mean correlations (approx. 0.3) can be observed to lie well above the chance levels (approx. 0.2).*

Discussion: Although we cannot make a strong claim about learning effects at this point, we could observe a slight increase in correlation for the velocities in both directions across sessions. Further measurements with additional participants will allow for statistical evaluation of correlations and PCs over all individuals.

Significance: An occurrence of a learning effect over multiple sessions of EEG measurements for trajectory inference would imply that neuroplasticity can be used to increase decoder performance and thus BCI user control. Devising specific learning tasks for the participants to train between sessions may be worth investigating at a later point.

Acknowledgements: This research was supported by funding from the European Research Council (ERC-CoG 2015 681231 'Feel Your Reach') and NTU-TUG joint PhD program.

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Brain Computer Interface-driven Neuromuscular Electrical Stimulation Therapy for Motor Recovery of Sub-Acute Stroke Patients: Preliminary Results

A. Nguyen-Danse[1], Z. Hernandez[2], R.Y. Fakhreddine[2], H. Alaweih[2], P. Nicolo[1], D. Mac-Auliffe[2], A. Guggisberg[1,‡], J.d.R. Millán[2,‡,*]

[1]University Hospital of Geneva, Switzerland, [2]University of Texas at Austin, TX, USA

‡Equal contribution, *Email: jose.millan@austin.utexas.edu

Introduction: Stroke is a leading cause of severe long-term disability, reducing motor function for over 50% of stroke survivors [1]. Studies have shown that changes in mobility in the first few months post-stroke exhibit two paths to recovery. Patients starting with low to mild impairment following stroke tend to recover at about 70% of their initial impairment [2], while those starting with high impairment often result in poor recovery [3]. Disruption of the corticospinal tract (CST) by a lesion from the stroke as well as low neural connectivity to motor areas surrounding the lesion were related to this second group of patients with poor recovery [4]. Based on the recent success of a brain-computer interface (BCI) intervention on chronic stroke patients with severe functional deficits of their hand [5], we hypothesize that neuromuscular electrical stimulation (NMES) applied contingent to voluntary activation of primary motor cortex, as detected by a BCI, can help restore CST projections. This might greatly improve recovery of sub-acute patients with severe CST affection who currently often show catastrophic outcome. Here we report preliminary data from an ongoing clinical trial with such category of sub-acute patients, recruited within 8 weeks after stroke onset and who have a high motor impairment ($\leq$ 15 Fugl-Meyer Assessment score for the upper limb).

Material, Methods and Results: The BCI consisted of a 16-channel EEG over the sensorimotor cortex coupled to a 2-channel upper limb NMES device. Our custom-made software also provided a friendly user interface for calibration/training sessions. Sub-acute patients underwent 10 sessions (2 offline/8 online) of BCI treatment where decoded attempted movements of the paralyzed arm extending or flexing delivers contingent proprioceptive feedback via sensory-threshold NMES [6] of the arm at appropriate muscle sites, followed by motor-threshold NMES that triggers target muscle contractions and generates the desired functional movement. In this clinical study, patients are allocated into one of two groups, a BCI group (N=10) that goes through the BCI treatment, and a Sham group (N=8) where the decoded outputs are extracted instead from a previous subject allocated to the BCI group so that NMES is not contingent to brain activity. Experimenter, patient, and data analyst remain blind to the treatment group. Between treatment groups, clinical score differences before, after and at a follow-up point after the end of the intervention showed some non-significant separation, while the contingency between BCI outputs and motor-threshold NMES delivery was significantly different ($p<0.001$). We also found changes in resting-state and task functional connectivity, as well as changes in CST excitability, though none were statistically significant.

Discussion and Significance: Preliminary findings support the feasibility of BCI-NMES intervention for sub-acute stroke patients suffering a severe level of unilateral, upper-limb motor impairment. Although differences in clinical scores and neurophysiological markers before, after and at a follow-up point after the end of the intervention for each group (BCI and Sham) and between groups were not statistically different, this may be due to the small sample size (10 BCI/8 Sham) used for these preliminary results.

Acknowledgements: This project is funded by the Swiss National Science Foundation, Sinergia program.

Note: this abstract will be presented in 2 posters due to the complexity of the study and number of results.

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Brain Computer Interface-driven Neuromuscular Electrical Stimulation Therapy for Motor Recovery of Sub-Acute Stroke Patients: Preliminary Results

A. Nguyen-Danse[1], Z. Hernandez[2], R.Y. Fakhreddine[2], H. Alaweih[2], P. Nicolo[1], D. Mac-Auliffe[2], A. Guggisberg[1,‡], J.d.R. Millán[2,‡,*]

[1]University Hospital of Geneva, Switzerland, [2]University of Texas at Austin, TX, USA

‡Equal contribution, *Email: jose.millan@austin.utexas.edu

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Open iEEG-fMRI dataset from naturalistic stimulation with a short audiovisual film

Julia Berezutskaya[1,2*], Mariska J. Vansteensel[1], Erik J. Aarnoutse[1], Zachary V. Freudenburg[1], Giovanni Piantoni[1], Mariana P. Branco[1], Nick F. Ramsey[1]

[1]Brain Center, Department of Neurology and Neurosurgery, University Medical Center Utrecht, Utrecht, the Netherlands; [2]Donders Institute for Brain, Cognition and Behaviour, Radboud University Nijmegen, the Netherlands

*P.O. Box 85500, 3508 GA Utrecht, the Netherlands. E-mail: y.berezutskaya@umcutrecht.nl

Introduction: Human intracranial (iEEG) data are a valuable but rare source of information about the brain. These data are difficult and expensive to collect, and only a few medical centers in the world acquire them. These centers suffer from low patient rates (5-10 subjects a year), and due to various reasons cannot easily share the data. This limits iEEG potential for fundamental and applied neuroscience research and hampers research reproducibility. Here, we present the first openly shared large multimodal iEEG-fMRI dataset that is unique in a number of ways. First, it contains a large set of iEEG data (49 subjects who all did the same task). Second, it provides additional fMRI data from the same task (30 subjects). Third, the data were collected using a rich naturalistic stimulus – a short audiovisual film, for which extensive video and audio annotations are provided. The dataset can be used to study neural signal during speech, perception, social discourse and more, develop new analysis techniques and study neurovascular coupling.

Material, Methods and Results: The dataset is available online on openneuro.org. It includes 49 iEEG and 30 fMRI subjects, of which 19 subjects have both iEEG and fMRI data. The majority of iEEG data was recorded from clinical ECoG grids. There are 14 subjects with sEEG electrodes and six subjects with high-density ECoG grids. Data have been de-identified (MRI defaced, stripped of personal metadata) and are provided in the iBIDS format. Demographic details, handedness and language dominance hemisphere are provided per subject.

As the main task patients watched a short film (6.5 minutes) edited together from scenes of Pippi Longstocking (1969) with interleaved blocks of speech and music. For iEEG, additional resting state data (3 minutes) are provided. Rest data was either acquired during a resting state task (29 subjects) or cut from natural rest in continuous 24/7 recordings (20 subjects). FMRI data contains only the audiovisual film task. Detailed film annotations are provided with time stamps for spoken sentences, words and phonemes and labeling of the visual content (characters, objects and actions per frame).

Subsets of IEEG data have been previously analyzed and published with respect to visual and auditory processing. For the full dataset we report strong responses to the film that are similar across iEEG and fMRI (Fig. 1).

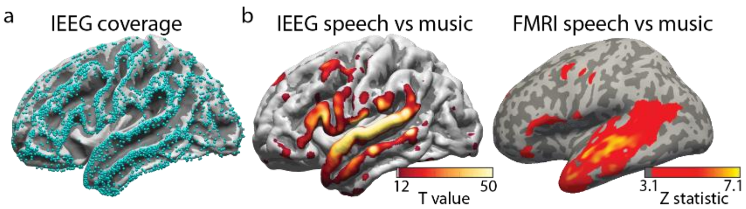

Figure 1 a. IEEG coverage in 49 subjects (left hemisphere). b. Response to the block design in the audiovisual film in IEEG (left hemisphere, high frequency band, Gaussian kernel of 10 mm from electrode center) and fMRI.

Significance: The present dataset offers an unprecedentedly large amount of iEEG data accompanied by fMRI recordings during a naturalistic cognitive task. Extensive use of these data can help us understand neural processing that supports different aspects of high-level cognition including speech processing, which is central to research on brain-computer interfaces for communication. We believe this shared dataset will help promote collaborative and open science in the field of iEEG as well as the neuroscientific community as a whole.

Acknowledgements: We thank the neurosurgery team and staff of the clinical neurophysiology department at UMC Utrecht for implantation and monitoring of patients; the members of the UMC Utrecht iEEG research team for data collection and the patients for their contribution to research.

Classification of P300 Using Convolutional Neural Network

Nazia Farhat[1*], C. W. Anderson[1], T. M. Vaughan[2]

[1]*Colorado State University, Colorado, USA;* [2]*Wadsworth Center, Albany, NY, USA*

*P.O. Box 80523, Colorado, USA. E-mail: nazia.farhat@colostate.edu

Introduction: Classification of P300 obtained from non-invasive EEG is a challenging task due to intersubject and intrasubject variability. Stepwise Linear Discriminant Analysis has shown consistent performance in recognizing a P300 signal [1] but it requires combining multiple trials and does not reveal much about the signal's features. We implemented Convolutional Neural Network [2] to perform the classification as well as observe the features being learned by the network.

Material, Methods and Results: Our analysis of single trial classification and feature extraction used data of 6 healthy subjects' responses to a P300 speller collected by Krusienski, et al. [1] using 64 channels.

CNN1D, CNN2D, and CNN3D were applied and compared for P300 recognition. Three different channel-arrangements (ascending-order, equal-weighted and variable-weighted virtual nodes) were used for CNN3D.

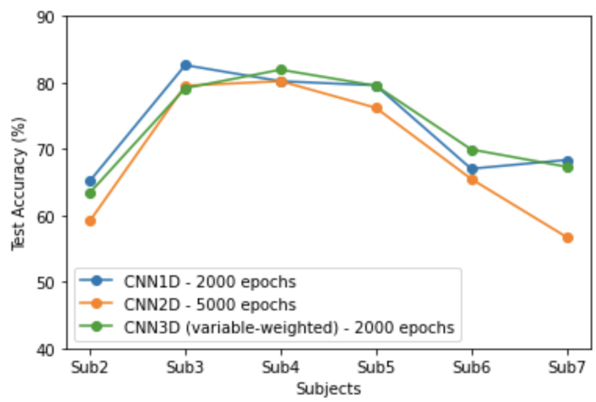

Figure 1. Single trial test accuracy percentage of CNN1D, CNN2D, and CNN3D (variable-weighted virtual nodes) models for each subject.

