BRAIN-COMPUTER INTERFACE RESEARCH AT COLORADO STATE UNIVERSITY

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1. The BCI Task

In our current work, our subjects do not attempt to exert control over some device. Instead, we simply ask them to perform various mental tasks. Our objective is to find patterns in their spontaneous EEG that reliably appear while they are performing one of the tasks.

Subjects were asked to perform the following five mental tasks.

Baseline Task: The subjects were not asked to perform a specific mental task, but to relax as much as possible and think of nothing in particular. This task is considered the baseline task for alpha wave production and used as a control measure of the EEG.

Letter Task: The subjects were instructed to mentally compose a letter to a friend or relative without vocalizing. Since the task was repeated several times the subjects were told to try to pick up where they left off in the previous task.

Math Task: The subjects were given nontrivial multiplication problems, such as 49 times 78, and were asked to solve them without vocalizing or making any other physical movements. The problems were not repeated and were designed so that an immediate answer was not attainable. Subjects were asked after each trial whether or not they found the answer, and no subject completed the problem before the end of the 10-second recording trial.

Visual Counting: The subjects were asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subjects were further instructed not to verbally read the numbers but to visualize them, and to pick up counting from the previous task rather than starting over each time.

Geometric Figure Rotation: The subjects were given 30 seconds to study a drawing of a complex three dimensional block figure after which the drawing was removed and the subjects instructed to visualize the object being rotated about an axis.

Data were recorded for 10 seconds during each task and each task was repeated five times per session. Most subjects attended two such sessions recorded on separate weeks, resulting in a total of 10 trials for each task.

2. EEG Components and Representations used

EEG from six electrodes at $C3$, $C4$, $P3$, $P4$, $O1$ and $O2$, was sampled at 250 Hz and filtered to 0.1-100 Hz. These six time series were divided into half-second segments that overlap by one quarter-second, producing at most 39 segments per trial after discarding segments containing eye blinks, identified by large voltage changes in an EOG channel.

Based on the success of others [Keirn and Aunon(1990)], we focused on signal representations based on AR models and on Fourier Transforms. In choosing an AR model order, we found that the AIC criterion is minimized for orders of two and three [Stolz(1995)]. However, based on previous results by Keirn and Aunon, an order of six was used. For one subject performing 10 trials of each of the five tasks, a total of 1,385 half-second segments were collected, with 277 segments from each of the five tasks.

To compare with the performance of the AR representation, a power spectrum density representation (PSD) was implemented using the same data segment of 125 samples, or one-half second, with a quarter-second overlap. Data segments were windowed with the Hanning window and a 125-point FFT was applied, resulting in a 63-point power spectrum density spanning 0 to 125 Hz with a resolution of 2 Hz.

We also generated reduced-dimensionality versions of the AR and PSD representations via a Karhunen-Loéve (KL) transformation [Jollife(1986)], in which the eigenvectors of the covariance matrix of all AR or PSD vectors are determined and the AR or PSD vectors are projected onto a subset of the eigenvectors having the highest eigenvalues. The key parameter of this transformation is the number of eigenvectors onto which each vector is projected. A common way to choose this number is to set it equal to the global Karhunen-Loéve estimate, given by the smallest index i for which $\lambda_i / \lambda_{max} \leq 0.01$, where the λ_i are the eigenvalues in decreasing order for $i = 1, 2, ...$

For the AR representation of all segments from the five tasks, the global KL estimate is 31, a small reduction from the original 36 dimensions of the representation. For the PSD representation, the global KL estimate is 21. This is a large reduction from the 378 dimensions of the PSD representation.

3. Neural Network Classifier

The classifier implemented for this work is a standard, feedforward, neural network with one hidden layer and one output layer, trained with the error backpropagation algorithm [Rumelhart et al.(1986), Hassoun(1995)]. The output layer contains five units, corresponding to the five mental tasks. Their target values were set to 1,0,0,0,0 for the baseline task, 0,1,0,0,0 for the letter task, 0,0,1,0,0 for the math task, 0,0,0,1,0 for the counting task, and 0,0,0,0,1 for the rotation task. After trying a large number of different values, we found that a learning rate of 0.1 for the hidden layers and 0.01 for the output layer produced the best performance.

To limit the amount of over-fitting during training, the following 10-fold, cross-validation procedure was performed. Eight of the ten trials were used for the training set, one of the remaining trials was selected for validation and the last trial was used for testing. The error of the network on the validation data was calculated after every pass, or epoch, through the training data. After 3,000 epochs, the network state (its weight values) at the epoch for which the validation error is smallest was chosen as the network that will most likely perform well on novel data. This best network was then applied to the test set; the result indicates how well the network will generalize to novel data. With 10 trials, there are 90 ways of choosing the validation and test trials with the remaining eight trials combined for the training set. Results described in the next section are reported as the average classification accuracy on the test set averaged over all 90 partitions of the data. Each of the 90 repetitions started with different, random, initial weights.

The neural networks were trained using a CNAPS Server II (Adaptive Solutions, Incorporated), a parallel, SIMD architecture with 128, 20 MHz, processors, upgradable to 512 processors. Training a neural network with a single hidden layer containing 20 hidden units (a 20-0 network) took an average of 3.2 minutes on the CNAPS, while on a Sun SparcStation 20, the same experiment took an average of 20 minutes. An experiment of 90 repetitions required 4.8 hours on the CNAPS and 30 hours on the SparcStation.

4. Results

Figure 1 summarizes the average percent of test segments classified correctly for various-sized networks using each of the four representations. For one hidden unit, the PSD representations perform better than the AR representations. With two hidden units, the PSD-KL representation performs about 10% better than the other three. With 20 hidden units, the KL representations perform worse than the non-KL representations, though the difference is not statistically significant.

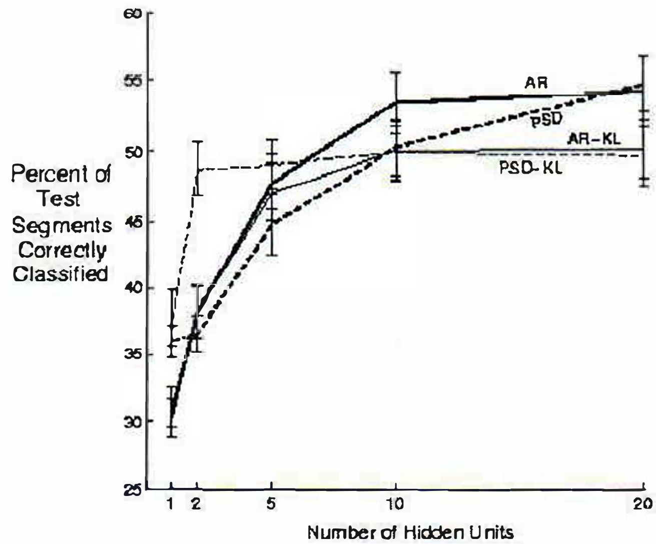

Figure 1: Average percent of test segments correctly classified. Error bars show 90% confidence intervals.

Inspection of how the network's classification changes from one segment to the next suggests that better performance might be achieved by averaging the network's output over consecutive segments. To investigate this, a 20-unit network trained with the AR representation is studied. The left column of graphs in Figure 2 show the output values of the network's five output units for each segment of test data from one trial. On each graph the desired value for the corresponding output is also drawn. The bottom graph shows the true task and the task predicted by the network. For this trial, 54% of the segments are classified correctly when no averaging across segments is performed. The other

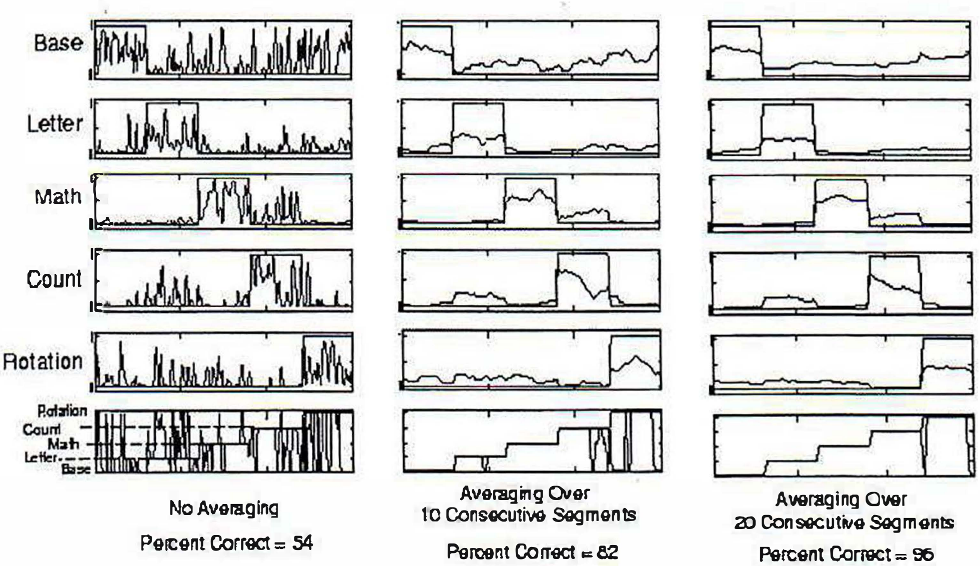

Figure 2: Network output values and desired values for one test trial. The first five rows of graphs show the values of the five network outputs over the 175 test segments. The sixth row of graphs plots the task determined by the network outputs and the true task. The first column of graphs is without averaging over consecutive segments, the second is for averaging the network output over ten consecutive segments, while the third column is for averaging over twenty segments.

two columns of graphs show the network's output and predicted classification that result from averaging over 10 and 20 consecutive segments. Confusions made by the classifier are identified by the relatively high responses of an output unit for test segments that do not correspond to the task represented by that output unit. For example, in the third graph in the right column, the output value of the math unit is high during math segments, as it should be, but it is also relatively high during count segments. Also, the output of the count unit, shown in the fourth graph, is high during count segments, but is also relatively high during letter segments.

For this trial, averaging over 20 segments results in 96% correct, but performance is not improved this much on all trials. The best classification performance for the 20 hidden unit network, averaged over all 90 repetitions, is achieved by averaging over all segments. Table 1 summarizes the significant information, showing that the AR representation performs the best whether averaging over 10 or 20 segments, but when averaging over 20 segments, the AR and AR-KL representations perform equally well. The PSD and PSD-KL representations do consistently worse than the AR representations.

	Percent Correct	
Representation	Averaging over 10 Segments	Averaging over 20 Segments
AR	68%	72%
AR-KL	65%	70%
PSD	65%	65%
PSD-KL	55%	57%

Table 1: Summary of performance on test data as average percent correct over 90 repetitions.

5. Future Plans

Our current work has three objectives. The results summarized here are not based on information about how EEG changes over time. One of our objectives is better classification accuracy through representations that include such temporal information. Therefore, we are continuing our exploration of various signal representations, including wavelets, independent component analysis, desynchronization, and coherence.

A second objective to our work is to develop tools to analyze and visualize what the neural networks are learning. We have found that by inverting the neural network, we can determine a set of fictitious EEG signals that the trained neural network would most strongly classify as one or another task. This gives us a sense of the discriminations the trained nets are making.

A third objective of our work is a portable EEG acquisition and analysis system will provide the type of classification results described here in real time. This would lead to an exciting biofeedback protocol in which the subject can modify how they perform a mental task while observing the system's classification confidence. Our hope is that even a small bit of training with such a system will result in increased classification accuracy.

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A VIRTUAL REALITY TESTBED FOR BRAIN–COMPUTER INTERFACE RESEARCH*

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1. The System

Recent BCI work has shown the feasibility of on–line averaging and biofeedback methods in order to choose characters or move a cursor on a computer screen with up to 95% accuracy [McFarland et al., 1993; Pfurtscheller et al., 1996; Vaughn et al., 1996; Farwell and Donchin, 1988]. Virtual reality (VR) promises to extend the realm of possible prototypes through allowing subjects to interact directly with the environment rather than a computer monitor while still maintaining environmental control. Furthermore, the safety of VR makes it an excellent candidate for BCI research on tasks such as driving.

The VR environment is rendered on a SGI Onyx with 4 R10,000 processors and an Infinite Reality graphics engine. A flexible program for graphics rendering enables researchers to easily switch environments. For immersion, subjects wear a head–mounted display (HMD) containing an eye tracker.

The heart of this system is a NeuroScan commercial package for EEG signal acquisition (called Acquire). After the EEG signal and trigger codes enter the Acquire program, they are grabbed from the acquisition buffer via a dynamic linked library (DLL) provided by NeuroScan. This library enables the locally written software to have access to the unprocessed data and trigger codes. The DLL is called from within a recognition and feedback program. This program chooses which data need to be sent for further processing via the Matlab program. This program may give audio feedback to the user after recognition occurs, send return information to the SGI through a serial port interface, save recognition data, calculate whether recognition has actually occurred (using trigger codes), and can read previously processed data from a Matlab file for a demonstration of the speed of recognition.

In order to enable easy use of different recognition routines, all routines are Matlab m–files. While compiled programs are faster than m–files, we have not had a problem with speed and find the general interface encourages the use of new computer algorithms for processing.

2. Assessment of Results

Several ways of assessing results are available. The most obvious is to analyze the EEG signals after a session. We use the NeuroScan analysis package as well as several locally written Matlab routines. On–line single trial EP recognition via different algorithms enables a direct assessment of BCI recognition abilities. During a session we record all visual data to videotape.

Our lab is also equipped with an eye tracker in the VR HMD. While the eye tracker is not necessary for BCI research, it may enable better analysis of results since subjects tend to look at what they're thinking about. It also allows comparisons between BCIs and eye tracking for particular subjects.

3. The Task

VR allows subjects to make on–line decisions in a dynamic environment. Thus, the best tasks for this environment involve interaction with physical objects. The flexibility of the VR environment allows a concentration on interface issues before building a BCI in the real–world.

To this end, we have used two environments; a driving environment to look at on–line driving issues and a two

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bedroom apartment in order to look at issues related to controlling appliances automatically as well as simple speech (see Figure 1).

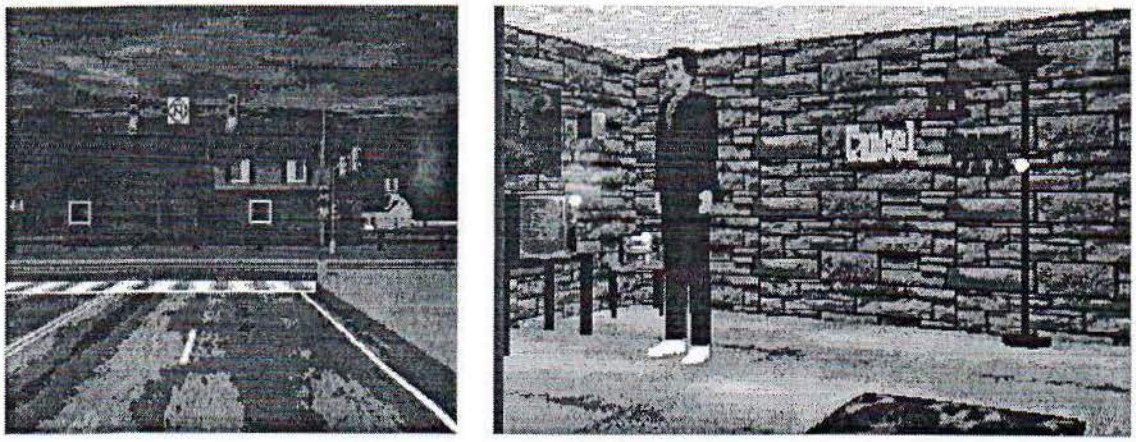

Figure 1. (Left) A typical stoplight scene in the virtual driving environment. (Right) The living room of a virtual apartment.

3.1. EEG Components Used

In order to test the feasibility of on–line recognition in the noisy VR environment, we recognized the P3 EP, discovered by [Chapman and Bragdon, 1964; Sutton et al., 1965]. It is a positive waveform occurring approximately 300–450 ms after an infrequent task–relevant stimulus.

Previous P3 research has concentrated primarily on static environments such as the continuous performance task [Rosvold et al., 1956]. In the visual continuous performance task, static images are flashed on a screen and the subject is told to press a button when a rare stimulus occurs or to count the number of occurrences of a rare stimulus. This makes the stimulus both rare and task relevant in order to evoke a P3. As an example, given red and yellow stoplight pictures, a P3 should occur if the red picture is less frequent than the yellow and subjects are told to press a mouse button only during the red light.

3.2. The Stoplight Experiment

We assumed a similar response would occur in a VR driving world if red stoplights were infrequent and subjects were told to stop their virtual cars at the red light. In order to make yellow lights more frequent, both green and red lights were preceeded by yellow lights. Red lights change to green after 3 seconds and the red light condition is triggered only when subjects are close to the stoplight so that subjects will have to begin stopping when the red light is triggered.

The subjects used a modified go cart in order to control the virtual car. We chose go cart driving because it is more like a "natural" driving task than driving and stopping with a mouse. While this choice may cause a more artifacts in the signal collection (due to turning the steering wheel and braking), most of the actual artifact in the data was discovered to be due to eye movement.

A trigger pulse containing information about the color of the light was sent to the EEG acquisition system whenever a light changed. While an epoch size from –100 ms to 1 sec was specified, the data was recorded continuously. Information about head position as well as gas, braking, and steering position were saved to an external file.

Eight electrodes sites (FZ, CZ, CPZ, PZ, P3, P4, as well as 2 vertical EOG channels) were arranged on the heads of five subjects with a linked mastoid reference. Electrode impedances were between 2 and 5 kohms for all subjects.

The EEG signal was amplified using Grass amplifiers with an analog bandwidth from 0.1 to 100 Hz. Signals were then digitized at a rate of 500 Hz and stored to a computer.

In order to determine that the P3 EP occurred only at red stoplights, we calculated the averages over red light and yellow light trials with trials where the subject ran a red light (approximately 2 per subject) removed. As expected, the data obtained while driving contained artifacts. In order to reduce these artifacts before averaging, we preprocessed the data and subtracted a combination of eye and head movement artifact using the linear regression technique described in [Semlitsch et al., 1986]. Results show that a P3 EP indeed occurs at red and not yellow lights [Bayliss and Ballard, 1999].

Table 1. Recognition Results ($p < 0.01$)

	Robust Kalman Filter %Correct		
Subjects	Red	Yel	Total
S1	55	86	77
S2	82	94	90
S3	74	85	81
S4	65	91	82
S5	78	92	87

Table 2. Return Subject Recognition Results

	Robust K- Filter %Correct		
Subjects	Red	Yel	Total
S4	73%	90%	85%
S5	67%	87%	80%

3.2.1. Results

While averages show the existence of the P3 EP at red lights and the absence of such at yellow lights, we needed to discover if the signal was clean enough for single trial recognition as the quick feedback needed by a BCI depends on quick recognition. We tried four methods for classification of the P3 EP: correlation, independent component analysis (ICA), a Kalman filter, and a robust Kalman filter. While all algorithms performed significantly better than correlation with the light averages ($p < 0.01$), we will only report the results of the best algorithm, the robust Kalman filter in Table 1. Approximately, 90 yellow light and 45 red light trials from each subject were classified. The reason we allowed a yellow light bias to enter recognition is because the yellow light currently represents an unimportant event in the environment. In a real BCI unimportant events are likely to occur more than user–directed actions, making this bias justifiable.

Data was preprocessed with the method described in the previous section. We used the robust Kalman filter framework formulated by Rao [Rao, 1997]. The robust Kalman filter is trained using red and yellow light averages from the maximal electrode site for obtaining the P3 for each subject. We used the whole trial epoch for recognition because it yielded better recognition than just the time area around the P3.

In order to look at the reliability of the robust Kalman filter two of the Subjects (S4 and S5) returned for another VR driving session. The results of this session using the robust Kalman Filter trained on the first session are shown in Table 2. The recognition numbers for red and yellow lights between the two sessions were compared using correlation. Red light scores between the sessions correlated fairly highly – 0.82 for S4 and 0.69 for S5. The yellow light scores between sessions correlated poorly with both S4 and S5 at around –0.1. This indicates that the yellow light epochs tend to correlate poorly with each other due to the lack of a large component such as the P3 to tie them together.

3.3. The Apartment Environment

The stoplight experiment showed that EPs could be reliably detected in a VR environment. In order to take full advantage of the benefits of VR, a two bedroom virtual apartment was constructed. Various items in the apartment perform a function. For instance, the light, tv, and stereo may turn on/off. Simple verbal utterances such as "hi" and "bye" may be said to the graphical figures in the apartment. In order to enable users to back up if they choose a wrong option, a "cancel" option has been installed.

3.3.1. An Apartment Communication Protocol

Since single trial P3 epochs are used in picking an option, we have adopted an interface design similar to that proposed by Farwell and Donchin [Farwell and Donchin, 1988]. In order to evoke a P3 they have constructed a matrix of flashing options. The idea behind this is that if a user wants to pick an option, (s)he will look at the box and a P3 will be evoked when the box infrequently flashes.

Our design differs in that the flashing "buttons" are actually connected to the objects they control or are on the wall of the apartment if there is no physical object involved in the command. In this way, the commands available at any one time are dependent on the context of the environment and the user may ignore certain commands by attending to another part of the room.

One basic reason for constructing this environment is that the user interface of the BCI may greatly affect recognition ability. A pilot experiment in the apartment seems to confirm this. Six different flashing options (detailed above) were available and flashed in a round robin fashion at approximately 1 every 4 seconds.

In a pilot experiment 10 tasks were attempted and 9 were completed. The average time for the completion of one simple task was 2.8 minutes. Now, at first glance this number appears horrible until one looks at the completion time for the tasks individually. If the two stereo commands accomplished are removed from the average, then the average completion time for one task drops to 1.1 minutes. The subject could not seem to pick the stereo command and eventually gave up trying to pick it on the tenth task. The reason for this appears to be the location/size of the stereo object.

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EEG RECOGNITION OF IMAGINED HAND AND FOOT MOVEMENTS THROUGH SIGNAL SPACE PROJECTION

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Abstract. EEG-based Brain Computer Interfaces require on-line detection of mental states from spontaneous EEG signals. This paper reports on the use of the Signal Space Projection (SSP) method as a classifier. SSP is applied to both raw and Surface Laplacian (SL) transformed EEG data from five healthy people performing three mental tasks, namely imagined right and left hand as well as right foot movements.

Keywords: Brain Computer Interface, Signal Space Projection, Surface Laplacian, Movement Imagination.

1. Introduction

It is well known that an EEG-based Brain Computer Interface (BCI) requires on-line detection of mental waveform patterns from spontaneous EEG signals. Several methods have been proposed to detect such patterns in the BCI framework. Here we report results obtained by applying the *Signal Space Projection (SSP)* algorithm [1,2] to EEG data from a group of five healthy people performing three motor-related mental tasks, namely imagined right and left hand as well as right foot movements.

Previously, it has been suggested that the use of *Surface Laplacian (SL)* transformations increases the recognition performance of an EEG-based Brain Computer Interface [3,4]. We also demonstrated that recognition scores of imagined movements increase if one analyzes the all 8-30 Hz band instead of the separate alpha and beta frequency bands [4]. Hence, in this study we report results by using the SL transformation applied spectral EEG data in the 8-30 Hz frequency interval. An important objective concerns the identification of a reduced number of channels for the SSP classifier to work. This is a critical issue in the design of a BCI: the fewer electrodes, the easier it is to operate by laypersons. Thus we have analyzed the results achieved using different number of electrodes placed over the fronto-central-parietal scalp areas.

2. Methods

The communication task.

The tasks used in this study consist in the imagination of the movement of left, right hand as well as right foot. Five healthy subjects (three male and two female) were recorded with 26 scalp EEG electrodes disposed over the scalp according to the extension of the 10-20 International system. Subjects were asked to imagine during 10 s the movement of the right middle finger or the left middle finger. As a control, subjects also performed actual right and left middle finger extensions during periods of 10 s each. Also, 10 s of rest EEG activity was recorded (subjects tried to relax with opened eyes) in between trials of actual and imagined movements.

The Signal Space Projection

In the Signal Space Projection method, the signals measured by n EEG electrodes are considered to form a time-varying vector M(t) in an n-dimensional signal space. Each component vector—i.e., the signals generated by a given neural source—has a fixed orientation in the signal space that, however, is different from each other. All the current configurations producing the same measured field pattern are indistinguishable on the basis of the field, and hence they have the same vector direction in the signal space and thus belong to the same equivalence class of current configurations. If the direction of at least one of the component vectors forming the measured multi-channel signal can be determined from the data, or is known otherwise, the SSP method can be used to simplify the subsequent analysis.

SSP, as well as Principal Component Analysis and related methods, may not require any source or conductivity model. No conductivity or source models are needed if the component vectors are estimated from data. Thus, SSP determines the patterns on which the recorded data will be projected directly from the measured signals. In contrast with Principal Component Analysis and other analysis methods, its source decomposition does not depend on the orthogonality of source components.

If M(t) is the *n*-dimensional time-varying vector, it can be stated [2] :

$$M(t) = S\,A(t) + N(t) \tag{1}$$

where the matrix S is formed by column vectors S_1, S_2, etc. that characterize time-independent spatial distributions. They are the "signal space components" of the signal. Each component $A_i(t)$ of the signal space waveform matrix A describes how the recorded EEG signals depend on the underlying sources over time. N(t) is the intrinsic system noise. The vector S_i contains all the information about the spatial distribution of the i^{th} equivalence class of sources, which is measured by the EEG array. The values of S_i can be determined from any conspicuous feature present either in the raw or Fourier transformed data. If N(t) is normally distributed, the unbiased estimate of A(t) is

$$\hat{A}(t) = S^{+} M(t) \tag{2}$$

where S^{+} is the pseudoinverse of S.

In this paper, we apply SSP to EEG spectral data in order to differentiate between three motor-related mental tasks, namely imagined right and left hand movements as well as right foot movement. To recognize mental tasks on-line from spontaneous EEG signals, we take short time segments (2 s) and estimate its log transformed spectral distribution. These data make up the matrix $M_{spectrum}(t)$. The three signal space components — or, just, spatial filters (S_1, S_2, S_3) — required to classify the incoming EEG measures are specific for every combination of channels and frequency bands. Individual spatial filters are obtained for every subject as the spectral estimation from 40 s of EEG activity while he/she was imagining a single movement (left or right hand, right hand). In our case, (2) becomes

$$\hat{A}(t) = S+ \text{Mspectrum}(t) \tag{3}$$

as $N_{spectrum}(t)$, the log transformed noise spectral distribution, is assumed to be normally distributed.

The EEG components used

Surface Laplacian transformation was applied to EEG data by using spherical spline of order 2 [5]. Previous results [4] led us to use the whole log-transformed spectrum from 8 to 30 Hz of the 6 centro parietal scalp electrodes (C3,Cz,C4,P3,Pz,P4) as well as of the 9 fronto-centro-parietal electrodes (F3,Fz,F4,C3,Cz,C4,P3,Pz,P4). The spectral estimation of each spatial filter, S_1 , S_2 and S_3, was calculated by means of the Welch procedure. Four 10 s blocks of Laplacian-transformed EEG data related to the imagination of right and left finger movement as well as foot movement were linked together and segmented into epochs of 2 s, with a 1 s shift. On each epoch a three half overlapping windowing, with windows 1 s long, was applied obtaining a resolution of 1 Hz. In this way we had, for each bin and for each channel, a number of spectrograms values depending on the epochs and windows overlaps. In order to obtain a reference spectrum to which normalize those values, the latter were averaged out along their epochs. In the end a log transformation was executed on all the spatial filters S_1 (imagined right motor task), S_2 (imagined left motor task) and S_3 (imagined foot motor task) to make them more spaced out.

3. Results

Fig.1 illustrates part of the spatial filters computed by means of the SSP method. In order to cover the whole cortex, these filters have been derived from all twenty-six electrodes. Also, for the sake of simplicity in the visualization, only the α band is used. The figure shows the distributions of the spatial filters in the subject RB for the imagined right and left movements as well as for the actual movements.

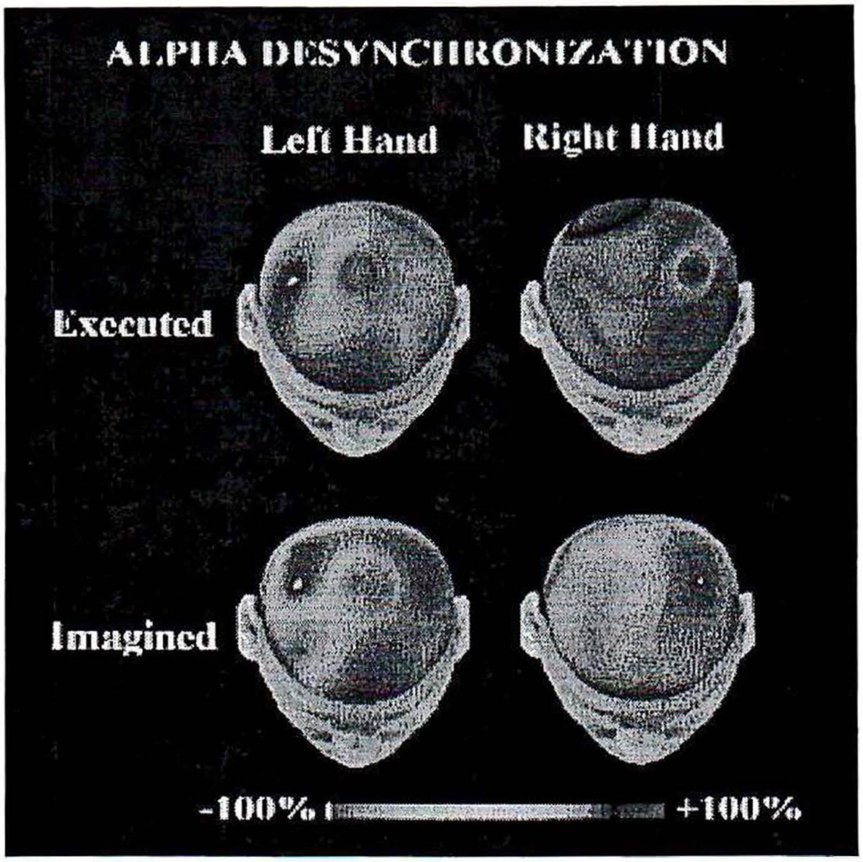

Fig.1. Representation of spatial filters in the αband, estimated from spectral data, registered using 26 channels set-up, for the subject RB

Note the similarity between imagined and actual distributions. Fig.2 (left) reports the averaged recognition rates of imagined right and left hand movements as well as imagined right foot movements using only the Surface Laplacian transformed data from the six centro-parietal electrodes. Results are shown for each of the five subjects investigated (CL, RA, MJ, RB, TA). Recognition scores for the detection of right imagined movements are in the range between 78% and 91%, almost the same obtained for left imagined movements (range between 77% to 90%) and for the right imagined foot movements (range between 80% to 92%). Fig. 2 (right) reports the averaged recognition rates of imagined right and left hand movements as well as the right foot imagined movements using all the nine fronto-centro-parietal electrodes. Results are shown for each of the five subjects investigated. For the right imagined movement the range of the recognition scores was between 85% to 95%, while for the detection of the left imagined movement the range was between 82 to 92% and for the right foot movement was between 81 to 97%.

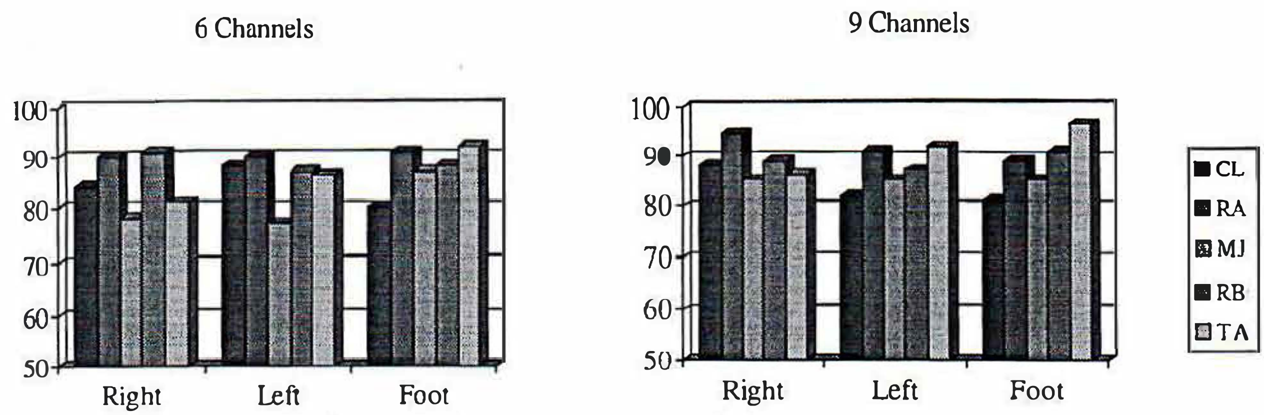

Fig. 2. (Left) Recognition scores obtained by using SSP classification from six electrodes)centro-parietal; C3, Cz, C4, P3, Pz, P4) and surface Laplacian transformation in five healthy subjects right hand, left hand and foot imagined movements. (Right) Recognition scores by using nine electrodes (fronto-centro-parietal: F3, Fz, F4, C3, Cz, C4, P3, Pz, P4) in the same subjects and in the same condition seen above.