About 80% test-accuracy was achieved with all these approaches, among which the variable-weighted virtual nodes arrangement of input data in a CNN3D network showed the most consistent results.

Discussion: Higher single trial accuracy was achieved compared to that (below 60%) reported by Krusienski, et al. [1]. Similar performance was observed for CNN1D and CNN3D models, whereas longer epochs were required for training the CNN2D model, as shown in Fig. 1.

Significance: Since P300 response is a reliable signal for the BCI systems [3], gaining more insights into the inherent features of this ERP signal can contribute in improving the performance of these systems.

Acknowledgements: The dataset was collected and shared by the National Center for Adaptive Neurotechnologies with the support of the National Institutes of Health under Grants P41 EB018783, NICHD HD30146 and Grant NIBIB/NINDS EB00856 and in part by the James S. McDonnell Foundation.

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Acoustic contamination of electrophysiological brain signals: implications for speech BCIs

P. Roussel[1,2*], G. Le Godais[1,2,3], F. Bocquelet[1,2], M. Palma[1,2], J. Hongjie[4], S. Zhang[4], P. Kahane[5], S. Chabardès[6], B. Yvert[1,2]

[1]Inserm, Braintech Lab U1205, Grenoble, France; [2]Univ.Grenoble-Alpes, BrainTech Lab U1205, Grenoble; [3]CNRS, Gipsa-Lab, Grenoble, France; [4]Zhejiang University, Qiushi Academy for Advanced Studies, Hangzhou, China; [5]CHU Grenoble-Alpes, Department of Neurosurgery, Grenoble, France; [6]CHU Grenoble-Alpes, Department of Neurology, Grenoble, France

* Braintech Lab U1205, UFR Chimie Biologie, Bât. Biologie B, 2280 rue de la piscine, 38610 Gières, France. E-mail: philemon.roussel@inserm.fr

Introduction: A current challenge to restore efficient communication in paralyzed people unable to speak is the development of speech brain-computer interfaces [1]. As a step towards it, simultaneously recorded audio and neural data can be used to build decoders to predict speech features from brain signals. A typical neural feature is the spectral power of field potentials in the high-gamma frequency band [2, 3] (between 70 and 200 Hz), a range that happens to overlap the fundamental frequency of speech. The present study shows that sound can contaminate the biopotential measurements, investigates the causes of this phenomenon and examines the consequences on the decoding of speech from brain activity.

Material, Methods and Results: We analyzed 4 human electrocorticographic (ECoG) and intracortical recordings during speech production and perception as well as a rat micro-ECoG recording during sound perception. We also performed potential measurements in a minimal *in vitro* setup (ECoG electrodes immersed in PBS) while pure-tone sounds were played by a speaker. Electrophysiological signals, obtained using these different recording configurations, contained spectrotemporal features highly correlated with those of the simultaneously recorded sound. Such correlations were reproduced in the *in vitro* setup. By acoustically isolating or exposing different components of the recording system, we further showed that a microphonic effect occurring in the cables and connectors causes the contamination. Using ECoG recordings of 2 participants, we showed that speech decoding based on high-gamma neural features could be strongly influenced by this phenomenon when the fundamental frequency of the participant's voice overlaps the high-gamma band.

Discussion: We showed that a microphonic effect can contaminate electrophysiological brain recordings in a variety of experimental conditions, due to a mechanical action of the sound waves onto the cables and connectors along the recording chain. Such phenomenon can possibly bias speech decoding from brain activity. Further studies should focus on fixing components of recording setups to prevent any microphonic effect to happen.

Significance: This study alerts on possible microphonic contamination of neural signals, so as to avoid possible biases when building decoders of neural activity underlying overt speech for the development of speech BCIs.

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Tripolar Scalp Electrodes Extract Gamma Activity to Maximize Performance in a Brain-Computer Interface (BCI) Spelling Paradigm

T. Memmott[1*], A. Kocanaogullari[2], D. Klee[1], A. Demir[2], D. Erdogmus[2], B. Oken[1]
[1]Oregon Health and Science University. Portland, Oregon; [2]Northeastern University. Boston, Massachusetts.
[*] 3181 SW Sam Jackson Park Rd. CR-120. Portland, Oregon 97201-3098; E-mail: memmott@ohsu.edu

Hypothesis: Rapid Serial Visual Presentation (RSVP) Keyboard™ is a BCI spelling paradigm developed through a partnership between OHSU and NEU [1]. This system is made possible by the rapid presentation of stimuli eliciting attention-based EEG responses, including the P300. While this RSVP system functions adequately, it is necessary to incorporate additional physiological signals in order to further improve classifier accuracy. We are examining the acceptability of gamma activity as one such candidate signal. Gamma activity is a known marker for cortical activation [2]. However scalp recordings of gamma activity with normal scalp electrodes are unreliable due to high frequency EMG artifact [3]. Tripolar electrodes act as a high-pass spatial filter and increase the spatial selectivity of recorded activity. These changes increase signal-to-noise ratio, eliminate artifacts such as remote EMG, and so facilitate scalp recording of cerebral gamma activity [4]. This noise reduction feature of tripolar electrodes stands to be a valuable BCI tool.

Data acquisition and Analysis. A new analysis was developed for the extant RSVP spelling paradigm [1]. Participants perform an RSVP calibration using the BciPy software package [5]. Calibration consists of 100 trials of ten letter sequences (1 target letter and 9 non-targets). EEG is recorded at 512 Hz with twelve gold disc electrodes using the g.USBamp (g.tec medical engineering GmbH, Austria) and later downsampled to 256 Hz. Conventional electrodes are placed at standard 10-20 coordinates for locations F7/8, C3/4, P3/4, PO7/8, Pz, Oz, Fz, and Cz. Four tripolar electrodes (Brain Products GmbH, Germany) are also placed. Acquisition of the tripolar electrodes is achieved via a preamplifier plugged into the g.USBamp. A Morlet wavelet method is implemented to generate a time-frequency transform of the gamma activity from the tripolar channels. The next step is to fuse a measure of gamma activity with the time-amplitude data that is used for the P300 detection. This fusion is performed by pooling outputs from the gamma detector with the P300 detector in a convolutional neural network. One measure of evoked gamma activity is gamma power (40 – 110 Hz) in the post-stimulus window (300 or 500 msec) relative to gamma power in the pre-stimulus window of the same length. Alternatively, the full wavelet time-frequency matrix from the four tripolar channels is fed into the classifier.

Discussion: Multimodal fusion is an active area of interest in BCI, e.g., fusing EMG with EEG activity [6]. Multiple electrode types and signal processing algorithms may combined simultaneously in the context of a single classifier. We believe that integrating tripolar electrodes in conjunction with traditional electrodes to extract gamma frequency activity relevant to BCI operation will improve performance of a BCI system. To further improve the useful contribution of the gamma activity to RSVP BCI performance, we will explore the spatial distribution and temporal pattern of the evoked gamma activity to optimize electrode placement and optimize letter presentation rate. Additionally, future development work and experiments are necessary to determine the optimal method of fusing within the classifier the detection of gamma activity with the conventional P300 detector.

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Mitigating the Impact of Refractory Effects on P300 Speller Performance via the Classifier

W. Kironji, L. M. Collins, C. S. Throckmorton, B. O. Mainsah*
Department of Electrical and Computer Engineering, Duke University, Durham, NC, USA
*E-mail: boyla.mainsah@duke.edu

Introduction: One of the main limitations to efficient P300 speller communication [1] is the negative impact of refractory effects on classification performance: the signal-to-noise ratio (SNR) of the elicited event-related potential (ERP) response decreases as the time interval between target stimulus presentations decreases [2]. Approaches proposed to mitigate refractory effects in the P300 speller include: designing alternative stimulus presentation paradigms to the row-column (RC) paradigm that impose a minimum target-to-target interval (TTI) between character presentations, e.g. [3, 4]; or using salient elements during stimulus presentation to enhance ERP SNR [5]. Alternatively, accounting for the temporal dependence between TTI and ERP SNR in the classifier model can potentially improve performance. However, the conventional P300 classifier model assumes independence between the target stimulus presentation sequence and elicited ERP responses, creating a data distribution mismatch that negatively impacts performance. We investigate the utility of matching the learning process of the P300 speller classifier to the target data distribution to mitigate the impact of refractory effects.

Material, Methods and Results: Our goal is to compare a conventional P300 classifier and a classifier that accounts for differences in the target data distribution due to refractory effects. In the conventional model, all the non-target and target features extracted from data collected during the BCI calibration run are used to train the P300 classifier. We propose a TTI-specific classifier model, where non-target features and only target features associated with a specific TTI value are used during training. Simulations were performed using data from P300 speller studies with checkerboard and RC paradigm using participants with and without ALS. For each trained classifier model, the discriminability between the resulting non-target and target classifier scores was evaluated using the detectability index (d), a distance metric that quantifies the separation between two normal distributions. The detectability index is calculated accordingly [6]: $d = |\mu_1 - \mu_0|/\sqrt{0.5(\sigma_1^2 + \sigma_0^2)}$, where μ_i and σ_i are the mean and standard deviation, respectively, of a distribution. A high d value indicates high discriminability between two distributions, thus higher classification performance. Fig. 1. shows the classifier detectability index as a function of TTI. In general, classifier performance increases as TTI increases, which is consistent with expectations. The performance of the TTI-specific classifier was statistically significantly higher than that of the conventional classifier across TTI values (mixed effects model, $p \ll 0.001$), with similar trends across stimulus paradigms and user populations.

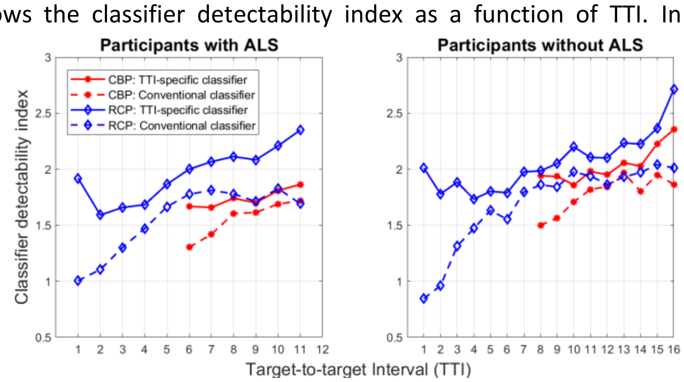

Fig. 1: Comparison of classifier detectability indices for a conventional P300 classifier and TTI-specific classifier. Results are averaged across participants using data obtained with checkerboard (CBP) and row-column paradigm (RCP).