Discussion and Future Plans

A critical issue in the design of BCI concerns the number of electrodes to be used; the fewer electrodes, the easier it is to operate by laypersons. This study has shown that six or nine electrodes, placed over fronto-centro-parietal areas, are sufficient to detect two mental states related to imagined movements with the SSP technique. This is a promising result that opens the possibility to deploy BCI outside laboratory settings. Since an accurate SL estimate from raw potentials needs many electrodes, it may be argued that there is a contradiction with the previous requirement of using as few electrodes as possible. Physical SL electrodes resolve this trade-off. Such SL electrodes are evaluated elsewhere [6].

To the best of our knowledge, this is the first time that SSP is applied to the recognition of mental states from EEG signals. Even though we have probably used the most elemental SSP-based classifier, the results achieved are quite promising. These results together with its computational simplicity make SSP particularly suitable for the on-line detection of mental states from spontaneous EEG signals. The simplicity of the classifier we have utilized suggests that it is still possible to increase the recognition rates if SSP is combined with more powerful classifiers. In particular, SSP can be used as a preprocessor for an artificial neural network. This is subject to ongoing research.

In this paper we have applied SSP to the recognition of motor-related mental tasks. Work in progress concerns the evaluation of SSP-based classifiers for cognitive mental tasks such as relaxation, cube rotation, and arithmetic.

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LAPLACIAN ELECTRODES FOR ADAPTIVE BRAIN INTERFACES

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1. Introduction

A major step in the direction of improving the quality of the recorded EEG data is the use of reference-free potentials instead of the reference-dependent potentials. In fact, it is well known that the potentialsgathered by conventional EEG systems are blurred by the activity of the reference electrode used [3-6].

In the framework of the design of an EEG-based brain-computer interface, Wolpaw and Mc Farland's results [1] suggest that EEG patterns can be better detected with EEG data transformed with Surface Laplacian (SL) computation than with the unprocessed raw potentials. SL transformation of EEG data has been largely used in brain-computer interfaces although the computation of SL requires the use of many EEG electrodes (typically 40-64). Such a necessity for a high number of electrodes is in contradiction with the requirement of portability and ease of use that a brain-computer interface device must exhibit to allow its operation by laypersons. Currently, in the framework of a joint European project, we are developing an Adaptive Brain Interface (ABI) device that uses a helmet with up to 8 electrodes and portable battery-driven amplifiers for the detection of several EEG patterns [7]. In this context, the trade-off between the need for reference-free EEG data and the constraint of a low number of electrodes leads to employ a particular class of concentric insulated electrodes that produce a signal roughly proportional to the SL computation of the recorded EEG. Such electrodes, previously introduced in the EKG field [8,9], are characterized by different values of inner and outer radii of the conductive rings. The aim of the study was to determine the optimal inner and external radii of such laplacian electrodes in order to produce a signal as close as possible to the computed SL. Results indicate that SL electrodes made of a concentric ring of 3 or 5 cm diameter return a SL signal very similar to the SL computed analitically. Hence, such SL electrodes could be successfully applied in all EEG recordings in which the number of electrodes prevents accurate numerical estimates of the Surface Laplacian, as in the case of brain-computer interfaces.

2. Methods

2.1 Surface Laplacian Electrodes

Two class of SL electrodes were built and used in this study. The first class of SL electrodes was designed with two conductive rings separated by a concentric insulated one. Such a design follows from the original proposal made in 1992 by He and Cohen [9] for the application of SL electrodes to EKG. Starting from the original measures for the inner and outer rings proposed by He and Cohen, we produced several SL electrodes with variable sizes. In particular, three types of coassial SL electrodes were built: type A with an inner radius of 8.5 mm and an outer radius of 10.5 mm; type B with 13.5 mm and 16.5 mm for the inner and outer radii, respectively; and type C with 15.0 mm and 18.5 mm for the internal and external radii, respectively. The Ag-AgCl material was chosen for all the implementation of the conductive rings of the SL electrodes. The coassial conductive rings were insulated by a ring of plastic material.

A second class of SL electrodes was also designed and tested in the present study. It relies on a conductive ring of variable diameter size surrounding a normal EEG electrode placed at the center of the SL electrode. Two sizes were used for the diameter of the outer ring of such SL electrode, namely 3, and 5 cm, respectively. The signal of interest in all the SL electrodes employed was picked up as a difference between the central and the outer ring signals. Fig. 1 shows an example of some of the SL electrodes developed and used in this study. It can be recognized from the figure the changes in size from the SL electrode originally proposed for the EKG (measure similar to the smaller electrode at the left of the figure) to the SL electrode composed by a conductive ring of 3 cm diameter size coupled with a standard EEG lead (right of the figure).

2.2 EEG Recordings and Surface Laplacian

Somatosensory Evoked Potentials (SEP), as obtained in response to a delivered electrical shock at the right wrist, were recorded by twenty three electrodes placed over the sensorimotor areas contralateral to the stimulated hand.

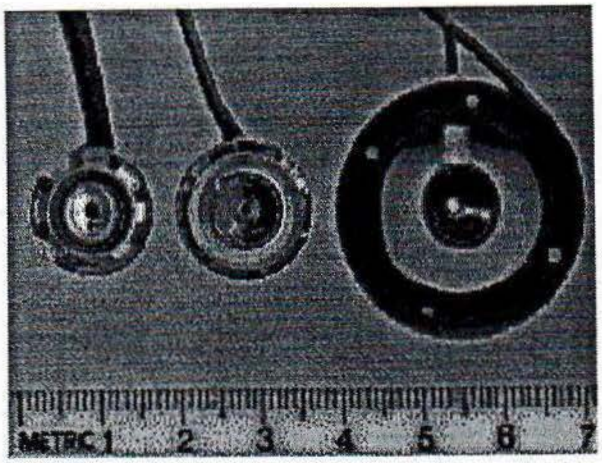

Fig.1. Some of the Laplacian electrodes used in the present study. On the left is presented the small SL electrode with a 1.5 mm of insulator ring between the two conductive ones. At the center is represented a larger coassial SL electrodes, while at the right there is the SL electrode composed by a circular ring of 3 cm diameter and a conventional EEG lead in the center.

The FC3 position was chosen as the site to place the different Laplacian electrodes, since in such a position a clear SEP response was expected. Separate recording sessions were conducted by changing only the Laplacian electrode at the site FC3. The computed SL estimation was based on the implementation of Hjiorth method, thus approximating SL with the second order finite differences of the scalp potential distribution [2,10]. To assess the agreement between the signal picked-up by the SL electrode and those produced by the numerical computation of the SL in the same recording we used the correlation coefficient.

3. Results

The practical montage of the small SL electrodes of type A, B and C—i.e., those concentric coassial electrodes with the insulated ring of 2 mm and 3 mm width—was very difficult due to the shunts produced by the conductive gel injected between the electrode and the scalp. In fact, the very small separation (2-3 mm) between the two conductive rings in the coassial SL electrodes of type A, B and C made the gel to spread out from the rings and produce a shortcut between them. However, with a very carefully montage such shunting effects were avoided and the reported results for the small SL electrodes refer to experiments free from such effects. Such a problem was not present in the recording of the second class of electrode, principally for the increased distance between the two conductive rings (1-3 cm). Fig. 2 gives an example of the quality of the recorded SEP data picked up from the rings of the SL electrodes. This figure shows waveforms from the external ring (Ring) and the central lead (FC3) of a SL electrode with a diameter of 5 cm, together with SEP waveforms recorded from the standard EEG leads surrounding the SL electrode. Such EEG leads are those used for the numerical estimation of the SL in the FC3 position. The labels for the waveforms presented in Fig. 2 correspond to those of the 10-10 International system. Table 1 reports the results of the correlation coefficient between the SEP signals recorded from all the SL electrodes employed in this study and the signal derived from the numerical SL on the same SEP recordings. The first row gives the value obtained for the correlation of unfiltered signals, while the second row provides the correlation values obtained by two of the signals filtered with a frequency bandpass between 1 and 350 Hz. It is worth noting that correlation coefficients lower than 0.3 were obtained for coassial SL electrodes of all three types—A, B and C—, what demonstrates their unfeasibility.

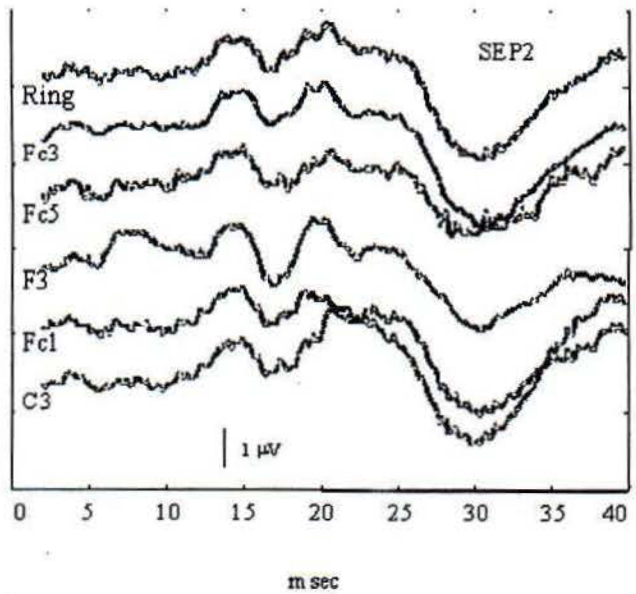

Fig. 2. An example of the quality of the recorded SEP data picked up from the rings of a SL electrode with a diameter of 5 cm. The waveforms relative to the conductive rings of the SL electrode are labelled with Ring for the external ring and FC3 for the inner ring. The other waveforms are relative to the electrode nearest to FC3 and used to compute the numerical SL in FC3. The label for these waveforms correspond to those used in the 10-10 International system.

Correlation values improve considerably for SL electrodes with concentric rings. In the case of a concentric ring of 3 cm of diameter, the correlation coefficient was 0.6. Even better was the value of the correlation coefficient for a concentric ring of about 5 cm of diameter. In this case, the value increased up to 0.82. It is also worth noticing that the correlation coefficient between the numerical estimation of the SL and the signal from the SL electrodes with a large diameter ring (3-5 cm) increased when low-pass filtering was applied to the recorded signals. For instance, in the case of the circular ring of 5 cm of diameter the correlation coefficient improved from 0.82 to 0.87.

Table 1. Correlation values between the numerical estimates of the SL and the signal provided by the different SL electrodes. SL electrode of type A was built with an inner radius of 8.5 mm and an outer radius of 10.5 mm, those of type B with 13.5 mm and 16.5 mm for the two radii, and those of type C with 15. mm and 18.5 mm for the internal and external radii, respectively. Other SL electrodes were built with a circular ring of 3 cm or 5 cm of diameter.

Correlation Coefficient	Type A	Type B	Type C	Ring diameter 3 cm	Ring diameter 5 cm
Raw	0.11	0.14	0.23	0.62	0.82
Filtered	0.13	0.15	0.23	0.64	0.87

4. Discussion

Results obtained in this study suggest that SL electrodes of type A, B and C (i.e., SL coassial electrodes with an insulation ring of 2-3 mm width) return waveforms poorly correlated with the numerically computed surface Laplacian. It is worth noticing that such electrodes presented measures of the inner and outer radii that were similar to those used successfully in the EKG field to produce reliable surface Laplacian waveforms. A possible explanation of this discrepancy in the results could rely on the different voltage of the EKG and EEG field over the torso and scalp, respectively. Such a different voltage is due to the existence of a highly resistive tissue between the cortical electrical sources and the sensors in the case of EEG, namely the skull, that is not present in the EKG case.

Different results were obtained with the SL electrodes made of a couple of electrodes, the central as a normal lead and the external as a circular ring of 3 - 5 cm of diameter. The large distance between the conductive rings prevent the shunting effects of the injected gel. The correlation between the data provided by this SL electrode and the numerical estimation of SL was rather good, reaching a value of 0.82 for the electrode with a concentric ring of 5 cm diameter. An even greater correlation was obtained by low-pass filtering the SEP waveforms with a maximum frequency of 350 Hz. A possible explanation for this results might be the higher sensitivity to the noise of the SL electrode with respect to the numerical computation of the SL. This figure can be improved by using low-noise amplifiers with more advanced characteristics than those provided by standard commercial EEG devices. However, for the purpose of the Adaptive Brain Interface, the band pass 1-350 Hz is adequate since the major part of EEG correlates of spontaneous mental processes are allocated in a frequency band not exceeding 70 Hz.

SL electrodes over 5 cm diameter were not investigated since the conductive rings are made of no-flexible material. This prevents its positioning on scalp areas with large curvature.

In the context of a Brain Computer Interface the use of the SL electrodes improves the quality of the acquired signals while, at the same time, limits the amount of electrodes needed to achieve it. In the case of the Adaptive Brain Interface (ABI) project where a battery-driven cap is planned with 8 electrodes, the use of SL electrodes will return SL EEG signals as if the number of electrodes were 20 or more. It is also worth noticing that by using 32 SL electrodes, EEG laboratories can work with signals of the same quality as if they were using 64 standard electrodes.

In conclusion, the proposed circular SL electrodes with a diameter of 5 cm return a signal roughly proportional to the numerical implementation of the surface Laplacian. Such electrodes could be usefully utilized in all the situations where the number of recording amplifiers was not sufficient to produce accurate estimates of the surface Laplacian.

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THE THOUGHT TRANSLATION DEVICE (TTD)

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The Communication Task

A communication device for the completely paralyzed was developed and tested by using an operant learning approach for the self-regulation of EEG signals. The procedure was tested in completely and partially locked-in patients: partially locked-in patients had rudimentary eye or muscle control, while completely locked-in patients had no voluntary function left. The device may prove to be useful in other severe communication disorders also because it allows to communicate without the language channel (i.e. in autistic syndromes). A detailed description of the device and the training procedure can be found in Kübler et al (1999), the results of two patients with amyotrophic lateral sclerosis (ALS) are described in Birbaumer et al (1999), the language support program is described in Perelmouter et al (in press), possible applications in severe communication disorders are discussed in Birbaumer (1999).

EEG components for the thought translation device

Slow cortical potentials (SCP) are used in the thought translation device to select letters or words from a language support program (LSP). Slow cortical potentials are shifts in the depolarization level of the upper cortical dendrites which are caused by intracortical and thalamocortical afferent inflow to neocortical layers I and layers II. Negative slow cortical potentials are the sum of synchronized ultraslow excitatory postsynaptic potentials from the apical dendrites. Positive slow cortical potentials are the result of a reduction of synchronized inflow to the apical dendrites or may be caused by inhibitory activity or by excitatory outflow from the cell bodies in layer IV and V. Our group has shown (Birbaumer et al, 1990) that positive slow cortical potentials lasting from 300 ms to several seconds or minutes are correlated with a disfascilitation of the involved cortical networks. Behavioral and cognitive performance improves after subjects or patients have learned to increase the negativity of the slow cortical potentials, while cognitive and behavioral performance is usually reduced during self-regulation of positive cortical potentials. Over the last 25 years our laboratory developed a psychophysiological model of slow cortical potentials and demonstrated in more than 100 published papers that slow cortical potentials can be instrumentally conditioned. After instrumental conditioning (self-regulation) of slow cortical potentials the behavioral and cognitive outflow from the involved cortical regions is improved or attenuated (see for a summary Birbaumer 1999). Slow cortical potentials are used for the thought translation device, because their neurophysiological basis is well understood, and the rules of the learned acquisition of slow cortical potential self-control are wellknown. Since slow cortical potentials indicate the overall preparatory excitation level of a cortical network, they are universally present in the human brain: in patients with extensive lesions or atrophy of the brain, such as in amyotrophic lateral sclerosis (ALS), slow cortical potentials can be recorded without much pathological deviations from most but not all cortical areas. The same is true for all known pathological conditions which may be candidates for brain-computer-communication, such as stroke, muscular dystrophies, autistic and schizophrenic disorders. In an extensive series of studies with neurological and psychiatric disorders, the pathophysiology of the self-regulation of slow cortical potentials was researched by our group and several therapeutic applications of the self-regulation of the slow cortical potentials were described, particularly in untreatable epileptic disorders (Rockstroh et al 1993, Kotchoubey et al 1997).

Patients

In the present report the results of six patients with advanced amyotrophic lateral sclerosis (ALS) is described. One patient did not continue training for motivational reasons, after discontinuation of training became depressed and died. Another patient who still had rudimentary muscular abilities discontinued training after several months of successful learning of slow cortical potential control. After a change in the training program he lost control over the slow cortical potentials, never regained control and lost motivation. From the three remaining patients two (published in Birbaumer et al 1999) acquired reliable slow cortical potential self-control and are now using the thought-translation-device for communication since several months. Both patients are artificially ventilated and artificially fed since more than 4 years, one has rudimentary control of a small face muscle for about 15 minutes, the other has some rudimentary control of eye movements, but only for a short period of time. The sixth patient (L.B.) is completely locked-in since one year, artificially fed and respirated, there are no eye movements or any other sign of muscular control. His eyes can be opened or closed only with assistance. Movements of the eye balls are irregular and cannot be used for communication. The relatives had not communicated with the patient for eight months. The sensory and mental capabilities of these patients is tested with a special sequence of electrophysiological tests developed by Kotchoubey in our group.

Apparatus and recording

A detailed description can be found in Kübler et al (1999), here only the most important aspects are mentioned. All experiments are taking place at the home of the patients with portable training devices which remain with the patients. The patients are lying in bed or sitting in wheelchairs. Conventional 16-channel EEG-amplifiers with a high time constant ranging from 3 – 16 s (dependent on the patients response) are used. EEG is recorded from the vertex relative to linked mastoids at a sampling rate of 256 Hz. Vertical eye movements are simultaneously recorded with standard on-line removal of eye movement artifacts. 8 mm Ag/AgCl-electrodes are fixed with an elefix electrode cream with an impetance of less than 5 kOhm. Electrodes are fixated with collodium and remain on the patient's head for several days before they are cleaned and reattached. Therefore patients have 24-hour access to the thought-translation-device. Slow cortical potentials are extracted from the regular electroencephalogram on-line, filtered, corrected for eye movement artifacts and fed back to the patient with visual or auditory feedback. Visual feedback of the SCP consisted of an updated EEG signal (every 64 msec) as a ball-shaped light that moves towards or away from the box which is highlighted when the patients had to produce a negativity (upper box) or a positivity (lower box) on a screen. In the case of auditory feedback a high or low pitched tone indicates the required SCP polarity and increasing or decreasing frequency of the tone provides feedback of the achieved negativity or positivity. An on-line classification system presents reinforcement to the patient by appearance of a smiling face or a melodic sound sequence. Usually the slow cortical potential after a 2 s baseline are fed back for another 2 seconds, if the patient achieves the required amplitude change reinforcement is provided and a new baseline interval begins. A training day usually consists of 6–12 sessions each of which comprised about 70-100 trials which last about 5-10 minutes. Patients are trained if possible on a daily basis, most of them received training every second day. Initiation of the baseline period is indicated by a high-pitched tone, initiation of the 2s feedback period is initiated by a low-pitched tone. Tones are presented in a rhythmic succession if necessary for 24 hours. The training procedure follows a <u>shaping schedule</u> in which progressively difficult amplitude changes are reinforced according to the past performance of the patients. Response criterion is usually increased from 5 to 8 μV. If stable performance of at least 75% correct trials is achieved the patients began to work with the language support program (LPS). With the exception of one patient who achieved 75% self-control after a few weeks of training only, all other patients had to be trained for several months before they achieved the criterion of 75% correct trials.

For the language support program (spelling device) at level 1 the alphabet is split into 2 halves (letter-banks) which are presented successively at the bottom of the screen for several seconds. If the subject selects the letter-bank being shown by generating a slow cortical potential shift, it is split into 2 new halves and so on, until each of the 2 letter-banks had only one letter in it. When one of the two final letters was selected, it is displayed on the top text field of the screen and a selection begins again at level 1. A "return function" which appeared as an option after two successive letter-banks allows the patient to erase the last symbol written in the text field. Figure 1 shows the accuracy of responses during feedback training, copy-spelling and free spelling for 2 patients, the curves are from Birbaumer et al 1999. Figure 2 gives a full letter written entirely by the brain of patient A in Figure 1. Patients are now switched to internet and e-mail, in order to help them communicate with the ALS community world-wide. All patients are video-documented during training and spelling, selective video sequences can be demonstrated.

Results

Figure 1 represents the result of 2 patients, one patient achieved 75% control after several months training but then discontinued training because he lost self-control of SCP after a program change. Despite 10 sessions of new training he never regained control. One patient with less advanced ALS (N.M.D.) discarded training for several reasons: the trainer made several mistakes during the training procedure, so that the patients received frequently false feedback. In addition, the patients will to live and to change from mask respiration to respiration through a trachiatomic device was low. He later refused to continue his life. Patient S.R. is of Turkish origin and never learned to read and write. He has more than 90% control of his slow cortical potentials and he is now selecting pictograms symbolizing his wishes and desires. The last patient was diagnosed as semi-comatic, his eyes have to be opened and closed mechanically, there was no communication possible between family members and the patient for more than 8 months. His mental status therefore was completely unclear. With an electrophysiological diagnostic procedure developed by Kotchoubey in our group, which presents increasingly complicated stimuli and language material, it was clearly found that the patient is fully capable of understanding and elaborating incoming auditory and tactile information. Before beginning training it was considered by doctors and family members to discontinue the life of the patient. He is now using a auditory feedback device and achieves more than 60-70% correct responses within a session. However, since his performance is not stabile he was not switched to the spelling device. His data will be available at the conference, video of this extreme case is also available (in European format).

The spelling speed in those patients who are now routinely spelling with slow cortical potential control is varying: for the letter presented in Figure 2, patient HPS needed 16 training days with 8 training sessions consisting of 100 trials each. The first letter ever written with the human EEG published in Birbaumer et al 1999 needed 16 hours at a rate of about 2 characters per minute. Communication speed can be considerably improved by presenting words and pictograms in the language support program. Despite the improved spelling speed all our patients refused to use pre-selected word sequences, because they felt less free in selecting and presenting their own intentions and thoughts. Therefore all patients with the exception of the Turkish patient are selecting letters on a rather slow speed. Since completely paralyzed patients have less time pressure, they all feel satisfied with the achieved communication speed.

Future plans

The thought-translation-device has to go on-line, a program which is using a windows surface is under construction. This internet version of the thought-translation-device should allow patients to communicate world-wide with their brain activity only. We hope that through this form of communication many ALS patients which decide against artificial respiration (and therefore dy) continue to live. Our as well as others work has shown that quality of life completely depends on the possibility to communicate with the social environment. Depression and quality of life scores are not different from healthy subjects after a period of half a year adaptation to artificial respiration. All reported data on life expectancy in respirated ALS patients should be interpreted with caution because health and life expectancy of these patients depends more on psychological variables influencing the immunological condition then on the course of the illness. With appropriate physical care, patients with the thought-translation-device remain psychologically healthy and therefore continue their life with a high quality of life over extended periods.

We see no need of an invasive procedure such as implanting electrodes in the brain or the skin because 24 hour self-control of slow cortical potentials and sufficient communication speed can be achieved with the completely non-invasive thought translation device. Because obviously a minority of patients do not show sufficient learning speed and success, the main future task will be the combination of the slow cortical potential thought-translation-device and the brain-computer-interface developed by Wolpaw, Vaughan and McFarland (1996) and Donchin's P300 methodology (Farwell & Donchin 1988). Also we intend to use some of the ideas presented by the Donchin group in Illinois in order to increase communication speed.

The combined thought-translation-device with the brain-computer-interface by Wolpaw and collaborators will then be tested on severely retarded and non-communicative autistic disorders with idio-savant characteristics (such as lightning-fast multiplication, eidetic memory, absolute pitch). The rational for this new application is described in Birbaumer 1999.

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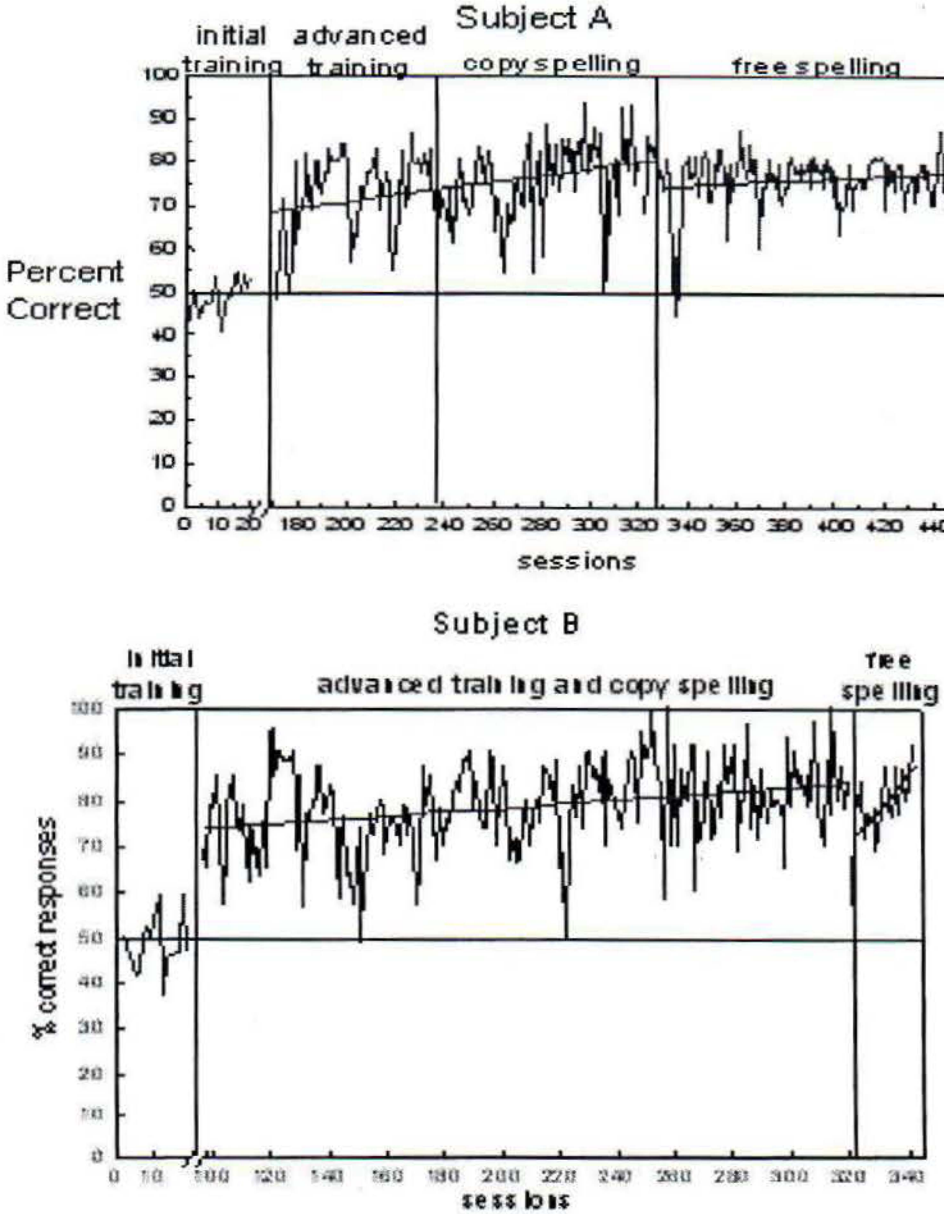

Figure 1 Response accuracy of subjects A and B across sessions. Subject A began with feedback training of SCP amplitude (initial and advanced training), proceeded to copy spelling (copying of letters and then words) and finally to free spelling (self-selected letters). Subject B began with feedback training (initial training), then switched to a combination of feedback training and copy spelling and finally to free spelling. Subject A: Correct selections were 71.3% for advanced training, 78.7% for copy spelling and 66.4% for free spelling. Correct rejections were 75.0% for advanced training, 75.3% for copy spelling and 82.9% for free spelling. For free spelling, correct selections and correct rejections were computed offline. Based on the final content of the sentence the patient had produced, correct and incorrect responses could be determined. Subject B: Correct selections for both advanced training and copy spelling were 77.5%, respectively, and for free spelling they amounted to 86.2%; correct rejections were 68.8% for advanced training, 67.6% for copy spelling and 73.7% for free spelling. (From Nature 1999)

Figure 2

SEHR-GEEHRTE-FRAU-LAHRTZ—WENN-ICH-DIE-ODER-DEN-RICHTIGEN-BUCHSTABEN-TREFFEN-WILL,MUSS-ICH-DEN-CURSOR-NACH-UNTEN-BEWEGEN,UND-DAS-VERSUCHE-ICH-DURCH-ENTSPANNEN-UND-ANSCHLIESSENDEM-ANSPANNEN-DES-GEHIRNS-INNERHALB-EINER-VORGEGEBENEN-ZEITSPANNE-VON-VIER-EINHALB-SEKUNDEN-ZU-ERREICHEN.—DAS-SCHREIBEN-IST-NICHT-SEHR-ANSTRENGEND,ABER-ES-FÄLLT-MIR-MANCHMAL-SCHWER,MICH-LÄNGER-ZU-KONZENTRIEREN.—DAS-WICHTIGSTE-AN-DIESER-NEUEN-MÖGLICHKEIT-IST-FÜR-MICH-MIT-EINEM-STÜCK-WIEDERGEWONNENER-SELBSTÄNDIGKEIT-VERBUNDEN.-ICH-KANN-WIEDER-ALLEINE-BRIEFE-SCHREIBEN-.-WAS-DIE-ZEIT-FÜR-DIE-BEANTWORTUNG-DER-FRAGEN-BETRIFFT,SO-HABE-ICH-WIE-AUCH-SONST-DIE-ENTDECKUNG-DER-LANGSAMKEIT-GEMACHT-.-ES-IST-VIELLEICHT-VERGLEICHBAR-MIT-EINEM-ERSTKLÄSSLER,DER-GERADE-DAS-SCHREIBEN-LERNT.-DAMIT-MÖCHTE-ICH-ZUM-SCHLUSS-KOMMEN-UND-SIE-NOCH-DARAUF-HINWEISEN,DASS-DIESER-TEXT-NUR-FÜR-IHREN-ARTIKEL-IN-DER-NZZ-GESCHRIEBEN-WURDE-UND-JEDE-WEITERE-VERWERTUNG-DURCH-SIE—ODER-DRITTE—MEINER-VORHERGEHENDEN-EINWILLIGUNG-BEDARF.—MIT-FREUNDLICHEN-GRÜSSEN—HANS-PETER-SALZMANN-

BRAIN COMPUTER INTERFACE RESEARCH AT THE NEIL SQUIRE FOUNDATION

G.E. Birch and S.G. Mason

Introduction

The Neil Squire Foundation is a Canadian non-profit organization whose purpose is to create opportunities for independence for individuals who have significant physical disabilities. Through direct interaction with these individuals the Foundation researches, develops and delivers appropriate innovative services and technology to meet their needs. Part of the Research and Development activities of the Foundation, in partnership with the Electrical and Computer Engineering Department at the University of British Columbia, have been to explore methods to realize a direct Brain-Computer Interface (BCI) for individuals with severe motor-related impairments. The ultimate goal of this research is to create an advanced communication interface that will allow an individual with a high-level impairment to have effective and sophisticated control of devices such as wheelchairs, robotic assistive appliances, computers, and neural prostheses. This type of interface would increase an individual's independence, leading to a dramatically improved quality of life and reduced social costs.

The main focus of our work has been the advanced signal processing of EEG signals. The techniques developed to date, the Outlier Processing Method (OPM) and the Low-Frequency Asynchronous Signal Detector (LF-ASD), have been design to automatically recognize single-trial, voluntary motor-related potentials (VMRPs) from scalp-recorded EEG signals with reasonable accuracy.