Discussion: The results demonstrate the benefit of matching the P300 classification model to the data distribution. The conventional classifier trained on all the data generally performs relatively poorly for shorter TTIs, which reflects the relationship between ERP SNR and TTI. However, if the classifier model is matched to TTI-specific conditions, the impact of refractory effects due to shorter TTIs is minimized and performance overall is higher. Future work will investigate an ensemble TTI-based P300 classifier.

Significance: A P300 classification model that relaxes the temporal constraints on target stimulus presentations while mitigating refractory effects has the potential to significantly improve P300 speller communication rates.

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Convolutional Networks with Label Aggregation and Transfer Learning for EEG Signal Classification During Mental Tasks

Elliott Forney[1], Charles Anderson[1]

[1] *Colorado State University, Fort Collins, CO, USA.*

* 1873 Campus Delivery, Fort Collins, CO 80523, USA. E-mail: Chuck.Anderson@colostate.edu

Introduction: The ability to accurately classify EEG signals recorded during a variety of mental tasks may enable the development of flexible Brain-Computer Interfaces (BCIs) that allow fluid, asynchronous control. Classifying these types of signals is challenging, however, due to the lack of a single known control signal and because of the noisy, high-dimensional, sophisticated and transient patterns contained in EEG signals. Recent studies have suggested that Convolutional Neural Networks (CNNs) can be an effective machine learning structure for classifying EEG signals, especially when combined with transfer learning [1, 2, 3]. We extend this work by investigating a network architecture that uses one-dimensional convolutions in combination with label aggregation readout layers. Avoiding densely connected layers and leveraging cross-subject transfer learning are shown to be valuable for preventing overfitting and achieving good generalization.

Materials and Methods: EEG data were recorded from 14 participants, including four with disabilities, during four mental tasks: count backward from 100 by threes, imagine making a left-handed fist, visualize a rotating Rubik's cube and silently sing a favorite song. These data were used to train one-dimensional, fully convolutional networks consisting of 1–4 layers. The use of label aggregation readout layers, which sum the logits output by the network at each timestep, were directly compared with more traditional densely connected layers. Transfer learning was also leveraged to initialize these networks using a leave-one-subject-out paradigm. Classification accuracies and information transfer rates were then compared with a baseline approach that leveraged Power Spectral Densities (PSDs) in combination with Linear Discriminant Analysis (LDA).

Results: These experiments achieve a mean four-class classification accuracy of 58% (chance is 25%), which is nearly 9% higher than the mean accuracy of 49% achieved by the baseline approach. For some individuals, classification accuracies as high as 90% were achieved, which yields an information transfer rate over 34 bits per minute. Label aggregation readout layers contain many fewer parameters than densely connected layers and, as a result, are far less susceptible to overfitting. Transfer learning is also clearly valuable and contributes roughly 3% classification accuracy to the final results. Computing the frequency responses of the resulting network weights reveals that α, β and γ-band information are viewed as important by these networks.

Discussion: CNNs appear to hold considerable potential for classifying EEG signals in asynchronous BCIs. It is important, however, to select an appropriate network architecture that is robust to overfitting, achieves good generalization and that can be easily interpreted. The proposed CNN architecture achieves these goals and outperforms baseline approaches that leverage PSDs.

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Causal Graphical Modelling of Functional Connectivity from Reconstructed EEG Sources

A. Faes[1,*], M. Fahimi Hnazaee[1], and M. Van Hulle[1]

[1]KU Leuven, Belgium
[*]Laboratorium voor Neuro- en Psychofysiologie, O&N2 Herestraat 49 - bus 1021, 3000 Leuven, Belgium.
E-mail: axel.faes@gmail.com

Introduction By placing EEG electrodes on the scalp, brain activity can be gauged, e.g. in response to an experimental paradigm. What is measured results from mixing activity from different sources within the brain. Of special interest are directional causal dependencies, or functional connectivity, between these different sources. We propose a new method based on graph theory and graph signal processing for modelling functional connectivity. [1]

Methods The Temporal Causal Discovery Framework, an attention-based convolutional neural network with a causal validation step, is used to discover causal relationships [2]. These causal relationships are used as a skeleton-solution in a Causal Graphical Process Model [3] [4].

Experiments A functional network was simulated in order to validate the developed method. The simulation assumes several steps: generation of brain sources with a given connectivity pattern, generation of noisy sources, forward modelling of brain and noisy sources using a given signal-to-noise ratio, generation of sensor noise, inverse modelling of resulting signal and connectivity estimation [5]. The connectivity pattern used was selected from [6], shown in equation 1.

$$\begin{cases} x_1(n) = 0.5x_1(n-1) - 0.7x_1(n-2) + 0.25x_2(n-1) + w_1(n) \\ x_2(n) = 0.7x_2(n-1) - 0.5x_2(n-2) + 0.2x_1(n-1) + 0.25x_3(n-1) + w_2(n) \\ x_3(n) = 0.8x_3(n-1) + w_3(n) \end{cases} \tag{1}$$

Results Within the simulation framework, 500 noisy sources were implemented with a signal-to-noise ratio of 0.9. Sensor noise was added with a signal-to-noise ratio of 0.9. As a forward model the 'New York Head Model' was used to map activity from brain sources to the scalp [7]. The resulting connectivity estimation is given in equation 2. These preliminary results show that the described method can accurately estimate simulated connectivity patterns.

$$\begin{cases} x_1(n) = 0.5x_1(n-1) - 0.4x_1(n-2) + 0.14x_2(n-1) + 0.14x_3(n-2) + 0.2x_2(n-1) \\ x_2(n) = 0.77x_2(n-1) - 0.28x_2(n-2) + 0.18x_1(n-1) + 0.31x_3(n-1) \\ x_3(n) = 0.8x_3(n-1) \end{cases} \tag{2}$$

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How to improve the classification in P300 Spellers

L. Bianchi[1*], C.Liti[1], V. Piccialli[1], C. Salvatore[1]
[1]*DICII, University of Rome Tor Vergata, Rome, Italy*
*Via del Politecnico 1 00133 Rome. E-mail: luigi.bianchi@uniroma2.it

Introduction: Within P300 Spellers, each selection step requires multiple iterations. Typically, brain responses to target and non-target stimuli are averaged across the iterations and then distinguished using a classifier, that computes for each stimulus a decision value exploiting a linear discriminant function [2]. In [1], a new P300 classification function namely score-based function (SBF) has been proposed. The SBF exploits a set of heuristically-determined scores to weight each stimulus according to its decision value. In this work, the SBF has been improved using a set of scores automatically determined by solving an integer linear programming (ILP) problem.

Material, Methods and Results: The optimized score-based function (OSBF) has been tested on nine online-available datasets (see [1]). For each participant, data has been split into training and test sets. During the training step, five zones have been defined based on the decision values' distribution. The ILP has then been solved for assigning a score to each zone, and to determine the early stopping threshold. Problem's objective and constraints take into account both the accuracy and the communication performance. During the test step, each stimulus gets a score according to the solution of the train-based ILP problem. The assigned scores are then summed up iteration by iteration. The target class is assigned to the stimulus having the highest total score at the last iteration (no-stopping setting) or that first meets the stop condition (early stopping setting). Table 1 depicts the results in terms of accuracy (target stimuli correctly classified) and ITR.

Dataset	Accuracy (%)					ITR (bit/min)		
	Standard NS	SBF-NS	OSBF-NS	SBF-ES	OSBF-ES	OSBF-NS	SBF-ES	OSBF-ES
AMUSE	0.86(0.12)	**0.88(0.11)**	**0.88(0.11)**	0.82(0.11)	0.85(0.11)	6.94(1.91)	**17.58(10.21)**	17.24(9.28)
Hex-o-spell	**0.93(0.08)**	**0.93(0.09)**	**0.93(0.09)**	0.92(0.09)	0.92(0.09)	9.79(2.21)	**19.88(7.83)**	19.06(7.43)
Center speller	**0.97(0.08)**	**0.97(0.09)**	**0.97(0.09)**	0.96(0.09)	0.96(0.09)	11.12(2.23)	**30.93(8.10)**	29.71(8.99)
Cake speller	0.94(0.09)	0.93(0.10)	**0.95(0.09)**	0.92(0.10)	0.93(0.09)	10.27(2.15)	**23.02(8.77)**	22.38(7.85)
RSVP	**0.94(0.05)**	0.93(0.07)	0.93(0.05)	0.85(0.12)	**0.94(0.05)**	10.29(1.16)	**26.64(13.45)**	18.46(4.30)
MVEP	**0.85(0.21)**	0.84(0.20)	**0.85(0.20)**	0.84(0.20)	**0.85(0.20)**	6.7(2.46)	**12.64(6.86)**	12.47(6.58)
P300 Speller Healty	0.98(0.03)	0.99(0.03)	**0.99(0.03)**	0.98(0.04)	0.98(0.04)	9.47(1.06)	**33.88(8.81)**	29.91(6.47)
P300 Speller ALS	0.96(0.04)	0.97(0.03)	**0.98(0.04)**	0.93(0.04)	0.96(0.04)	12.62(0.96)	20.24(9.18)	**20.79(8.55)**

Table 1. *Classification performance (standard deviation in brackets) on nine P300-based (best performance in red) comparing different classification strategies within both the no-stopping (NS) and the early stopping (ES) settings.*

Discussion and Significance: The OSBF allows reaching the best/second-best result over all the datasets within the NS framework. It increases the ITR on all the datasets preserving the accuracy levels. The SBF and OSBF results are comparable, but only the OSBF is a self-tuned EEG-classification method that automatically generates the best scores for each dataset.

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Decoding Visual Scenes from Visual Cortex Spikes Using Deep Learning

Alexander McClanahan[1,2*], Kiminobu Sugaya[1,2]

[1]College of Medicine, University of Central Florida, Orlando, Florida, United States

[2]Department of Neuroscience, University of Central Florida, Orlando, Florida

*Correspondence: 6900 Lake Nona Blvd, Orlando, FL 32827, alexmcclanahan@Knights.ucf.edu

Introduction: Systems neuroscience has long been after a detailed understanding of how populations of neurons encode information in their patterns of action potentials, or spikes. Neural decoding has co-evolved in recent years the arrival of CMOS-fabricated electrophysiology probes (1) and miniaturized neural amplifier chips (2), both of which have enabled large scale neural recording. Machine learning-based neural decoding has shown incredible feats in recent years (3); namely, the decoding of: spatial coordinates of a rodent using hippocampal place cells, and motor activity (4). We explore the utility of deep learning in decoding images from neural spikes in V1 & LGN.

Materials & Methods: Electrophysiology recordings and stimulus presentations were obtained from the Allen Institute for Brain Sciences Visual Coding: Neuropixels Dataset (5) using the AllenSDK. Three deep learning models (shallow, deep, recurrent neural networks) were trained on spike counts across thousands of mouse V1 & LGN neurons and over 100,000 natural scene stimulus presentations across 26 sessions. Models were tested on held-out test spikes and evaluated for image decoding accuracy. Accuracies were then averaged across 26 recording sessions.

Results & Discussion: All three deep learning architectures performed better than chance (1/119, or, 0.84%) in decoding natural scene labels purely from spiking data recorded in V1 & LGN. The average decoding accuracies across all recording sessions of each neural network architecture are depicted in Figure 1 and are quantified as follows: shallow (64.4% ± 16.4), deep (67.7% ± 15.3%), recurrent (62.1% ± 16.5%). The deep neural network slightly outperformed shallow and recurrent neural networks on average across recording sessions.

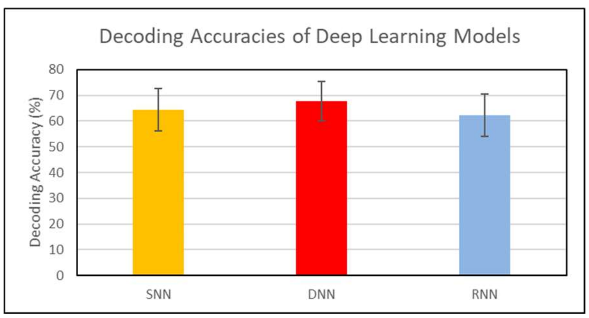

***Figure 1.** Average decoding accuracies for each of the three deep learning architectures trained: shallow neural network (SNN), deep neural network (DNN), recurrent neural network (RNN). Standard deviation bars for each model are shown.*

Significance: Recent years have unveiled a rapid acceleration in development of neural recording technologies, in both clinical and scientific communities, making large datasets containing electrophysiology data widely available. Deep learning has emerged in recent years as a viable method for neural decoding. While conventional neural decoding algorithms suffer from having to make assumptions about the encoding of neural representations, deep learning makes no neuroscientific assumptions. Accurate decoding of electrophysiology signals from brain structures involved in visual processing hold great promise in better informing our understanding of sensory processing, artificial intelligence, and BMIs for visual prosthetics.

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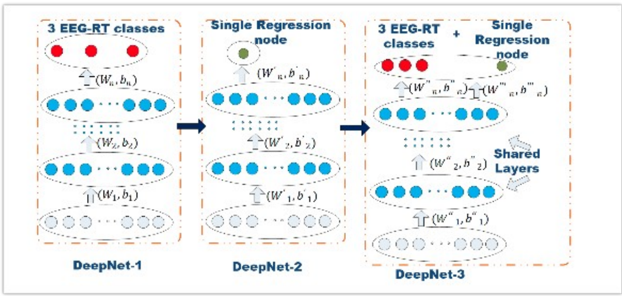
Optimal Cooperative Learning and Spatial Filtering with Deep Neural Networks in EEG Reaction Time Prediction for Drowsiness Estimation

Tharun K. Reddy*[1], Vipul Arora[1], Laxmidhar Behera[1], Yu-kai Wang[2,3], Chin Teng Lin[2,3]

[1]*Indian Institute of Technology Kanpur, tharunreddy.iitk@gmail.com, University of Technology, Sydney[2] and NCTU, Taiwan[3]*

Introduction: The goal of this research is to pretrain machine learning blocks by the data recordings from drowsiness simulations. The so-obtained models can be later fine-tuned in the absolute day to day world environment. To accomplish this goal, data has been collected for an EEG based sustained attention task in a lab setting. In particular, studies have indicated that EEG can be applied to detecting drowsiness [2], evaluated by response time (RT) values [3]. The EEG RT prediction pipeline consists of three blocks: signal preprocessing block, feature extraction block and prediction (regression/classification). Signals are also liable to artefacts and noise, hence adequate preprocessing is enforced on raw EEG prior to extracting features for classification/regression. Properly chosen spatial filters improve the signal quality and afterwards, the rate and performance of prediction blocks. In [5], we extend common spatial patterns (CSP) to EEG state space using fuzzy time delay (FTDCSSP) and thereby propose a novel approach for spatial filtering. The approach also employs a novel fuzzy information-theoretic framework for spatial filter selection. Amplitude based features (theta and alpha power) [4] constitute the baseline features for drowsiness detection. The so obtained features are passed through a deep-network based dual-task [4] HJB based optimal [3] cooperative learning [4] framework. EEG-based Reaction Time prediction and drowsy state classification are formulated as primary and ancillary problems in the context of multi-task learning. This study proposes a complete pipeline for Reaction Time prediction using FTDCSSP and multi-task cooperative optimal learning. ***Materials and Methods and Results:*** Simulated driving experiments are conducted on a virtual reality (VR)-based dynamic driving simulator. The EEG signals are recorded from 30 active electrode sites which were placed according to modified international 10-20 electrode montage system. Fig. 2 presents the experimental paradigm. EEGLAB PREP pipeline is used for preprocessing EEG trials. RTs are filtered for outliers. Further, Theta and Alpha powerband features extracted from EEG trials filtered by FTDCSSP. The obtained features are passed through DNN trained in the multitask cooperative framework with HJB optimal learning. Fig. 1 refers to the Multitask Learning block using DNNs with HJB based learning. A comparison is made among the learning algorithms and the regression methods like Support Vector Regression (SVR) and Ridge Regression (RR). In particular, the best performing multitask network recorded a 15.49% smaller RMSE, a 27.15 and a 10.13% larger Pearson's Correlation than SVR. Here RMSE is root mean squared error (indicator of difference between actual and predicted Reaction Time values (cf. Sec II E (27) of [5])). For Statistical comparison and individual results of RR and SVR models, reader can refer to Sec V C of [4].



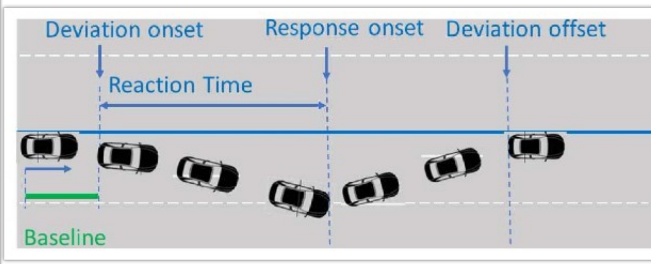


Figure 1: Cooperative Learning DNN Block (Fig 3 of [4]) *Figure 2: Sustained Attention Experimental Paradigm*

Significance: 1)This study proposed the jointly optimized spatial and spectral filters for preprocessing and feature extraction and proposes the Fuzzy Mutual Information as a conjoined filter selection metric. 2) This study also developed a dual-task cooperative learning paradigm with Deep Neural Networks for EEG-based Fatigue detection which can be fine-tuned to improve its practicality for real-world use.

Acknowledgements: ARC support under discovery grant DP180100670 and DP180100656. The research was also sponsored in part by the Army Research Laboratory.

Discussion: Our results showed that the classification and regression rates obtained with the multitask DNN highly exceed those of the SVR and RR. Also, error in driving distance is smaller for multitask DNN in comparison to SVR and RR. Also, we showed that a trial of 5 seconds is sufficient to achieve reliable regression.

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Design and Development of a Haptic BCI

Karthikeyan Ganesan*, Karthiga Mahalingam, Melody Moore Jackson

*GT Brain Lab, 85, 5th St NW Atlanta, GA 30308. Email : karthikeyan@gatech.edu

Introduction: Brain Computer Interfaces (BCIs) traditionally deploy visual or auditory stimuli to elicit brain signals. However, these stimuli are not very useful in situations where the visual or auditory senses are involved in other decision making processes. In this paper, we explore the use of vibrotactile stimuli on the fingers as a viable replacement. Using a five-level Wavelet Packet feature extraction on the obtained EEG signals, along with a kernel Support Vector Machine (SVM) algorithm, we were able to achieve 83% classification accuracy for binary user choices. This new BCI paradigm shows potential for use in situations where visual and auditory stimuli are not feasible.

Materials, Methods, Results: The designed hardware consists of two Linear Resonant Actuator (LRA) motors which vibrate at two different frequencies, which are 5Hz apart (eg. 15 & 20Hz). The frequency of vibration is controlled by interfacing the motors to a Teensy 3.1 microcontroller. Real-time EEG signals are obtained at 250Hz through the OpenBCI acquisition system. The vibrating motors are placed on the fingertips to elicit steady state somatosensory evoked potentials (SSSEP). The 10-20 electrode placement system is used to collect EEG signals from F3,Fz,F4,C3,Cz,C4,P3,Pz, and P4 scalp locations. The obtained signals are bandpass filtered between 0.1Hz and 60Hz along with notch filtering at 50Hz. Further, the multi-channel signals are denoised with the multi-scale principal component analysis (MPCA) algorithm and decomposed with five-level Wavelet Packet decomposition [1]. Lower and higher order statistical features are obtained from each band of the decomposition. These features are then used in a downstream classifier for identifying user preferences. Higher order statistical (HOS) features along with a SVM classifier (Gaussian Kernel) are found to classify user choices with a classification accuracy of 83%. Figure 1 compares the performance of four classifiers on both lower order statistical (LOS) and higher order statistical (HOS) features.

Discussion: Results indicate that a combination of HOS features and a kernelized SVM algorithm act as an effective classification pipeline. Superior performance of HOS features indicate that the features are heavily-tailed Gaussian distributions. The kernel SVM algorithm is seen to perform better than other classifiers that model data to be a Gaussian distribution. This implies that features of one class are heavy left-tailed, whereas the corresponding features of the other class are heavy right-tailed.