Overview of Work to Date

Outlier Processing Method

Our initial research effort was focused on developing, evaluating and improving the Outlier Processing Method (OPM) [1] [2] [3] designed to extract single-trial VMRP from EEG. The OPM uses robust, statistical signal processing methods to estimate the spontaneous (background) EEG from the one-dimensional observed EEG signal. The single-trial VMRP is then calculated as the difference between the observed EEG and estimated spontaneous EEG sequences. The heart of the OPM algorithm is a robust signal estimator that is used to generate the spontaneous EEG estimate from the observed process. This estimator treats the VMRP as a collection of (correlated) additive outliers and it uses robust statistics and time-invariant influence functions to remove these outliers from the observed sequence

Results from this work on the OPM were promising as hit rates of greater than 90% were achieved on a thumb movement task. However, its relatively poor performance on spontaneous, idle EEG (ie. false positive rates ranging from 10 to 30%) restricts its use as a BCI to environments where idle EEG is being controlled for by some other mechanism. This observation lead to the work described in the following section.

Low-Frequency Asynchronous Signal Detector

Our current research effort is primarily focused on developing an effective Asynchronous Signal Detector (ASD). Asynchronous signal detection is an essential function of an unsupervised BCI that has generally not been addressed by other researchers [4]. This is surprising since commands would be typically issued infrequently in many applications and it is unrealistic to expect the operator to consciously produce *do nothing* signals continuously at all other times. Based on extensive exploration of spatiotemporal characteristics [3] we developed an ASD based on new movement-related EEG features in the 1-4 Hz frequency band.

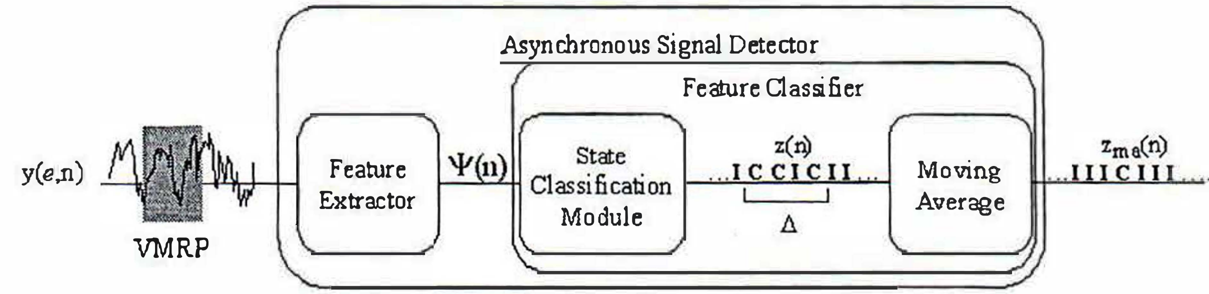

Figure 1. Components of the Low-Frequency Asynchronous Signal Detector. *y(e,n)* is the observed EEG signal at electrode *e* and discrete time *n*. Ψ(n) is the feature vector generated by the Feature Extractor. $z_{ma}(n)$ is the final classification sequence and the sequence, z(n), is the sequence of sample-by-sample feature classifications.

The LF-ASD design [5] [6], shown in Figure 1, was based the feature values defined by (1).

$$g_{ij}(n) = \sum_{k=-\infty}^{\infty} W(k) \cdot E_i(n+k) \cdot E_j(n+k) \tag{1}$$

where the elemental (2) features, E_i and E_j, which where defined by

$$E_i(n) = e_{k_i}(n+\alpha_i) - e_{k_i}(n+\beta_i) \tag{2}$$

$$E_j(n) = e_{k_j}(n+\alpha_j) - e_{k_j}(n+\beta_j) \tag{3}$$

and

$$W(k) = \begin{cases} 1 & E_i(n) > 0 \, and \, E_j(n) > 0 \\ 0 & else \end{cases} \tag{4}$$

In these formulae, $e_k(n)$ is the *k*th observed, bipolar EEG signal (filtered to 1-4 Hz).

In order to increase the robustness of the signal detection to trial-by-trial latency variation, these feature values were collapsed into the aggregate features defined by
where max() represents the maximum.

$$G_{ij}(n) = \max(g_{ij}(n-8), g_{ij}(n-7), .., g_{ij}(n+7)), \tag{5}$$

For our initial studies, a six dimensional feature vector was generated from six electrode pairs F_1-FC_1, F_z-FC_z, F_2-FC_2, FC_1-C_1, FC_z-C_z, and FC_2-C_2 positioned over the SMA and Sensory-Motor Cortex. The optimal feature dimensions are summarized in Table I. Note that during feature selection, the feature delay values for common electrode pairs (e.g., F_i-FC_i) were constrained to be equal (as seen in Table I). The aim of this constraint was to generalize the Feature Extractor to all types movements instead of optimizing it for our training data.

The LF-ASD Feature Classifier, using Learning Vector Quantization (LVQ3) [7], performed a sample-by-sample classification of each feature vector generated by the Feature Extractor. The output of the State Classification Module is denoted by z(n). The classification accuracy was found to improve when the z(n) values were averaged over time. We believe the reason for this was that the features vectors were over sampled because the optimal classification rate for this new feature set was not known. The result being temporally redundant information in neighboring z(n) values.

TABLE I

OPTIMAL FEATURE DELAYS (128 Hz SAMPLES)

	$E_i(n)$			$E_j(n)$		
	$e_{ki}(n)$	α_i	β_i	$e_{kj}(n)$	α_j	β_j
f_1	F_1-FC_1	-1	+25	F_1-FC_1	0	+50
f_2	F_z-FC_z	-1	+25	F_z-FC_z	0	+50
f_3	F_2-FC_2	-1	+25	F_2-FC_2	0	+50
f_4	FC_1-C_1	-1	+15	FC_1-C_1	-12	+30
f_5	FC_z-C_z	-1	+15	FC_z-C_z	-12	+30
f_6	FC_2-C_2	-1	+15	FC_2-C_2	-12	+30

The LF-ASD was initially evaluated on five able-bodied subjects who were tasked with changing the direction of the centre ball in the pong style display shown in Figure 2 by executing a non-standard right index finger flexion. The subjects worked on a trial-to-trial basis, where the start of each trial was controlled by an automated system. Refer to [5][6] for details.

The LF-ASD demonstrated false positive (FP) error rates of less than 5% and hit rates as high as 78% on this asynchronous signal detection task. These error rates were significantly lower than the Outlier Processing Method and a mu-rhythm power classification algorithm on the same task. Although feature model parameters determined for one subject worked reasonably well on other subjects, performance was found to significantly improve by customizing the features. This customization allows the LF-ASD to be optimized for individual differences in brain patterns. We also demonstrated that by pairing the LF-ASD with other BCI techniques, we could significantly lower the FP rate of OPM and a mu-rhythm based classifier [5] [6].

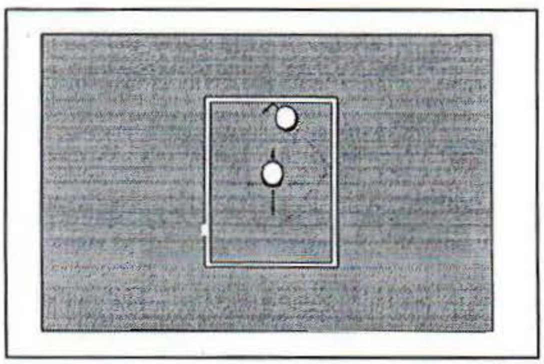

Figure 2. Experimental display

On-Line Implementation of the LF-ASD

Our most recent study implemented an on-line version of LF-ASD [8]. In this system, EEG was continually classified for the same control task defined above. The only time the subjects were not controlling the display was when a monitoring system detected ocular artifact.

The on-line system was tested on two right handed male subjects who each participated in three sessions [8]. During each session, the ASD was trained on 25 (artifact-free) movements and tested on 75 movements during the operating phase. The LF-ASD continuously monitored and classified the EEG and the subject received visual feedback one second after a detected movement or if a false positive occurred. The on-line performance with the two new subjects demonstrated hit rates in the range of 50% while maintaining FPs to a very low level (for subject 1: between

1-2% and for subject 2 between 3-6% for first two sessions and 10% for the last session). In terms of overall correct decisions, given that the system was making an idle or active classification every 1/8 of a second, the average performance over both subjects and all three sessions was over 95%. The results also indicated that subject training can occur rapidly as the number of hits approximately doubled for each subject in the second session. In addition, these results were all obtained using a feature model based on a prior subject. Based on the indications to date we would expect the performance to improve significantly with customization and further subject training.

It was interesting to note that in this on-line study, both subjects reported that many of their false positives were detected when they thought about making a movement but did not execute one. This appeared to happen far too often to be due to chance, but we have not yet had the opportunity to investigate this phenomenon any further. However, it provides some very preliminary evidence that it may be possible to activate our ASD simply by planning a movement. This observation is also consistent with the recent work by Pfurtscheller where their subjects used only imagined movements [9]. Given the promising results that we have obtained to date with able-bodied subjects, we are now in the early stages of developing a methodology to test our approach on persons with a high level spinal cord injury.

Future Work

The introduction of the LF-ASD provides the first step towards a critically needed component of unsupervised BCIs. Our current research plan has five stages.

- Stage 1 - Test the following hypothesis: Individuals with a spinal cord injury (SCI) can control our existing techniques as well as able-bodied individuals.
- Stage 2 - Develop methods that will automatically customize the BCI to a subject during a training period. We hypothesize that this is possible based on our ability to manually adjust the ASD system model for able-bodied subjects.
- Stage 3 - Test the following hypothesis: With training, subjects with a SCI can learn to control our BCI techniques to the same degree as able-bodied subjects.
- Stage 4 - Test the following hypothesis: Our ASD method can reliably discriminate idle state from multiple control states.
- Stage 5 - Test the following hypothesis: The statistical characteristics of attentive idle EEG is significantly different from those of non-attentive idle EEG for both LF-ASD features and mu-power features.

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ROBOTIC CONTROL FROM REALTIME TRANSFORMATION OF MULTI-NEURONAL POPULATION VECTORS

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To investigate the possibility of controlling robotic devices from brain-derived neural population vectors, up to 46 neurons were simultaneously recorded in the forelimb motor cortex, ventrolateral thalamus and/or cerebellum of eight rats trained to obtain water by moving a bar to position a robot arm under a water dropper. These neuronal signals were then electronically weighted and integrated into a realtime brain-derived signal whose timing approximated the onset of bar pressing movement. In recording experiments, control of the robot arm was suddenly switched from the bar press to the brain-derived signal. Four rats successfully used this signal to position the robot arm and obtain water rewards. Over continued training using the brain-derived signal to control the robot arm, the bar-pressing movements steadily diminished or changed their character, indicating a dissociation from the forelimb movements they originally encoded. Various mathematical techniques were investigated to further improve the selectivity and temporal resolution of these brain-derived population vectors. Discriminant analysis was used to derive selective linear weighting functions that successfully encoded limb flexion and extension in multiple dimensions. Moreover, artificial neural networks were used to transform the normally phasic brain-derived signals into control signals that successfully replicated the timing and magnitude of whole limb movements. Thus, brain-derived signals can be used as direct surrogates for operant movements, or with further training, to ultimately replace such movements. Such signals might be therefore be useful for controlling prosthetic devices.

THE MENTAL PROSTHESIS: ASSESSING THE SPEED OF A P300-BASED BRAIN-COMPUTER INTERFACE

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(Presented at the Society of Psychophysiological Research, 1998, Denver, Co.)

Introduction

Farwell and Donchin (1988) described a Brain Computer Interface (BCI; Vaughan, Wolpaw, & Donchin, 1996) that exploited the properties of the oddball paradigm to allow a user to communicate a sequence of letters to a computer by observing a continually displayed matrix of characters (Figure 1), and focusing attention successively on the characters to be communicated.

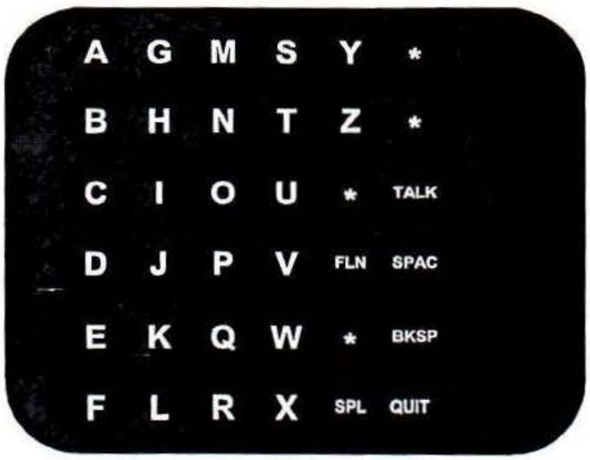

Figure 1 Display presented to the subject. The rows and columns of the matrix are intensified in a random sequence for 100 msec.

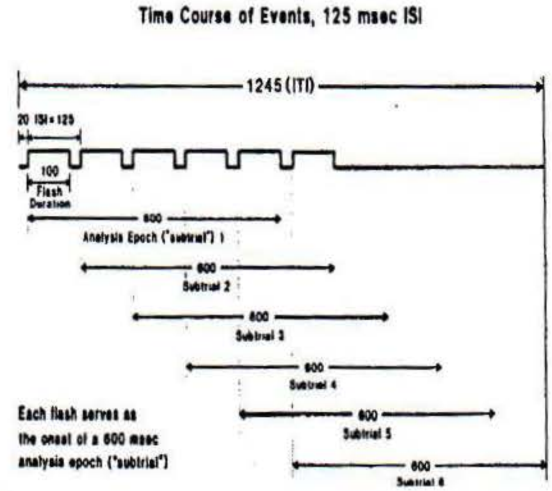

Fig 2. Sequence of events in a trial (From Farwell and Donchin, 1998).

An oddball sequence was produced by intensifying, in a random sequence, each of the 6 rows and 6 columns of the matrix. Each intensification lasted 100 ms, with and SOA of 125ms. The interval between trials (6 row and 6 column intensifications) was 1500ms. (See Fig. 2 for details.)

Farwell and Donchin hypothesized that the rows and columns that contain the character to which the subject is attending will constitute a distinct category among the stimuli and, being rare, will elicit a P300.

The BCI used the following procedure:

1. Obtain a 600 ms record of the EEG following each of the intensifications.
2. Compute the ERP associated with each row and with each column.
3. Intensifications of the row and column containing the target character elicit easily detectable P300s.
4. No P300s are elicited by the intensifications of rows and columns that do not contain the target.

The P300 was easy to detect when the data associated with 40 trials were averaged. Thus, 100% correct communication can be achieved if enough time is allocated for each character. Naturally, a practical BCI should provide faster communication. The speed depends on the number of trials required for an accurate detection of the P300 (see Table 1).

N trials	1	2	4	5	16	32
Communication rate Items per minute)	40	20	10	5	2.5	1.25

The Current Study

Under the circumstances of the system used by Farwell and Donchin (1988), the system was able to operate at maximum rate of about 8-10 characters per minute. While under some circumstances this is an acceptable rate, it was our goal to capitalize on the increased computational power currently available to determine if we can improve the rate of transmission. The current BCI was implemented in a Wintel system, using a Gateway 2000 PC.

Figure 3. Revised version of display. Note the elimination of the replacement of operating codes with the nine digits.

Methods

Subjects

10 able-bodied (6 female) and 4 disabled subjects (wheelchair-bound; 3 with complete paraplegia, 1 incomplete paraplegia; 2 female) from the university community participated in the experiment.

Stimuli and Procedure

1. Stimuli and procedures were the same as in Farwell and Donchin (1988; see Introduction).
2. A modified version of the display was used (Fig. 3).
3. A trial is a sequence of 6 row and 6 column intensifications.
4. Inter-trial interval was 2500 ms (1500 ms + 1000 ms pause, inserted for technical reasons).
5. Subjects were instructed to count the number of times the row or column containing the target letter "P" was intensified.
6. P(Target) = 2/12 = 0.167
7. Each subject performed 5 blocks of 15 trials each.