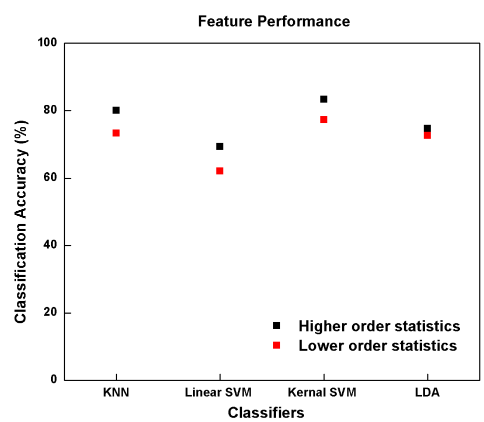

Figure 1: *Performance plot of Lower and Higher Order Statistics*

Significance: This paper introduces a new type of haptic BCI and an associated algorithm that could be used where traditional stimuli cannot be used to fully capture user attention. The algorithm surpasses the current classification rate for a haptic BCI by 13% [2]. However, the lengthy pipeline of MPCA denoising, wavelet packet decomposition and kernelized SVM classification make it computationally less efficient and not viable for real-time usage. The efficiency of this algorithm can be improved by determining the optimal number of decomposition levels and exact sub-band that contains the most discriminating information, consequently reducing feature extraction time and execution time. Upon incorporating these improvements, the existing algorithm can be be used in real-time haptic BCI systems.

Acknowledgements: The authors would like to thank the GT Brain Lab for providing the logistics and the National Science Foundation for funding this work (NSF Grant IIS-1718705).

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False Nearest Neighbor Test as a Tool for Channel Selection in BCI

Fatih Altindis[1*] Bulent Yilmaz[2]
[1,2] Abdullah Gul University, Kayseri, Turkey
* Barbaros Mah. Erkilet Bul. Abdullah Gul University Sumer Campus A103.
E-mail: fatih.altindis@agu.edu.tr

Introduction: Channel selection reduces computational complexity of subsequent processing by finding most relevant channels, and it prevents overfitting of data that may rise due to irrelevant channels. These advantages enable BCI systems to operate in real time and respond quickly to users. False nearest neighbor (FNN) test was introduced by [1] to find optimal embedding dimension for scalar time series. Here, we propose adaptation of false nearest neighbor test as a channel selection algorithm for EEG signals to find most relevant subset for the further steps.

Material, Methods and Results: We used BCI competition-III EEG dataset IVa, which includes 118-channel EEG signals of 5 subjects (two imagery tasks; right hand and foot). FNN test aims to find out similarities of scalar time series by projecting them into d-dimensional Euclidean space. We used FNN test on 118-channel EEG data to find out a subset of similar channels. FNN test algorithm was implemented to find a collection of three EEG channels that provide the lowest FNN score for a given starting channel. Cz, C1, C3 and C5 were used as the starting channels. FNN score of every possible channel subset that includes these channels were calculated. The subset that provided the lowest FNN score was chosen. Then, symmetric channels -if there are- from the right hemisphere (C3, C4, C6) were added into this subset; resulting in 21 channels out of 118. For each trial, EEG signal coming from the subset and the full set were filtered (7.5 - 13.5 Hz) and event-related desynchronization (ERD) features were extracted. The final classification on 280 trials was performed using logistic regression (10-fold validation) on ERD features. Proposed channel selection algorithm increased classification performance up to 15% by using only 21 channels (Table 1).

Subject	All Channels	Selected Channel
aa	63.5	54.3
aw	67.9	69.6
al	**75**	**90.4**
av	56.2	62.5
ay	**77.5**	**82.5**
Average	67.84	71.86

Table 1. Classification results of the each subject before and after channel selection was shown.

Discussion: [2] reviewed and compared different channel selection techniques that used the same dataset. Reviewed studies were mainly focused on common spatial pattern filtering (CSP) approaches for channel selection. [3] reduced number of channels to 13 using CSP based algorithm, but overall classification performance decreased 4%. Another CSP based study [4] reduced number of channels to 20, while overall performance increased by 1%. Fisher's discriminant analysis based wrapper technique reduced the number of channels to 11, while classification performance remained same [5]. Our approach showed that FNN test can be used to reduce number of channels and to find the most similar (synchronized) channels from large channel set. FNN test is a simple and straight-forward algorithm compared to above-mentioned techniques.

Significance: For the first time, we show the feasibility of the false nearest neighbor test algorithm for channel selection in BCI.

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A deep learning approach for imagined speech discrimination

Jesús S. García-Salinas*[*a]**, Luis Villaseñor-Pineda**[a]**, Carlos A. Reyes-García**[a]*

[a]Biosignals Processing and Medical Computing Laboratory, Instituto Nacional de Astrofísica Óptica y Electrónica
[*]Luis Enrique Erro No. 1, Santa María Tonatzintla, Puebla, México. Email: jss.garcia@inaoep.mx

This study explores imagined speech as a neuroparadigm for BCI. Three dimensions of the signal (time, frequency, space) are analyzed as a unique element. The EEG data is given in the time domain from each channel. This is seen as a bi-dimensional representation. Nevertheless, the frequency domain provides relevant features of neural activity. Then, applying a frequency domain transform to each channel the signal becomes a three-dimensional tensor. Moreover, the frequency information of the data will be used without additional mappings or transforms.

The three-dimensional EEG data is used to feed a neural network (Fig.1). The first step is a bi-dimensional convolution layer with a rectangular filter that moves along one of the front dimensions. Next, a max-pooling layer reduces the data in a similar rectangular shape as the previous convolution. Then the data is flattened to feed a fully connected layer. To finish a dropout is set and then a softmax layer to predict the outputs.

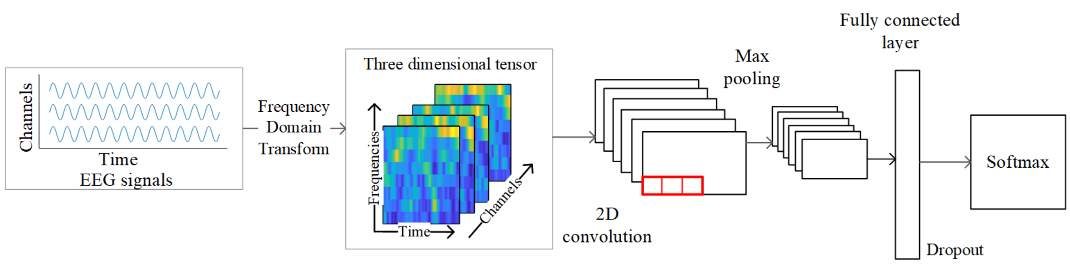

Figure 1: Network architecture

Four public databases are analyzed, in order to compare the different results, all the databases were down-sampled to 128 Hz and a Common Average Reference was applied for noise reduction. Due to the different protocols, some databases have no consistent recording lengths. Thus, the length of the data was trimmed to the shortest epoch. Bayesian optimization is applied for convolution filters number, convolution filters size, dense layer size, dropout, and batch size. For the experiments, data is randomly split 75% for training and 25% for tests. Moreover, from the training section, 20% was used for validation.

Work	Classes	Subjects	Trials	Channels	Baseline	Results
[1]	5	27	33	14	68.17 ± 16	63.66 ± 11.5
[2]	3	6	100	64	50 ± 3.5	46.6 ± 3.1
[2]	2	6	100	64	66.18 ± 4.82	69.5 ± 2.1

Table 1: Databases features and results

As can be seen in Table 1, the results achieved are encouraging despite the simple signal processing, the differences in the protocols of each database, number of words and acquisition devices. It can also be observed seen that the results show a high standard deviation, this is because the Bayesian optimization was performed for each subject. Hence, additional analysis is required to determine the general parameters for each database.

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Active Recursive Bayesian Inference with log-Posterior Momentum for Faster BCIs

D. Erdoğmuş[1], A. Koçanaoğulları[1], Y. Marghi[1], M. Akçakaya[2], B. Peters[3], B. Oken[3], M. Fried-Oken[3]

[1]Northeastern University, Boston MA; [2]University of Pittsburgh, Pittsburgh PA; [3]Oregon Health & Science University

Introduction: Brain computer interface (BCI) typing systems help people with disabilities communicate. These systems operate on recursively streaming electroencephalogram (EEG) excited using different stimuli paradigms (e.g. SSVEP, RSVEP). If a confidence level is achieved, the systems make a decision on user intention. Since languages are structured, language models expedite the estimation. For that, BCI systems are usually supported with a language model (LM) that provides the prior information in the beginning of each cycle. With all that, system operates in recursive Bayesian inference (RBI) framework. Due to low SNR levels in EEG, the estimation cycles are time-consuming. Especially, if the user is trying to type a statistically uncommon word (based on appearance on the LM training data-set) the user is also tasked to overcome the effects of the language model. Active RBI (ARBI) focuses on designing queries and determining termination conditions to achieve faster estimation cycles without losing accuracy. In this work we elaborate our previous work on active inference [1, 2, 3] and propose a weighted prediction term for faster inference.

Material: We use RSVP Keyboard python implementation BciPy [github.com/BciPy/BciPy], with EEG data acquired using a DSI-24 dry electrode system by Wearable Sensing (San Diego, CA USA).

Method: In our previous work, we used averaged log likelihood scores (named momentum) to perform one-step ahead prediction for stimulus selection. In this work we investigated the further adjustment of momentum to have a better one-step estimation for stopping and query selection that results in faster convergence by proposing a weighted averaging that allows recent observations to have higher impact. We test proposed approach in 3 different cases: adversarial LM (target letter is one of the least likely candidates wrt. prior), no-LM (uniform prior), supportive LM (target letter is one of the most likely candidates wrt. prior).

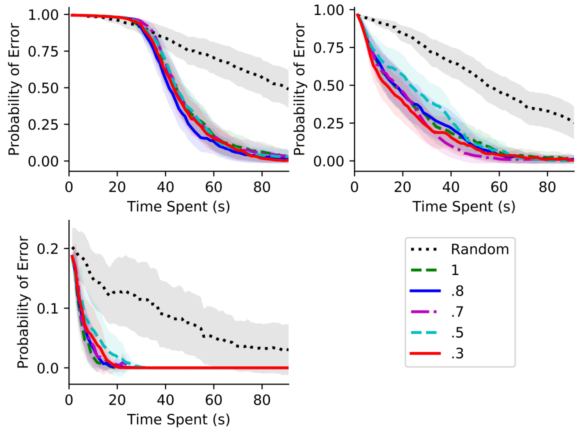

Figure 1: MC Simulations representing probability of error in target letter detection. top-left: adversarial LM, top-right: no LM, bottom-right: supportive LM

Results: We used Monte Carlo (MC) simulations using generative models for EEG features developed on real calibration data from 10 healthy subjects with different performance levels. We simulated typing schemes to support our claims. We performed 1000 simulated typing schemes for each of the methods. Each letter typing scenario includes 70 recursions of stimuli flashes that include 4 letters. Therefore, in total, we simulated 280000 samples from generative evidence distributions and visualize our results in Figure1. We weighted the time average by a scalar factor $\gamma \in \{1, 0.8, 0.7, 0.5, 0.3\}$ at each step that yields exponentially decaying importance on previous evidence observations. By design $\gamma = 1$ means an ordinary time average and $\gamma = 0$ means considering the final sample only. We observed the existence of a γ hyper-parameter that surpasses the drop speed in error probability of the conventional method ($\gamma = 1$).