Data Acquisition and Processing

1. EEG was recorded with Biologic amplifiers (0.01 - 100 Hz passband, 200 Hz digitization).
2. Electrode sites were Fz, Cz, Pz, O1, O2, and right mastoid, referenced to left mastoid, re-referenced off-line to averaged mastoids.
3. Vertical and horizontal EOG artifacts were removed from the EEG by an eye-movement correction method.

Single-trial epochs for each cell of the display matrix were derived by averaging together each combination of row and column single-trial epochs. Thus, there were 6 rows X 6 columns = 36 epochs for each trial.

Grand Average ERPs

As can be seen in Fig. 4, the targets elicit a large P300. The ERPs for "Target Letter" were associated with the cell at the intersection of the correct row and correct column. The ERPs for "Target Row/Column" were associated with the cells at the intersection of the correct row or column, and an incorrect column or row, respectively

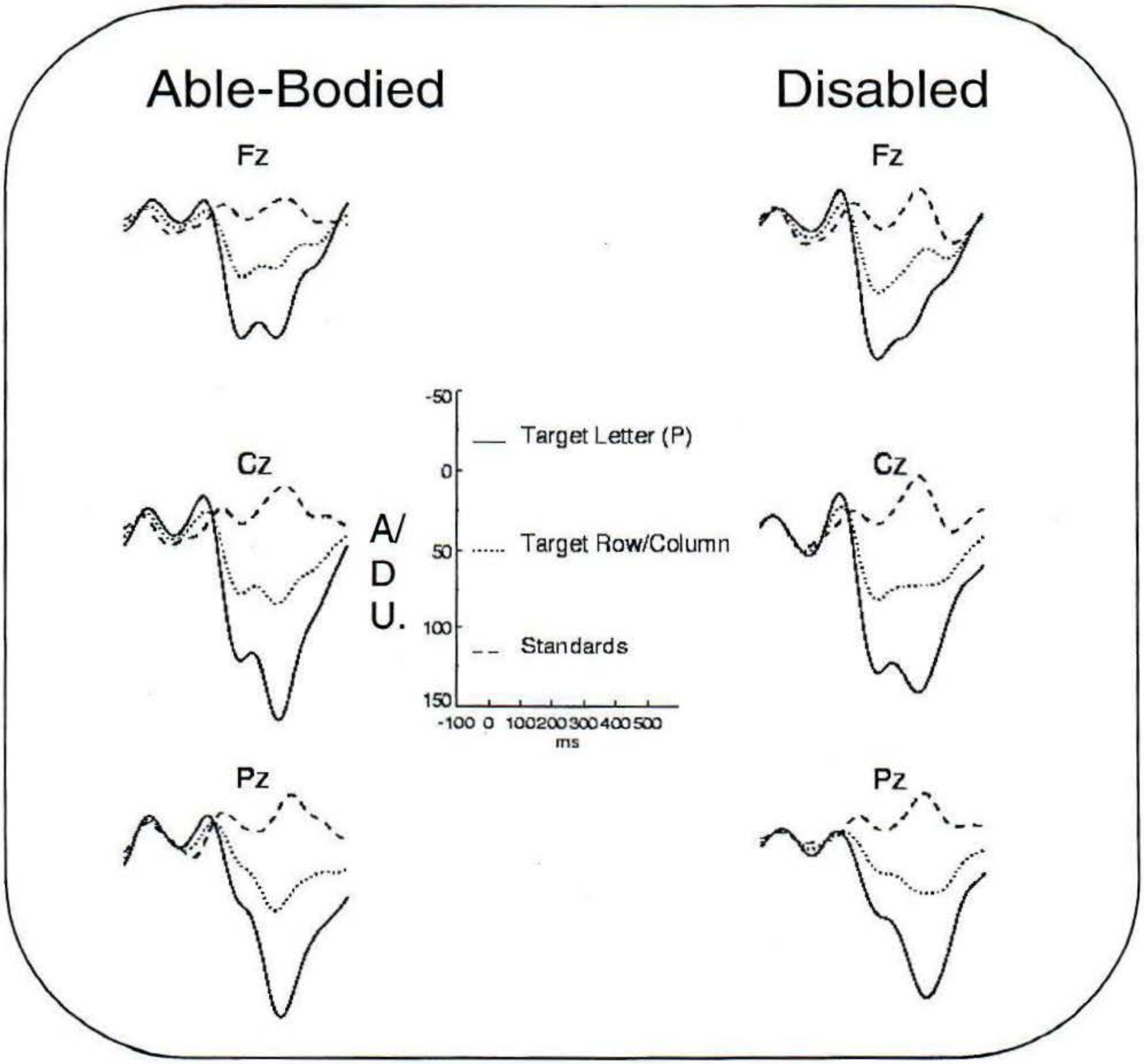

Fig.4

Bootstrap Analyses

Stepwise discriminant analysis (SWDA) was applied to a data set constructed by bootstrapping to assess the accuracy with which the target cell was detected as a function of the number of trials used for averaging. This procedure was applied with two pre-processing methods:

1. SWDA: Single-trial cell epochs were filtered at 0-8 Hz and resampled at 50 Hz, yielding 30 timepoints for the 0-600 ms period of each epoch.
2. SWDA/DWT: Single-trial cell epochs were filtered at 0-50 Hz and resampled at 50 Hz, yielding 32 time points for the 0-640 ms period. These timepoints were converted to wavelet coefficients with the Discrete Wavelet Transform (DWT).

Bootstrapping Procedure

To assess the accuracy given N trials (see Table 1), repeat the following procedure 1000 times:

1. Obtain a random sample of N trials for each cell by sampling w/replacement from the set of 75 trials.
2. Compute the average of N trials for each cell.
3. Apply SWDA to the set of cell averages.
4. Compute the discriminant score for each cell.
5. Select the cell with the maximum discriminant score.
6. If the selected cell is the defined target cell, count a hit, otherwise count a miss.

When done, record the percentage of hits among the 1000 samplings. This is the percent accuracy at the communication speed determined by the N trials.

(These values assume that the BCI can proceed with no delay between trials. In the current implementation of the BCI, technical considerations dictated a 1000 ms pause between trials.)

Table 2

		Accuracy Level	
Subject	**Pre-processing**	**80%**	**95%**
Able-Bodied	**SWDA**	**6.3 items/min**	**3.4 items/min**
	SWDA/DWT	**7.8 items/min**	**4.3 items/min**
Disabled	**SWDA**	**4.8 items/min**	**2.8 items/min**
	SWDA/DWT	**5.9 items/min**	**3.2 items/min**

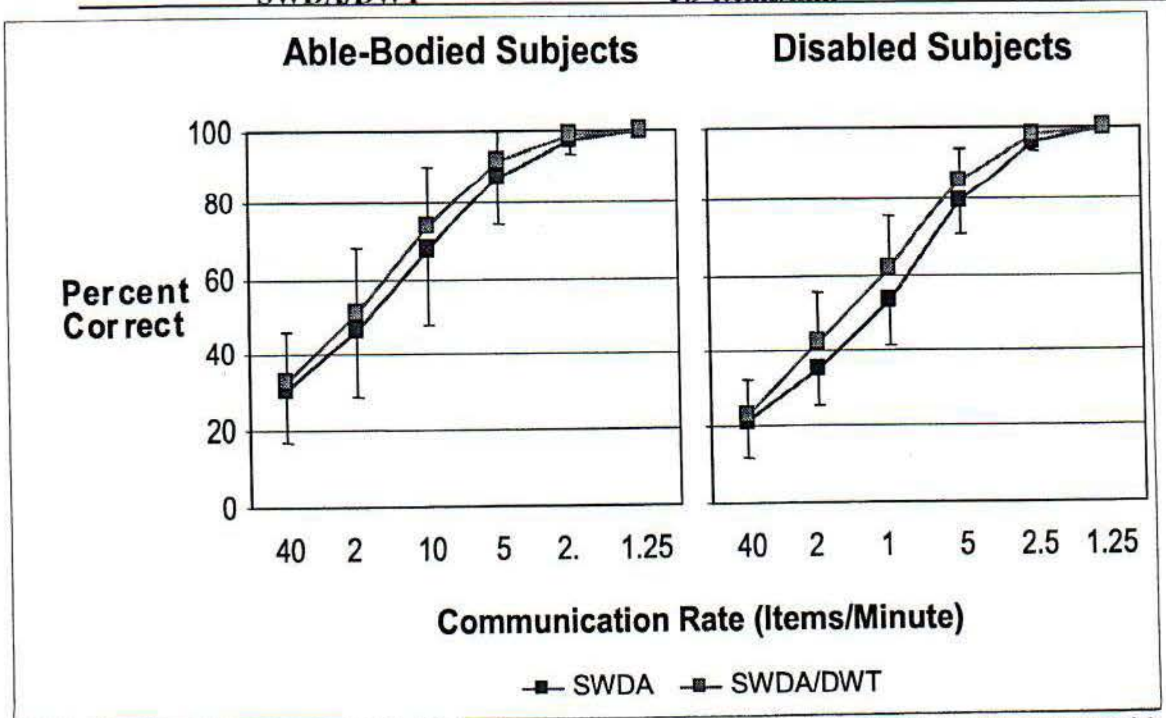

Figure 5: Faster communication rates were obtained with the Able-Bodied subjects than with the Disabled subjects. Furthermore, the SWDA/DWT pre-processing method produced somewhat faster communication rates than the SWDA method. (See Fig. 5 and Table 2.)

Online Test

Five of the 10 able-bodied subjects participated in a test of the ability of the BCI to detect characters online and in real time.

Each subject was run first in the bootstrap analyses to calibrate the BCI (see above). In the online test, each subject selected successively 5 individual characters. Using discriminant scores based on the number of trials required to reach 90% accuracy in the SWDA analysis, the BCI selected a character which appeared to match the character selected by the subject. The logical flow is presented below (Fig. 6):

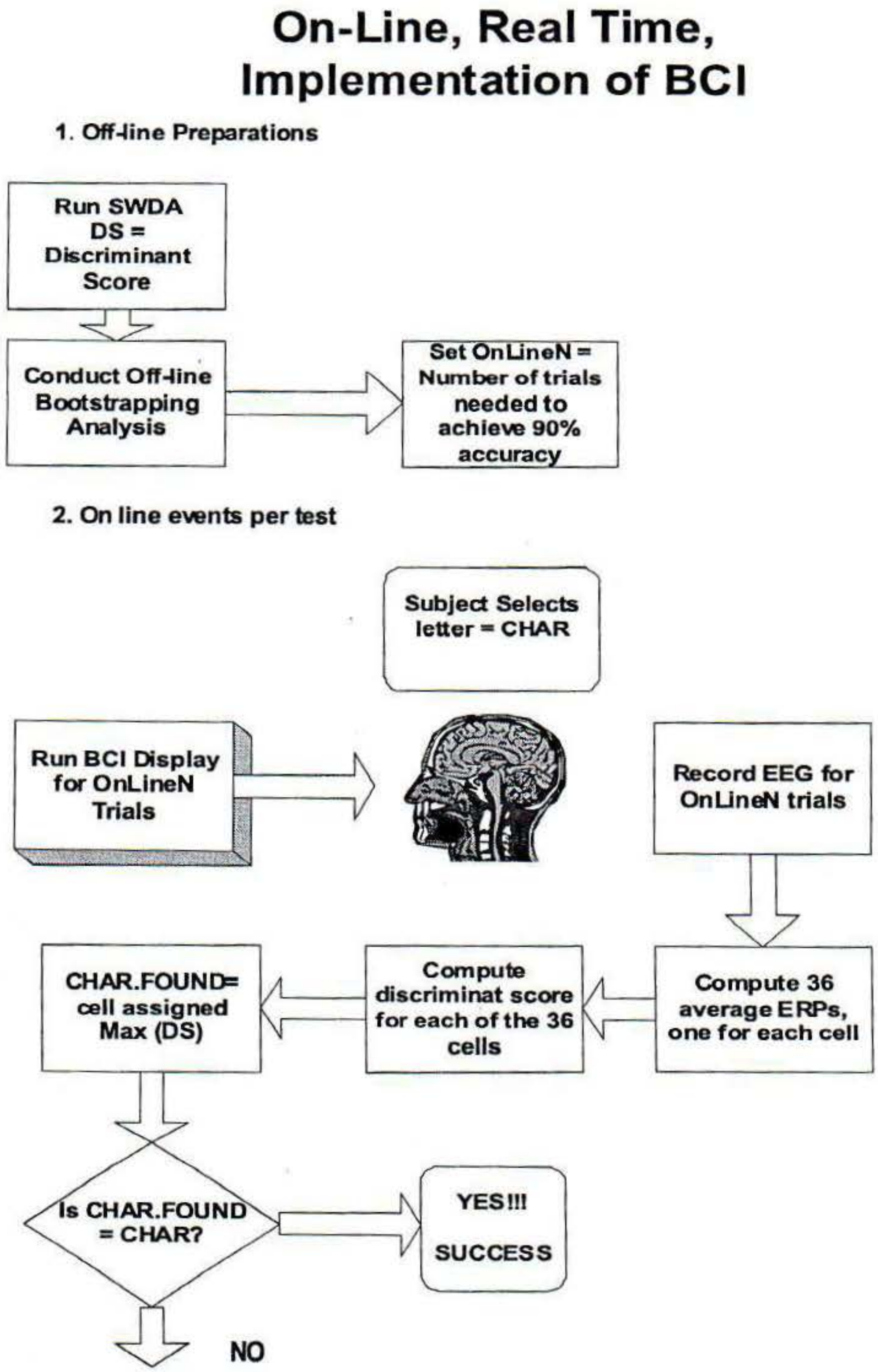

Figure 6

Online Test Results

Averaging the number of trials that produced 90% accuracy in the SWDA analysis for the online test, the BCI identified the cell to which the subject was attending 56% of the time. On 36% of the cells, the BCI chose the correct row or column. For only 8% of the cells the BCI chose incorrect row/column combinations. (See Table 3.)

Correct Cell	Correct Row/Column	Incorrect Cell
56 %	36 %	8 %

Table 3

Conclusions

We confirm the report by Farwell and Donchin (1988) that it is possible to construct a Brain Computer Interface that, using the P300, allows an individual to operate a virtual keyboard without using or requiring any activation of skeletal muscles.

The speed of the BCI used in this study is substantially faster than that used by Farwell and Donchin. The factors accounting for the speedier action are:

1. Improved SWDA algorithms in commercially available packages.
2. The use of the Discrete Wavelet Transform.
3. The application of the Discriminant function to the 36 individual cells.

The current study also tested the feasibility of the P300 based BCI with wheel-chair bound individuals with encouraging results.

Assessment

In evaluating the speed of the P300-based BCI it is important to recall that the device is intended for use by individuals who are completely disabled. As a base of comparison one needs to use the communication method used by Bauby (1997), a "locked-in" patient, to write his book, "The Diving-Bell and the Butterfly".

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REAL-TIME CONTROL OF A CORTICAL NEURAL PROTHESIS

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Brain Computer Interfaces primarily use non-invasive devices – EEG-based methods - to interact with the central nervous system. Since the 1960's, with the development of the phrenic nerve stimulator, implantable devices that interact with the peripheral nervous system have been widely accepted. More recently, as signified by the FDA approval of a deep brain stimulator for movement disorders, interest has shifted towards direct communication with the brain. Research being conducted at Arizona State University, as a part of the NIH's Neural Prosthesis Program, is developing a cortical motor prosthesis. The goal is to design a system to record and analyze the activity of neurons in the motor cortex, and implement this as a control system for a robotic arm. One potential benefit of this type of system includes a more accurate and versatile means of manipulating an artificial limb. We have demonstrated, in an initial step, the feasibility of this approach.

Neurons in the cerebral cortex typically display broad cosine tuning, and those in the motor cortex have been shown to be broadly tuned to the direction of hand movement. These neurons will fire most rapidly for movements in their 'preferred direction', and least when movements are in the opposite direction. Knowing the parameters that describe a given neuron, very little information about of the action of the hand can be derived. When analyzed as a population, using a population vector or pattern recognition, a reconstruction with a high correlation to the true instantaneous velocity of the hand can be formed. The foundation of this work has been established using single-unit recording techniques; the same level of accuracy has yet to be proven in real-time using multi-unit recording. Technological advances are improving the ability to record and process the activity of multiple cells simultaneously. Concomitant with this, analytic techniques designed to extract information inherent in simultaneous recordings are making it possible to extract the information encoded in the neural signal with fewer numbers of cells. With this, we are progressing towards the goal of online robotic control.

When a large number of neurons is present, a vector sum of weighted preferred directions (a population vector) should well describe the task being performed. With fewer, relatively noisy cells, pattern recognition can provide a better estimation of the information present in the cortical signal. A new method is being developed to use a principal component analysis (PCA) to find the patterns of co-activation that can identify the ensemble activity throughout each movement. To do this, the cross-covariance of each neuron's activity with one another is calculated. After performing the PCA, the eigenvectors of the covariance matrix illustrate the patterns that best identify the group activity at any given moment. Once new cortical activity is related to known movements, an instantaneous velocity can be assigned.

Rhesus monkeys, implanted with chronic electrode arrays, were trained to perform a 3D center-out reaching task in a cubic workspace. Normalized neural activity from over 30 task-related, simultaneously recorded neurons was grouped to find the temporal patterns of co-activation. A PCA was employed to define these patterns and reduce the data to a handful of unique identifiers. This constituted the calibration process. Every 20ms, a sliding window of activity from all of the neurons was multiplied by the previously derived eigenvectors. This new set was compared with the training data in principal component space. The instantaneous velocity from the training data set to which the new data most closely matched was assigned for that time instant. No velocity was given if the pattern matched a point in time not associated with movement. Adding these velocities tip-to-tail formed the trajectory.

The system used to access the neural activity and the chronic electrode arrays were available commercially. Recordings from each microwire in the electrode assembly (NB Labs, Denison, TX) were obtained using a JFET buffer amplifier that connects to a multi-channel neural recording system (Plexon Inc., Dallas, TX). The recording system provided channel-selectable, variable gains (up to 30,000x) and bandpass filtering (50-12,000 Hz), before sampling each channel at 40,000 samples/sec. On-line spike discrimination was controlled interactively by the investigator by applying standard techniques to isolate the neural activity from the background noise. The system saved spike waveforms and timestamps for all of the channels simultaneously, and can be accessed in real-time using client programs. This architecture has been extended to include online analysis of the cortical signal and will eventually be used to drive the robotic arm.

Using the system described above, client programs can be written which can make the necessary calculations to relate the neural activity to a control signal at 50 Hz. To run a robotic arm, an on-off signal, direction, and speed must be derived at every instant in time, and can be related back to the original arm movement for comparison. Over a two-month time period, the system correctly predicted when the hand was in motion over 80% of the time – with the most consistent errors occurring at the beginning and end of the movements. Comparing the angle formed between the true and the derived movements, a daily average angle ranged from less than 33 degrees to over 60 degrees. Endpoint prediction, being dependent on the prediction of movement onset, termination, and the instantaneous velocity at each movement interval, varied more substantially. The average displacement difference from the best day was approximately four cm off from the true endpoint, which lies 10 cm from the center of the cube.

Research is being directed at the formation of a real-time control signal to drive a cortical motor prosthesis. Although the accuracy of the current system is limited, it does provide three-dimensional motion control, deriving direction, speed, and movement initiation and termination, from the firing activity of motor neurons. Using the system described above, the conversion from neuronal activity to movement on a millisecond time-scale is attainable. Visual feedback should allow for learning and cortical remodeling. Once the animal is allowed to interact with the robotic arm as the task is being performed, we expect that the ability to control this device should improve. Therefore, further refinements in technology coupled with the addition of biofeedback should aid us in accomplishing our goal of an implantable, intracortical BCI.

PROPOSED PRESENTATION/DEMONSTRATION OF THE CYBERLINK™ CONTROL SYSTEM

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Brain Actuated Technologies Inc.

The Cyberlink™ System is controlled by the bio-potentials found on the surface of the forehead. The Cyberlink™ system combines eye-movement, facial muscle, and brain wave bio-potentials detected at the user's forehead to generate computer inputs that can be used for a variety of tasks and recreations.

The forehead is a convenient, non-invasive measuring site rich in a variety of bio-potentials. Three different channels of control signals are derived from the forehead signals by the Cyberlink™ Interface. The lowest frequency channel is particularly responsive to eye movements thus we call it an EOG signal. This EOG signal is typically used to detect left and right eye motion. This signal can be mapped to left and right cursor motion or on/off switch control.

A second channel of information is band pass derived (1 -50 Hz). The Cyberlink™ software further subdivides this region into ten component frequency bands called 'Brainfingers™'. These frequencies reflect internal mental/brain-wave activity as well as subtle facial muscle activity. A wide range of facial muscles affect these frequency bands. Users typically learn control of their Brainfingers™ first through subtle tensing and relaxing of various muscles including forehead, eye and jaw muscles. After a little experience with the Cyberlink™ System, most users begin to experiment with more efficient, internal brain-based control methods. Since this frequency region is sensitive to both mental and muscular signals it is called the 'Brain-Body' signal.

Brainfinger™ control is continuous or analog and is typically used for such things as control of cursor vertical or horizontal movement. For example, one Brainfinger™ may be used to control vertical movement while a second Brainfinger™ (or other signal channel) is used to control horizontal movement.

A third channel is an EMG envelope detected signal (70-3000 Hz) which primarily reflects facial muscle activity. It is typically used in the Cyberlink™ System for discrete on/off control of program commands, switch closures, keyboard commands, and the functions of the left and right mouse buttons. It can also be used nicely for analog cursor control.

Specific facial and eye movement gestures can be discriminated by the Cyberlink™ software and mapped to separate mouse, keyboard, and program functions.

Continuous and discrete control capabilities have been incorporated into a Win 95/98 mouse driver. This hands-free mouse enables the user to steer the cursor, change its speed and resolution, perform left and right mouse button functions, and send keyboard characters and character string commands. This makes hands-free two-axis control possible not only with Cyberlink™ specific games and applications, but also with third-party software such as Gus, Words Plus EZ Keys, WiViK2 and Clicker Plus.

For individuals with limited control of their facial muscles, the Cyberlink™ software can be formatted to use Brain-Body or EOG inputs (instead of EMG) to activate switch closures and mouse button clicks.

The use of the Cyberlink™ system with a computer will be demonstrated. The presentation will demonstrate how the training software helps the user to learn to control the computer through the biofeedback paradigm provided in the venue of on screen visual presentations of the users brain and body signals and video games such as Pong and Tetris. This training facilitates the development of precursor skills for the higher level skills needed for written and voice output communication of the Internet and other third party applications using windows 95/98. A demonstration of the music generation program, on screen keyboards and other more advanced applications will give the audience the sense of the wide range of potential for this Cyberlink™ interface brain actuated technology. It is hoped that the audience will see ways to adopt and apply techniques that we have developed for the Cyberlink system to their BCI applications.

DIRECT CONTROL OF A COMPUTER FROM THE HUMAN CENTRAL NERVOUS SYSTEM

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Introduction

Patients with locked-in syndrome are alert and cognitively intact but cannot move or speak. They face a life-long challenge to communicate. They may use eye movements, blinks or remnants of muscle movements to indicate binary yes or no signals. To enhance communication for these patients several devices have been developed including EEG control of a computer. These systems can provide these patients with the ability to spell words as shown by Niels Birbaumer and his colleagues in this volume (also, Kubler et al 1999), and control of hand opening and closing as shown by Peckham and his colleagues in this volume. In theory, however, none of these systems can produce the speed and precision that ought to be provided by directly recording neural activity from the human cortex.

Our approach is to use trophic factors to encourage growth of neural tissue into the hollow tip of a two-wire electrode (Kennedy 1989). The neural tissue is held firmly within the tip because it grows through both ends and joins with neighboring neuropil. This has provided stable long-term recordings in the rat and monkey for up to sixteen months (Kennedy et al, 1992a, 1992b) and in the patient described below for over a year. The histology shows normal neuropil without neurons but with an abundance of myelinated axons. The same action potentials are recorded over long time periods and behavioral correlates are described (Kennedy et al, 1992, 1997). Recently, this same type of electrode has been implanted into two patients. The first patient was an ALS patient who died 76 days after implantation from her underlying disease. She showed that stable signals could be recorded and she could turn them on and off (Kennedy et al, 1998). The results in the second patient demonstrate the ability of this electrode to provide long-term stable signals that can be separated from the multi-unit activity. The patient can control these signals to some extent and is able to use them to drive a cursor across a computer screen. The rate of movement of the cursor is proportional to the firing rate. He has provided learning curves whereby his performance improves with repeated execution of the same task. The focus of this paper is the performance of the patient using neural activity to drive the cursor.

Methods

Implantation: Electrode fabrication and implantation are described in Kennedy '89, Kennedy, Bakay and Sharpe '92 and Kennedy and Bakay '98. Two recording wires are placed in the glass conical tip and two neurotrophic electrodes are implanted using full general anesthesia and standard sterile protocols. As described in the recent paper on the first patient (Kennedy & Bakay '98), a functional MRI is performed to determine the localization of neural activity. These fMRI results guide selection of the implantation site (Olsen et al, 1997). A craniotomy is performed over area 4 motor cortex, and two electrodes are implanted, one over the digit/hand area and the other near the face area identified at surgery by alignment with the active area noted on the pre-operative *functional* MRI. The implanted device is coated with Elvax for insulation against fluid leak. Elvax is an ethylene-vinyl acetate copolymer resin from DuPont de Nemours, Wilmington, DE. For mechanical insulation, the Elvax is coated with bio-compatible silastic (R-1144 RTV Dispersion coating, Silicone Technology Inc., McGhan Nucil Corp., Carpenteria, CA). The device is held in place using acrylic cement and standard neurosurgical techniques. These devices have been used in animal experiments without any problems attributable to the devices.

Recording: Recording techniques are summarized here and described in detail in the papers in Kennedy '89 and Kennedy, Bakay and Sharpe '92 Kennedy & Bakay '98. The electrode routinely has two wires spaced 0.5 mm apart, one about 0.5 mm from the deep end of the cone and the other about 0.5 mm from the wide superficial end. Differential recording (without ground) using both wires offers a number of advantage. (1) It excludes the possibility of recording from tissue outside either end of the cone (for an example, see figure 3 of Kennedy '89), and (2) it minimizes artifacts such as scalp muscle EMG. A simple telemetry system allows complete skin closure thus minimizing the risk of infection (and unsightly wires coming through the scalp). The radio telemetry system consists of a custom FM transmitter and a modified commercial FM receiver (Mackay, 1970; Motchenbacher and Fitchen, 1973). The transmitter is constructed with surface-mount components. During data acquisition, the patient is lying in bed and the power induction coil is held between the pillow and his head. The antenna of the FM telemetry receiver is placed within inches of his head. Transmission frequency ranges from 34 to 44 MHz, bandwidth of the transmitter extends from near 0.1 to 5 KHz (the 3-db point), and the filter cutoffs of the post-transmitter amplifier (BMA 831, CWE Inc.) are set at 0.5 and 5 KHz. The total system gain is 20,000. The neural data is archived on an 8-mm digital video tape (Sony recorder EV-S350) whose bandwidth is DC to 12.5 KHz in the PCM mode, with signal amplitude ranging from 10 mV to 1.25 V. The neural signals are recorded in synch with the video signal from the camera that monitors the patient and the computer screen. To drive the cursor, all waveshapes are usually fed back as a group.

Signal Processing: The analog output of each electrode is routed to the computer containing signal separation software (Discovery Software, DataWave Technology Inc., Boulder CO.). Neural spikes (waveshapes) that exceed a user-determined voltage level are digitized at a user-determined frequency, typically 16 or 32 KHz. When digitizing waveshapes, the user can allow some overlap of waveshapes within the 1 ms time bins so that rapidly recurring waveshapes are minimally missed. Eight different parameters are used: 1) peak to peak amplitude, 2) amplitude above baseline, 3) amplitude below baseline, 4) width, 5) time to peak, 6) time to valley and 7) user selected sample points at point 2 (of the 32), and 8) at point 20. Waveshapes must fall within 1 standard deviation of the waveshape average, thus excluding points outside these values. In addition, only a minimal section of the waveshape (determined by the user) needs to be included in the analysis, thus saving real time on-line processing time. The eight separation parameters are stored in a dedicated set-up parameter file and used for classifying waveshapes at subsequent recording sessions, or for retrospective off-line analysis from the videotape.

Cursor Control: Each waveshape is converted into a TTL pulse. When EMG signals are substituted for neural signals (see below) these also are converted into TTL pulses. Three pulse outputs are routed to a second computer as a substitute for the "mouse" input. During normal "mouse" operation, the position of the cursor on the screen is a function of the X and Y voltage input. The signals from one pulse determine the position of the cursor in the X direction, the other in the Y direction. The rate of increase of firing determines the velocity at which the cursor moves over the screen. The third pulse is used to trigger the "enter" or "select" command or "mouse click". To simplify operation for the patient, we have differentiated the firing rate and removed the hysteresis. In other words, only increases in firing rate move the cursor from left to right. With decreases in firing rate or with any sustained tonic firing rate it does not move. Furthermore, when the "enter" command is activated, the cursor immediately returns to the top left position on the screen. The patient receives visual feedback by observing the rate of cursor movement. Auditory feedback is provided by a brief tone that is distinct for any pulse that fires. Early in training, there was a dwell time that required the patient to remain over an icon for two seconds before activation.

Patient Training: The monitor is attached to a computer containing software that displays either a row of icons representing common phrases (Talk Assist developed at Georgia Tech), or a standard 'qwerty' or alphabetical keyboard (Wivik software from Prentke Romich Co.). When using the keyboard, the selected letter appears on a Microsoft Wordpad screen. When the phrase or sentence is complete, it is outputted as speech (using Wivox software from Prentke Romich Co.) or printed text. There are two paradigms using the Talk Assist program and a third one using the visual keyboard. In the first paradigm, the cursor moves across the screen using one group of neural signals and down the screen using another group of larger amplitude signals. Starting in the top left corner, the patient enters the nearest (or leftmost) icon. He remains over the icon for two seconds so that the speech synthesizer is activated and phrases are outputted such as "See you later. Nice talking with you". In the second paradigm, the patient is expected to move the cursor across the screen from one icon to the other. The patient is encouraged to be as accurate as possible, and then to speed up the cursor movement while attempting to remain accurate. In the third paradigm, a visual keyboard is presented on the monitor and the patient is encouraged to spell his name as accurately and quickly as possible and then spell anything else he wishes.

Results

Our first implanted patient, MH, was able to control multiunit firing using visual and auditory feedback (Kennedy and Bakay, 1998). Recording signals until her death 76 days post implantation demonstrated that growth of neural tissue into the electrode could occur in humans. She could turn the signals on and off on request, thus demonstrating that binary output is feasible. Our second patient, JR, continues to control a computer cursor over a year after implantation. He suffered a brainstem stroke in December 1997. He has residual facial expressions, cannot speak around his tracheotomy, has disconjugate eye movements with nystagmus, but is cognitively intact and fully alert. Neural signals appeared as expected (from the first patient and in all animal studies) near day twenty, and stabilized at about three months. Robust signals continue at day 426 at time of writing. Multiple signals of different amplitudes can be recorded unless JR is tired, toxic or on analgesics. Presently he is given Neurontin and Fentanyl for pain associated with severe decubitus ulcers and peripheral neuropathy so he works with great difficulty and for short periods of time. At month two after implantation, the neural signals fired in relation to mouth and tongue movements. At month four they appeared to fire with eye and eyebrow movements as determined by observing the patient during activation and by questioning him. From month five onwards, JR makes no movements during activation of the signals. He has learned to use these neural signals to control the X direction of a cursor on a computer screen. Initial attempts produced poorly controlled movements of the cursor because no tonic firing occurred at any firing rate level. Only phasic bursts occurred that sometimes continued as runaway firings. To negate this unwanted constant rate, we continuously averaged the firing rate and subtracted this from the actual rate: When rates were equal, the cursor did not move. Thus, it now moves only in response to *increases* in phasic activity. We initially allowed the cursor to drift back in the opposite direction in order to provide bi-directional movement, but this was too difficult for him to control. Now the cursor does not drift to the left, nor does it move with decreases in firing rate. It wraps around the screen when it reaches the right side. With these simplifications he has produced learning curves with all three paradigms.

Paradigm #1.

In the first paradigm, he moved the cursor across and down the screen to activate icons to produce synthetic speech. Panel A in figure 1 illustrates improvement in performance during three different sessions on days 120, 121 and 122 after implantation. He attempted to move from a start position on the top left corner of the screen, and drove the cursor across to the right and downwards to enter one of five icons in a row scored one through 16. A high score indicates poor performance and a low score indicates rapid movement down into the icon nearest the start position. As illustrated, poor performance (shown in the Y-axis) on the initial trials improved on subsequent trials.