Discussion: The proposed approach of taking a weighted average temporally has shown to improve performance with different hyper-parameters in different settings. We note that, these empirical results encourage us to formulate a hyper-parameter learning problem to achieve faster inference.

Significance: BCI communication performance is significantly impacted by the level of assistance LMs provide to users. To help improve communication speed, adaptive querying methods are designed to ensure the user has a chance to reflect the decision to the system. In this setting, stimulus subset selection plays a crucial role. Stimulus subset selection can be posed as an active inference problem where query selection and stopping criterion objective design is mandatory to optimize the reward (speed).

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EEG Data Augmentation for BCI Applications

S. Madsen[1*], C. Arnold[1], W. Speier[1]
[1]*University of California Los Angeles, Los Angeles, CA, USA*

[*]*924 Westwood Blvd Suite 420, Los Angeles, CA 90049, E-mail: sjmadsen@ucla.edu*

Introduction: Brain-computer interface (BCI) technology restores some functionality, such as communication, to those suffering from neurodegenerative diseases. Deep learning models have proven to be effective end-to-end feature extraction and classification algorithms for motor imagery EEG signals [1, 2]. However, deep learning models often require a large amount of training data, which is impractical for a BCI setting. Minimizing the amount of data needed for classification decreases training time and can reduce the latency between user intention and system response. The present study analyzes the effect of shortening the signal window used for classification in a four-class motor imagery task.

Material, Methods and Results: This study used the BCI Competition Dataset 2a [3], which consists of four-class motor imagery. Each trial in the dataset consists of a four second window during which the user performs one of four cued tasks (left hand, right hand, feet, and tongue). Windows of length one, two, and three seconds were taken from the beginning of each of these trials and models were trained on each of these shorter windows. On the original four seconds of data, the model EEGNet [2] achieves an average subject accuracy of 64.6 percent. The results for the windowed data are similar: 65.5 percent accuracy for the three second window, 65.5 percent for the two second window, and 58.2 percent for the one-second window. To further analyze the trends in the data, each of the trials were split into four one-second windows and each window was analyzed separately across subjects. The first two windows achieved 58.2% and 55.4% accuracies, respectively. The third window achieved an accuracy of 32.4% and the fourth window achieved an accuracy of 28.8%.

Discussion: The results of the varying window length experiments suggest four seconds of data collection is more than what is necessary for the model to accurately classify motor imagery tasks. The results of the one-second window experiments highlight the signal fidelity trends in the data. The model is unable to extract high-quality features from either of the of the last two seconds of data, which suggests that the discriminating signals for motor imagery are more present at the onset. This trend might explain why decreasing the window length does not hurt performance in the first experiment.

Significance: These results suggest a BCI designed around motor imagery EEG data could classify the user's intention in as little as two seconds. This result has important implications for BCIs as the time it takes the system to determine the user's task limits the speed at which the system can respond.

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Task-relevant Deep Representation Learning via Mutual Information Maximization for BCI

Eunjin Jeon[1], Wonjun Ko[1], Heung-Il Suk[1,2*]
[1] *Department of Brain and Cognitive Engineering, Korea University, Seoul, Korea;*
[2] *Department of Artificial Intelligence, Korea University, Seoul, Korea*
*Anam-Ro 145, Seoul 02841, Korea. E-mail: hisuk@korea.ac.kr

Introduction: It is estimated that almost 15% to 30% of subjects are regarded as BCI-illiteracy [1]. BCI-illiterate subjects do not show any clear brain activity patterns showing large variation in a power spectral density (PSD) curve evaluated from their EEG signals. Azab *et al.* showed that a transfer learning method that takes advantage of other subjects' EEG enhances the classification performance of motor imagery [2]. In this work, we propose a deep neural network that learns a subject-invariant and task-relevant feature representation by maximizing mutual information among different subjects, thereby improving the decoding performance to BCI-illiteracies.

Material, Methods and Results: We used the KU-Motor imagery dataset which consists of 2 motor imagery tasks, *i.e.*, left-hand and right-hand, recorded from 62 electrodes of 54 subjects [3]. Basically, our proposed network is based on an autoencoder structure. The encoder, inspired by Hjelm *et al.* [4], takes a PSD of raw EEG signal as an input and then extracts the subject-invariant feature by maximizing mutual information between *high-level representation* (spatio-spectral patterns in EEG) and *low-level representation* (spectral patterns in EEG) among multiple subjects. Here, the subject-invariant feature is decomposed into the task-relevant feature and the task-irrelevant feature. Subsequently, these features enable the decoder to reconstruct a PSD in order to keep *spatio-spectral* information. We compared our methods with the state-of-the-art deep learning methods designed for motor imagery decoding. Our methods showed the improvement of performance by almost 10% on average. Furthermore, we analyzed our proposed framework by visualizing learned filters and plotting task-relevant and task-irrelevant feature using *t-SNE*.

Discussion: Our experimental results showed that our proposed framework can improve the BCI illiterate subjects' performance through exploiting other subjects' EEG data.

Significance: We proposed a novel algorithm to learn the task-relevant representation in an end-to-end manner. In addition, by finding the subject-invariant feature representation, we can utilize it to reduce calibration time for a new subject in terms of the transfer learning.

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A distinct representation of ipsilateral and contralateral hand movements in the sensorimotor cortex

FD Guerreiro Fernandes[1*], MLCM Bruurmijn[1], MAH Raemaekers[1], NF Ramsey[1], MJ Vansteenstel[1]

[1]*UMC Utrecht Brain Center, Department of Neurology and Neurosurgery, University Medical Center Utrecht, Utrecht, The Netherlands*

* P.O. Box 85500, 3508 GA Utrecht, The Netherlands. E-mail: F.GuerreiroFernandes-3@umcutrecht.nl

Introduction: Contralateral sensorimotor areas hold a vital role in movement generation, with the primary motor cortex (M1) and the primary somatosensory cortex (S1) showing a detailed spatial organization of contralateral body parts [1]. Previous studies provide indications that the motor cortex also plays a role in ipsilateral movement control [2,3,4,5,6], but its precise function is still unclear. This ultra-high field fMRI study shows the presence of a distinct representation of ipsilateral and contralateral complex hand gestures in both M1 and S1 of the same hemisphere.

Materials and Methods: Nine healthy participants conducted an fMRI session in which they performed a Hand Gesture Task, which involved making six different hand gestures of the Americal Manual Alphabet. Each participant performed the task twice with their left and twice with their right hand. A whole-body 7T MR system (Achieva, Philips Health Care, Cleveland, OH, USA) with a 32-channel head coil was used during image acquisition. Anatomical T1- and PD-weighted images (TR/TE=6/1.4ms, FA=8º, voxel size=$1\times1\times1 mm^3$) were acquired, followed by the Hand Gesture Task using an EPI sequence (TR/TE=1300/27ms for subjects C1 and C2, TR/TE=1600/27ms for all other subjects, FA=70º, voxel size=$1.6\times1.6\times1.6 mm^3$). Functional scans were preprocessed using SPM12 [7].

For each subject, a t-map was calculated per run by fitting a GLM without distinction between the different gestures. These were generated to investigate location of activity during task performance. The sensorimotor areas were subsequently divided into four ROIs: M1, S1, pre-M1 and post-S1. After training a support vector machine classifier on single-trial fMRI activation patterns, we attempted to discriminate the twelve different hand gestures (six contralateral and six ipsilateral) for all four ROIs of both left and right hemisphere separately.

Results: Contralateral activation mainly occurred in M1 and S1, areas close to the central sulcus. In contrast, ipsilateral hand movements were associated with activity further away from the central sulcus (but still in M1/S1), in the anterior precentral gyrus and the posterior postcentral gyrus. The twelve hand gestures were classified significantly ($p < 0.001$) above chance level in all four ROIs, for each hemisphere.

Discussion: The current results show that it is possible to distinguish the representation of ipsilateral hand movements from contralateral hand movements in the sensorimotor cortex of the same hemisphere. These findings suggest the presence of groups of neurons within the human M1 and S1 that are associated with ipsilateral hand movement, which is in agreement with earlier primate work [8,9,10]. This representation may be associated with transcallosal projections and may be important in the integration of information across hemispheres and in optimizing coordination of hand movements in relation to the rest of the body.

Significance: This study bears relevance for our understanding of the generation of movements, and may support the development of multi-dimensional brain-computer interfaces by demonstrating the feasibility of extracting information from the same hemisphere regarding both sides of the body.

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Brain-Computer Interface for the Classification of Brain Activation in Face of Ethical Decision Making

Y. T. Nakamura[1]*, Y. Gu[1 2], H. Jin[3], S. Kalla[1]

[1]The George Washington University, DC, USA; [2]University of Maryland in Baltimore, MD, USA; [3]Columbia University, NY, USA

*2134 G St., NW, Washington, DC 20052, USA. E-mail: yoshienakamura@gwu.edu

Introduction: Non-invasive EEG is used to examine the impact of decision-making processes at the neural level with ethical dilemma scenarios as stimuli. A mixed design with two factors of interest is utilized: ethical dilemma (easy or difficult) and type of decision-making processes (individual or group).

Material, Methods and Results: The EEG data are collected at 14 channels of the sensors on the scalp: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Both time-domain and frequency-domain data are stratified by means of six scenarios (three difficult and three easy scenarios) for individual versus group decision-making groups. The 14 channels are imported as 14 covariates in the time-domain data. The data (theta: 4-7Hz; alpha: 8-12Hz; beta: 13-30Hz; gamma: 31-40Hz), converted using the Fast-Fourier Transform (FFT), are also imported as covariates in the frequency-domain data. Cross-correlation is calculated in order to identify functional correlated brain waves. The measurements of different waves (amplitude peaks and the time lag) are visualized and subsequently compared. Our preliminary analysis shows that the brain waves are highly cross-correlated with each other in the first 50 ms given the ethical dilemma scenarios. The results from the logistic model of FFT data show that both alpha (p-value = 0.0024) and beta (p-value = 0.0319) are statistically significant. Both theta (p-value =0.0596) and gamma (p-value = 0.077) also have p-values which are close to the significant threshold (0.05). Machine learning models are also applied for making binary classifications and predictions. For example, using the Support Vector Machine (SVM) classifier, the 2 categories (difficulty vs. easy) are classified. The prediction accuracy of the SVM model is above 80% for one subject, demonstrating a good prediction result.

Discussion & Significance: The preliminary results from three methods (cross-correlation analysis, logistic regression model of FFT data, and SVM classifier) indicate that our EEG study incorporating ethical dilemma scenarios might significantly impact on delaying subject's reaction time, observing alpha and beta waves, and possibly predicts the difficult-versus-easy ethical dilemma, respectively.

For making more long-term predictions, other deep learning approaches will be also considered such as the Recurrent Neural Network (RNN) with Long-short Term Memory (LSTM) [1] in order to avoid the long-term dependency problem in the time series data. Significant features from 14 channels as well as from different frequency ranges can be selected according to the RNN modeling framework. BCI EEG data focusing cognitive processing and emotional arousal help us more precisely understand the impact of ethical dilemma situations in individual or group decision-making.

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Cortical connectivity in people with Spinal Cord Injury during attempted arm and hand movements

Kyriaki Kostoglou[1], Gernot Müller-Putz[2*]
[1]Institue of Neural Engineering, Graz University of Technology
*E-mail: gernot.mueller@tugraz.at

Introduction: In this work, our main focus was to examine the time-varying (TV) cortical connectivity patterns that arise in SCI subjects during attempted arm/hand movements (i.e., supination, pronation, hand open, palmar/lateral grasp) [1]. To this end, we employed an adaptive formulation of the so-called multivariate autoregressive (TV-MVAR) models [2]. MVAR models provide metrics that describe causal interactions and directional effects between different signals. Herein, we used the TV directed coherence (DC) to quantify temporal variations in the direction of information transmission in the frequency domain. Specifically, we aimed to capture the general dynamics during various attempts of arm/hand movements and identify/localize the main sources of information flow.

Methods: 61-channel EEG signals were pre-processed (ICA-based artifact removal, trial rejection) using EEGLAB and Matlab. Source localization was carried out in Brainstorm (minimum norm imaging and sLoreta). Since our main scope was to examine connectivity related to motor function, we extracted 26 spatially segregated signals from anatomical regions defined by the Brodmann atlas (Fig.1a). For each type of attempted movement, we used the corresponding source signals to estimate a TV-MVAR model based on multiple trials from all subjects. To capture possible time variations, we applied a Kalman filtering approach. This approach assumes that the model coefficients are not constant but follow a random walk. Based on the estimated models we obtained DC time-frequency distributions. At each time point the total information outflow [3] from a particular region was defined as the sum of statistically significant connections (e.g., DC values) towards all other cortical regions.

Results and Discussion: In Fig.1b,c we present overlay plots depicting the total TV information outflow calculated from all attempted movements in the frequency range of [0.3 70] Hz, along with the average EEG signal in the sensor space. First, we observed an ipsilateral pattern (all subjects were right-handed), whereby dominant sources of information originated mainly from the right hemisphere. Second, the most prominent sources were detected in the sensorimotor and the primary motor area (specifically BA3a and BA4p) followed by the perirhinal and visual cortex (mainly in the contralateral side). Information outflow exhibited temporal patterns related to the onset of the cue. Sensorimotor outflow increased 0.5 sec prior to the cue and decreased after the onset of the cue. The opposite pattern was observed in the primary motor area, where outflow started increasing 0.5 sec after the cue onset and attained its maximum during the negative reflection of the average sensor signal (+1 sec). The visual and perirhinal cortex displayed increased outflow during the start of the trial and immediately after the cue onset, indicating possibly cognitive processing. This validates the hypothesis in [1], that the positive peak in the MRCP (+0.5s) is related with the presentation of the class cue. We also observed changes in the outflow in different frequency bands before and after the cue. Delta band outflow increased overall by 7.25% after cue onset, whereas the outflow in the rest of the bands decreased. The maximum percentage decrease was found in the beta band (7%). This could be attributed to possible event-related desynchronization phenomena.

Significance: The DC time-frequency distributions for different type of attempted movements followed approximately the same temporal trends. However, we detected discriminative connectivity patterns in different frequency bands and between different regions. Our future goal is to incorporate this information and improve BCI decoding performance [1] with respect to different movements.

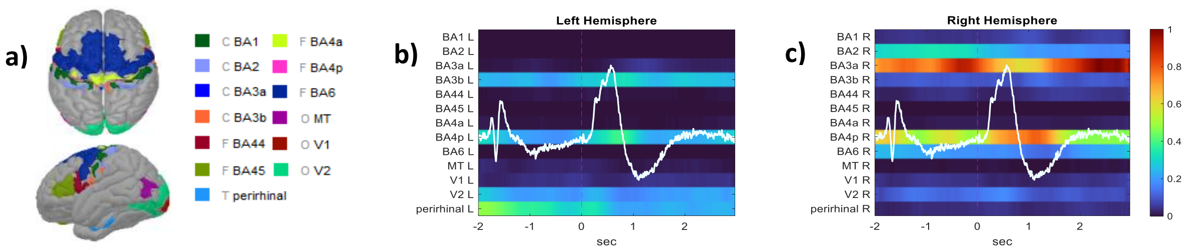

Figure 1. TV information outflow in the frequency range of [0.3 70] Hz for all regions depicted in (a), in the (b) left and (c) right hemisphere. Each line in (b) and (c) represents the TV outflow from the corresponding region, denoted on the y-axis, towards all other regions. The magnitude of the outflow has been color-coded as shown in the colorbar in the right side of the figure. The average EEG signal ([0.3 70] Hz) from all trials and subjects is overlayed with white color for visualization purposes. Time point 0 corresponds to cue onset.

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Preferences of individuals with locked-in syndrome

M. P. Branco[1*], E. G. M. Pels[1], Nick F. Ramsey[1], Femke Nijboer[2], M. J. Vansteensel[1]

[1]UMC Utrecht Brain Center, Department Neurology and Neurosurgery, Utrecht, The Netherlands; [2]Biomedical Signals and Systems Department, Faculty of Electrical Engineering, Mathematics and Computer Science, University of Twente, Enschede, The Netherland

*P.O. Box 85500, 3508 GA, Utrecht. E-mail: m.pedrosobranco@umcutrecht.nl

Introduction: Communication BCIs (cBCIs) have been proposed as an alternative access technology (AT) for individuals with locked-in syndrome (LIS) (e.g., [1-4]). To make sure that cBCIs are fully accepted by future users, their opinion should be considered during all steps of the research and development process of cBCIs. The opinion of users regarding BCI applications (beyond communication) has been investigated in the past [5-6]. However, none of these earlier questionnaires asked the users' opinions on different mental strategies for cBCI control, nor on when during their clinical trajectory they would like to be informed about AT and cBCIs.

Material, Methods and Results: We have investigated the opinion of 28 (potential) Dutch cBCI users regarding three topics:1) which applications they would like to control with a cBCI, 2) which mental strategies they would prefer to use to control the cBCI and 3) the time point during their clinical trajectory at which they would like to be informed about ATs, including cBCIs. We grouped and compared the opinion of participants with respect to the etiology of the LIS, that is, due to neuromuscular diseases (e.g. amyotrophic lateral sclerosis) or due to sudden onset events (e.g., brainstem stroke). Participants were interviewed during a 3-hour home visit. In this visit the participants were informed about BCIs and the possible mental strategies for control with the help of animation videos. Participants answered the questions using their current communication channel and AT. Results revealed that individuals with LIS, independently of their etiology, consider (in)direct communication, general computer use and environmental control important applications a BCI should offer. Moreover, they preferred, in general, attempted speech and movement as a control strategy over reactive strategies (such as P300 and SSVEPs). Lastly, both groups had a strong preference to be informed about AT aids and BCI when they reach the locked-in state and need the AT the most.

Discussion: Results show that users have a particular opinion about which cBCI applications and paradigms they prefer. These preferences should be taken into account when developing cBCI for home use. A possible limitation of this study is the fact that a large number of participants were not naïve to the concept of BCI before this study. Although this fact may influence the interpretation of the results, we explicitly described to the participants that this questionnaire was about an ideal home-use BCI and not the ones they experienced in the past.

Significance: This survey encourages the involvement of users and provides information to stakeholders in BCI and AT development that is valuable for the research and development process, ultimately reducing the risk of technology abandonment.

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Do we know what users want? Comparing the views of potential users, caregivers and researchers.

M.J. Vansteensel[1*], M.P. Branco[1], E.G.M. Pels[1], F. Nijboer[2], N.F. Ramsey[1]

[1]UMC Utrecht Brain Center, Department Neurology and Neurosurgery, Utrecht, The Netherlands; [2]Biomedical Signals and Systems Department, Faculty of Electrical Engineering, Mathematics and Computer Science, University of Twente, Enschede, The Netherlands

*P.O. Box 85500, 3508 GA, Utrecht. E-mail: m.j.vansteensel@umcutrecht.nl

Introduction: Communication Brain-Computer Interfaces (cBCIs) allow people with severe motor impairment to communicate using only their brain signals. A variety of mental strategies can be used to generate neural signal changes that can be converted into a cBCI control signal for alternative and augmentative communication aids, environment control units or computerized devices that provide various applications, such as spelling. The cBCI field is becoming increasingly aware about the importance of incorporating the wishes and needs of end-users in the design of BCIs [1,2]. To accomplish proper integration of the opinion of people with motor impairment in BCI development, researchers should be aware of any differences in point of view that the different groups of stakeholders may have.

Material, Methods and Results: We compared the opinion of 28 individuals with severe motor impairment ('users') with that of their caregivers and a group of cBCI researchers about the most desired output applications and the most usable mental strategies for BCI control. In addition, we addressed the question when during their clinical trajectory a potential cBCI user should be informed about assistive technology solutions including cBCIs. Results show that the three groups of stakeholders agree that 'direct personal communication', 'private conversation and writing', 'general computer use' and 'environmental control' are more important cBCI applications than 'emotions and facial expressions' and 'artistic expression'. Opinions about BCI control strategies, however, varied substantially across groups. Users had a strong preference for attempted speech and movement. Caregivers also preferred attempted speech, but rated attempted movement much lower and P300 and SSVEP much higher than users. Although researchers correctly estimated that users would prefer attempted movement and speech as mental strategies for BCI control, they also rated P300 and SSVEP much higher than users did. Finally, there was an important difference of opinion about the timing of information about assistive technology between users with neuromuscular disease (NMD) on the one hand and caregivers and researchers on the other. Whereas NMD users only preferred to be informed whenever they actually need assistive technology, caregivers and users most frequently selected 'as soon as possible' as an answer.

Discussion: Results show that users, caregivers and researchers agree on the most important applications a cBCI should offer, but often disagree about which mental strategies should be used to control the cBCI and about the time point (NMD) users should be informed about assistive technology and cBCIs. These findings indicate that caregivers and researchers are not always able to predict the opinion of users and underscore the importance of a proper user-centered design of cBCIs. Limitations of the study are the inclusion of only Dutch users and caregivers, and the fact that many users had heard of or tried BCIs in the past.

Significance: The differences of opinion identified in the current study are of relevance for the further development and implementation of cBCI solutions for use in the daily living environment of people with severe motor impairment.

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A deep learning model for creating feature-neutral faces of emotions.

Alberto Barradas[1*], Selina C. Wriessnegger[1,2]
[1] *Institute of Neural Engineering, Graz University of Technology, Graz, Austria.* [2]*BioTechMed-Graz, Graz, Austria*

*E-mail: barradaschacon@tugraz.at

Introduction: Variational Autoencoders (VAEs) are a specific architecture of Deep Learning (DL) networks that can abstract the features in an image into a statistical representation, presenting an early visual concept [1]. The concept of a DL network abstracting the Activation Units (AUs) described by the Ekman model of emotions [2] has been proven before [3], but this was done with a simple emotion classifier. This model is based on the hypothesis that evolutive pressure has shaped a common expression of emotions in humans, and thus, 7 facial expressions remain universal: anger, disgust, fear, happiness, sadness, surprise, and contempt. By using an Autoencoder, the reproduction of the input image is acheived, while the network learns the features that compose a specific dataset. Adding a classification loss to the latent variable of a VAE allows for the learning of an early visual concepts learned by the network. These concepts directly correlate to each of the emotions of the given facial expression model. This means the network is able to abstract the facial features that compose the expression of an emotion, while producing an image that contains these specific features.

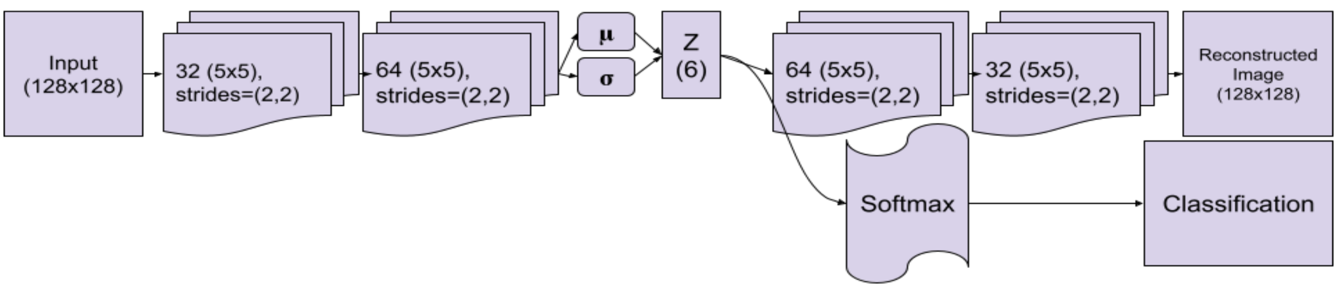

Figure 1: Designed architecture for this VAE

Method: The architecture selected for this network is pictured in Figure 1. By adding a classifier layer to the VAE's latent variable, the updated loss function considers both, the VAE's original reconstruction loss, plus a classifying term. The balance between these two losses is controlled by a multiplier for the classifier loss.
For training, the first two images of the facial expressions sequences from the extended Cohn-Kanade Dataset (CK+) [4] were used with the neutral label, while the last three images were used for the respective emotions. Random translation, slight rotation, contrast and horizontal mirroring were used to augment the dataset.
Discussion: We were able to create a DL model that reproduces accurate facial expressions of emotions while ignoring facial features that are not emotion-specific. This model can create as many images, with different intensities of each emotion in the model, allowing for the elicitation of emotions through neutral human facial expressions in emotional BCI research.

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Cognitive and Psychological Factors Influencing Motor Imagery Brain-Computer Interface Performance

Nikki Leeuwis, Alissa Paas, Maryam Alimardani*
School of Humanities and Digital Sciences, Tilburg University, Tilburg, the Netherlands
*E-mail: M.Alimardani@uvt.nl

Introduction: Motor imagery (MI) is one of the major paradigms for brain-computer interfaces (BCI) [1]. However, substantial interpersonal variations are observed in MI task performance, causing up to 30% of all users being defined as illiterate BCI users [2, 3]. The concept of MI is difficult to comprehend for the user [4] and it requires the ability to generate stable and distinct brain activity patterns [5]. Previous studies have reported factors correlating with MI performance such as visuospatial memory [6], personality [6], locus of control [7], and visual motor imagination [8]. However, each of these studies employed a slightly different BCI task and none have conducted a coherent and comprehensive analysis of cognitive and psychological factors that predict BCI illiteracy on a larger subject pool. Therefore, in this study, we aim to identify the cognitive profile and skillset that determine MI-BCI performance in novice users.

Material and Methods: Fifty-five novice participants took part in a two-class (left versus right hand movement) MI-BCI task with four runs (each 40 trials). In addition to the BCI task, the following questionnaires and tests were administered; 1) demographic questionnaire assessing gender, age, education, sports, music and game experience, 2) Vividness of Visual Imagery (VVIQ) measuring imagination ability, 3) Current Motivation (QCM), 4) Design Orientation Test (DOT) measuring visuospatial working memory, 5) Affinity for Technology Inventory (ATI), 6) Five-Factor Personality Inventory (FFPI), and 6) Mental Rotation Test (MRT) measuring the ability to rotate 3D objects mentally.

Results: Significant correlations were found between personality/cognitive factors and BCI performance in different runs. These factors include Orderliness, Autonomy and Vividness of Visual Imagery. Additionally, the performance could be predicted with linear models where Gender, Emotional Stability, Vividness of Visual Imagery and personality factors Orderliness and Autonomy were found as significant predictors of BCI performance. Finally, comparison between high and low BCI performers showed that high aptitude users had better visuospatial memory [9].

Discussion and Significance: The training to learn controlling a MI-BCI is time- and resource-consuming. Our findings reveal individual traits that might impact BCI performance and hence contribute to the possibility to predict a user's BCI aptitude earlier. The large subject pool and the unique combination of measured variables distinguish our study from previous research. Predicting users' success (or failure) on the basis of individual cognitive and psychological profile before the onset of training could avoid a loss of time and energy.

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Addressing between-session variability in MI-BCIs via Optimal Transport

Victoria Peterson[1*], Diego H. Milone[2], Dominik Wyser[3], Olivier Lambercy[3], Roger Gassert[3], Ruben Spies[1]

[1]Instituto de Matemática Aplicada del Litoral, IMAL, UNL-CONICET, Santa Fe, Argentina; [2]Instituto de Investigación en Señales, Sistemas e Inteligencia Computacional, sinc(i), FICH, UNL-CONICET, Santa Fe, Argentina; [3]Rehabilitation Engineering Laboratory, ETH Zurich, Zurich, Switzerland

*CCT CONICET Santa Fe, Colectora Ruta Nac. N° 168, Paraje El Pozo, 3000 Santa Fe, Argentina. E-mail: vpeterson@santafe-conicet.gov.ar

Introduction: Brain-computer interfaces (BCIs) based on electroencephalography (EEG) suffer from high signal variability. As a direct consequence, the performance of a BCI system can strongly differ across subjects and sessions. Between-session variability, due to changes at the level of the subject or the electrode position, leads to the need for re-calibration of the whole system before every use. One approach to tackle data distribution drifts is to use optimal transport for domain adaptation (OTDA) [1], in which a non-linear mapping is learned to make the distribution of the calibration samples "similar" to the testing distribution. Then, a new classifier is trained from the transformed calibration samples. In this work, we propose a backward formulation of OTDA in which the mapping is directly learned from testing to calibration data, avoiding classifier retraining.

Material, Methods and Results: We evaluated different OTDA alternatives in a 10 subjects motor imagery dataset with two classes (grasping movement vs. relax), acquired in two sessions (S1 and S2) [3]. In each session, a total of 160 trials (80 per class) were performed. We simulated a real adaptive scenario by taking S1 as the calibration set. As decoding algorithm, the traditional Common Spatial Pattern (CSP, with EEG patterns filtered between 5 and 30 Hz, 3 pairs of spatial filters) and a Linear Discriminant Analysis classifier were used [4]. OTDA was applied at the feature space level. Each simulated online testing run comprised 20 trials coming from S2. To learn the mapping, a subset of testing data, called here *transportation set,* was used. This set (with label information), was built using the N trials prior to the current testing run ($N = 20, \ldots, 140$). For both, the original (forward) as well our backward OTDA formulation, the regularized discrete version of optimal transport (OT-S) and its group-sparse version (OT-GL) [1] were implemented. For benchmark comparisons, we also evaluated the performance of a standard calibration (SC) method based on CSP without transfer learning, as well as with the adaptive method proposed in [5], named here as standard recalibration (SR). The overall accuracy across-subjects showed that our proposed backward *retraining-free* OTDA alternative can provide similar global performance as the retraining SR approach. In addition, our approach is about ten times faster than SR in making the adaptation.

Discussion: The proposed backward OTDA framework is a retraining-free model which is able to produce equivalent classification results as a complete re-training scheme. The simulated online testing scenario shows that OTDA could be a valuable alternative for rapid multisession BCI use.

Significance: Cross-session transfer learning can be conducted by domain adaptation based on optimal transport, in which the data distribution drifts between testing and calibration domains are learned.

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Poster Author Index

BCI Areas

A BCI Implant - Control

B BCI Implant - Other

C BCI implant- other

D BCI non-invasive - control

E BCI non-invasive - other

F BCI non-invasive- control

G Signal acquisition

H Signal analysis

I User aspects: experience, ethics

Poster Sessions

Poster Session 1 (7 June, 8am - 8:30am PST)

Poster Session 2 (8 June, 11:30am - 12pm PST)

Poster Session 3 (9 June, 7:30am - 8am PST)