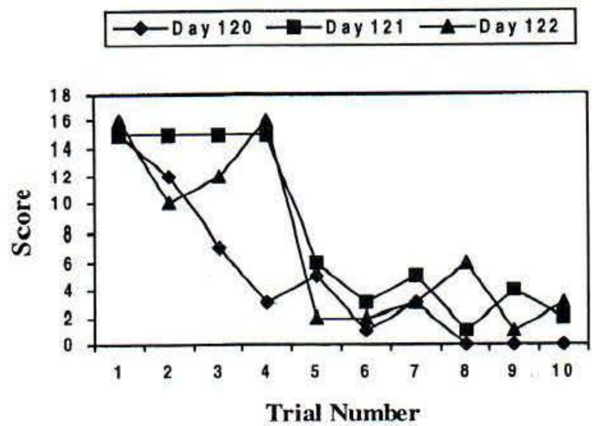
This performance did not endure, however, when JR was tired or toxic. This is shown in panel B where scores worsened as he became tired (day 120), remained poor (day 121) or fluctuated (day 122). On questioning he indicated his sense of effort was maximal.

In panel C, JR used the neural signals for the X direction and the toe EMG (Adductor Hallucis muscle) for the Y direction. He moved the cursor around the screen containing five icons in a horizontal row with the fourth icon from the left being the target icon. Thus a score of four indicated accurate attainment of the target. There was no time limit. The cursor could move from left to right and top to bottom and then wrap around to the top or left side. Initially, he was inaccurate for six trials and then maintained consistent accuracy for four trials (scores 4) until he tired and became inaccurate. He was seen to be slowing, so he was asked whether or not he wished to continue. He indicated "no" by one blink ("yes" by two). He was rested for 3 minutes and on resumption he regained accuracy for two trials. A rest of five minutes produced five accurate trials in a row. A short rest resulted in resumption of inaccurate trials. A five minute rest produced three more accurate trials followed by an inaccurate one and an indication that he was too tired and wished to stop.

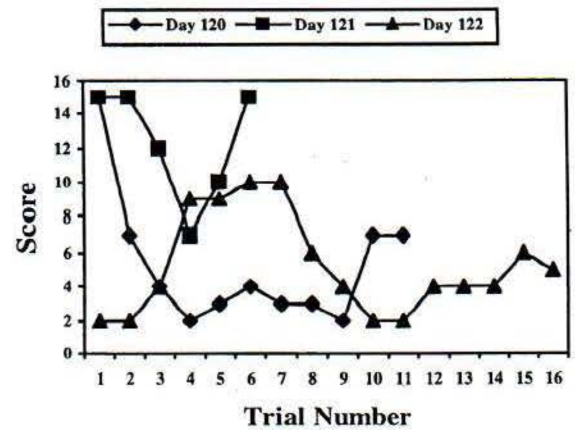
Paradigm #2.

In the second paradigm he moved across each of five icons as accurately and quickly as possible. To be accurate he had to move the cursor into an icon and remain there for two seconds to produce synthetic speech. This was accurately performed in 45 seconds on the first trial as shown in panel D. Speed of performance increased over five trials. On the sixth and seventh trials, errors in accuracy occurred. He was encouraged to slow down while maintaining accuracy. This he did. As he increased his speed, further errors occurred. At the end, he indicated effort was maximal.

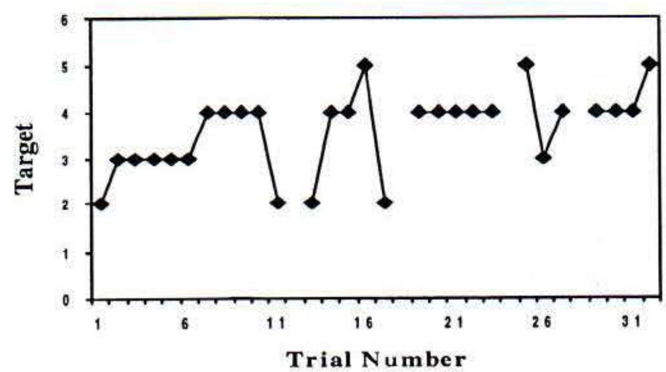
A: Learning Curve I



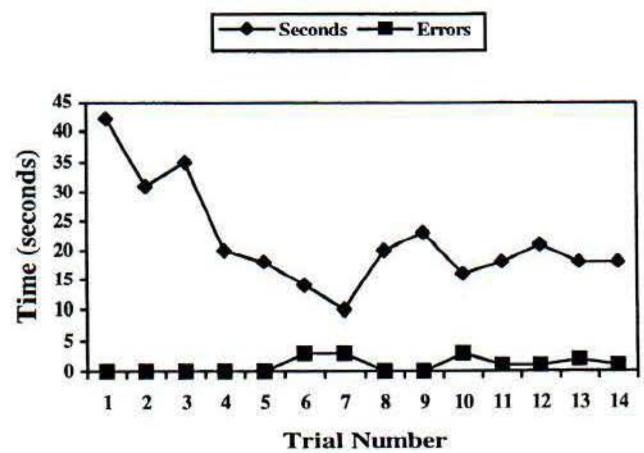
B: Learning Curve II



C: Day 243, Aiming for Target #4



D: Day 192, Time to Target



Paradigm #3.

JR has used a pop-up keyboard on the monitor to select letters and spell phrases that are outputted either as synthetic speech or printed words. He has spelled his name and ours with accuracy, but has become increasingly unable to generate neural signals for more than a few minutes due to the effects of the analgesics described above. To facilitate his use of the keyboard, we used EMG signals that were associated with some minute recovered movements of his left neck, arm or toe, though recently even these have not been available. We used neck EMG for the select command and left toe EMG for the Y direction (or more recently a constant input from a signal generator) that drove the cursor. The following example demonstrates he can recognizably spell his name beginning from below. (The letters are spelled from below upwards due to the fact that the Wivik keyboard covers the lower part of the Wordpad screen allowing only one line for viewing. After each line is full, we press 'return' and the 'text select pointer' is returned to the top of the screen.)

[4th attempt] **JOHN**
[3rd attempt] **JOHPN**
[2nd attempt] **JWU**
[1st attempt] **JOHN**

12/17/98 JRDAY265.UFF

In a further example, he spells his name first then several of ours. Again beginning from below upwards, he has some difficulties on the first two lines. Then he spells JOIH.N. To our surprise, he spontaneously spells PHIL with an X for 'and', and then he spells KIM. This is followed by MELODY with some errors. Then he spelled KENNEDY and GOLDTHWAITE with a few errors. He has not learned to use the backspace.

KENEDY GQLDXWAIJTF
PHILXKIM NMFELODY
JOIH.N
HIJJROHLN
- **JOHLQQQ.GYUVWABD N**

Day 266. 12/17/98

As an internal control we have recently had an opportunity to use EMG signals (without neural signals) to determine his maximum spelling rate with EMG. In this trial, the patient was not given a specific target word but was asked a series of conversational questions for which he determined the answer. His left eyebrow EMG drives the cursor horizontally, a signal generator provides a constant vertical displacement at a rate of 25 seconds per full screen, and the left neck EMG provides the 'enter' command. He achieved a maximum rate of three letters in 60 seconds spelling "GONE WITH" shown below. It was his eighth session over three weeks of practice using the EMG and signal generator. Substituting neural signals for the signal generator (vertical control) achieved an almost identical maximum rate of 3 letters over 72 seconds when spelling "THE WIND". This was his initial attempt to use neural signals in many months. It will likely improve. He uses a backspace to delete errors thus producing correctly spelled words as shown. Previous attempts months ago prior to his recent illness produced a similar rate. The answers to the various questions are shown below (Read upwards from 1st).

[4th]	**NOTHING**	[What were you thinking when moving the cursor?]
[3rd]	**THE WIND**	[Neural signals substituted for vertical EMG]
[2nd]	**GONE WITH**	[What is your favorite movie?]
[1st]	**BRANDON**	[Spell the new guy's name]

JRDAY423 5/24/99

The fourth question in that session concerned his thoughts while driving the cursor. As discussed at the beginning of the 'results' section, he used mouth and tongue movements, eye movements, eyebrow movements and eventually lay quietly while driving the cursor across the screen. Now, after five months without using the neural signals, he appeared to allow them to fire spontaneously. Thus when asked what he was thinking about after session 423, he answered 'NOTHING' as shown above. In the next session (day 430) he was required to fire the neural signals to drive the cursor from left to right across the five icons on the Talk Assist screen. At the same time he had to minimize eyebrow EMG to avoid driving the cursor down and out of the line of icons. Thus he had to *dissociate* the EMG activity from the neural activity. He took over a minute in the first two trials to move across the full screen of icons, but after five trials he succeeded in 23 seconds. In subsequent trials he then moved too quickly and made errors such as driving below the line of icons, or skipping over icons. Eventually he produced accurate performance taking 19 to 32 seconds to cross the screen. This was similar to the prior performance shown in panel D above for day 192. When asked what he was thinking, he denied thinking of moving his mouth, tongue, eyes, or eyebrows together or separately. Instead, he blinked twice (for 'yes') when asked if he was thinking of moving the cursor.

Discussion

These data indicate that the recorded neural signals can drive the cursor across the screen, accurately entering and resting in icons or letter squares. As shown in the four paneled figure, there are improvements in performance producing learning curves. Accurate performance is impaired by tiredness as a result of repeated performances, toxicity due to infections, pain or analgesics. These ongoing medical problems have produced long interruptions in his training (December to May 1999), and required the use of residual EMG activity and a constant input to drive the cursor downwards. Despite these problems, the patient has repeatedly produced a maximal spelling rate of three letters per minute. This is likely below the maximum output that could be obtained by further practice, refinements in the user interface and use of at least two neural signals, one in the X direction and the other in the Y, with a third neural signal to provide the enter command.

The spelling rate is slightly faster than the spelling rate attained with the use of other techniques. It compares well with Birbaumer's ALS patients who used a binary EEG control signal after many months of practice. Table 3 in Kubler et al (Exp. Brain Research, 1999, 124:223-232) shows time per letter ranging from 10 seconds to 192 seconds. The average time in seconds for spelling the simplest two level letter was 66 seconds for patient HPS and 65 seconds for patient MP. Three level spelling took 76 seconds for HPS and 54 seconds for MP. We expect JR and future patients to spell much more quickly. The techniques are not directly comparable, of course. We expect to make a comparison between the arbitrary cursor movements enjoyed by our patient and a binary selection task (identical to Birbaumer's task) made by the same patient.

The question of what drives the cursor is beginning to be answered. As described above, the patient indicates that the neural activity is no longer driven by specific face parts, though large activations of EMG activity are associated with activation of neural activity as would be expected in any general activation response. Recent results are suggesting that he can dissociate EMG activity from neural activity, and that when activating neural signals he is thinking only of driving the cursor. If this is borne out by further studies of performance and the underlying neural correlates, it implies that plastic changes can be induced in the underlying cortex. In other words, the patient may develop cortex devoted to controlling the cursor. We have expectantly named this phenomenon "cursor cortex".

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PARALLEL MAN-MACHINE TRAINING IN DEVELOPMENT OF EEG-BASED CURSOR CONTROL

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I. Introduction and Communication Task

Assistive devices are essential in enhancing the quality of life for individuals who have severe disabilities, such as quadriplegia and amyotrophyc lateral sclerosis, or who have had massive brainstem strokes. However, the effectiveness of most assistive devices are dependent on preserved residual movements or speech. Without any physical channels for control, the only alternative for these people may be in exploring indirect voluntary modulation of electrical fields resulting from neural processes in their brains. This can provide control signals for simple interface between the user and the computer known as Brain-Computer Interface (BCI). Frequently used model for development of BCI is to control the cursor movements and its positioning on computer screen. The problems that remain unsolved even with currently most successful systems are very slow training of subjects, low spatiotemporal resolution, and poor accuracy in two-dimensional control. Precise positioning of the controlled object has so far not been achieved. What adds to the difficulty of this research is that a new subject does not know what thought patterns are going to give the best results, so initially the subject and machine are learning in parallel. The goal of our research is to develop new training technology that will achieve simple control using various mental activities. The control actions that we want to achieve are two-dimensional (up - down - left - right) object movement on the computer screen, and precise positioning of the controlled object. In order to achieve our goal, we are working on the development of EEG recording and processing setup and training method that will maximize efficiency of extraction of user's intentions. In order to make the BCI practical, the following three constraints must be met:

1. Minimize the training time of subjects. Current systems often require weeks of training before reasonable performance is achieved. Long training is usually the main obstacle in acceptance of any practical assistive system.
2. Use as few EEG channels as possible. A brain-computer interface with too many electrodes becomes costly, cumbersome, and less feasible for implantation.
3. Achieve high enough accuracy to provide reliable interface between man and machine.

II. Methods and Communication Protocol

The subject is comfortably seated in front of a feedback monitor while EEG signals are recorded using an electrode cap with 28 gel-filled electrodes arranged according to the 10-20 international electrode system, one ground electrode and the linked ears reference. The electrode cap and EEG-preamplifiers are electro-optically isolated from the rest of the equipment. This provides safety for both the subject and the operator. For signal conditioning, i.e. amplification and initial filtering we use the Brain Imager (Neuroscience Inc.). Analog EEG signals are then digitized at 200 samples/s by a data acquisition card (DAQ) inserted in an IBM PC compatible computer. The same computer has special video card splitting the video output into two high resolution monitors, one for the subject and one for the operator supervising the experiment.

Adaptive Logic Network (ALN) is the adaptive neural network that we use to classify the EEG patterns in the on-line experiments. ALN is a non-linear adaptive machine learning system for supervised learning which is capable of learning any continuous function to any degree of accuracy [1].

During the real-time experiments, selected channels of EEG are processed and recorded on the computer's hard drive. Our method carries out signal processing on channels used for control, extracts important features from the signals, presents the selected features to the ALNs for training [2,3], evaluates the ALN to determine direction of cursor movement, and updates the cursor position on the subject's screen. The subject uses two manual switches to mark sequences of voluntary attempts to mentally control the movement of a circular object on the feedback screen. Since mental concentration is required to produce desired EEG signals, these switches allow the subject to rest during the experiment and avoid fatigue. The subject's goal is to move the object on the screen to a target. The position of the target is switched between UP and DOWN in one-dimensional setup or between UP, DOWN, LEFT and RIGHT in two-dimensional setup. New position of the target is decided at the end of each run when the object reaches the target or the opposite end of the screen is hit. An example of the subject's screen can be seen in Fig. 1. We chose cursor movement because it is objective, easily implemented, simple for the user to learn, and can serve as a prototype for control of a wide variety of applications.

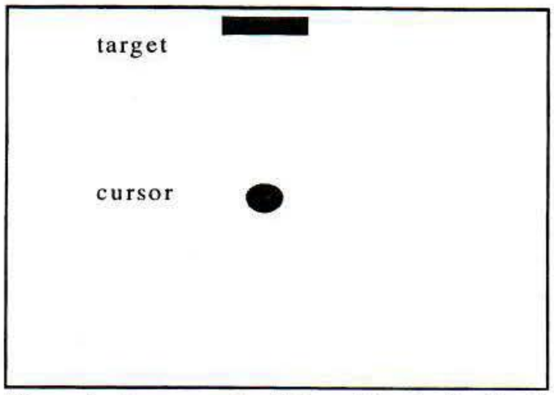

Figure 1: An example of the subject's feedback screen during an on-line experiment. The subject's goal is to move the cursor to the rectangular target.

III. THE ASSESSMENT OF RESULTS AND THE RESULTS

We had several subjects so far who learned to have reasonable control over the object on the screen in one dimension. Acquiring control with the BCI takes some training, but most of our subjects were able to show control after two sessions. Each of the sessions lasts approximately 30 minutes. The first half of each session is used to train a new classifier and the second half is used to evaluate the performance. Performance is evaluated in terms of how many times the target is hit versus missed at various movement speed of the object. During these sessions, position of the object is updated every 50 milliseconds and the speed of the animated object is determined by the number of steps that are required to hit the target, which is set by the operator before the experiment. Once fully trained in one-dimensional control, our subjects can hit the target close to 100% of the time when 32 full steps are required to hit or miss the target. The FFT calculated spectrum for one of our subjects during BCI cursor control is shown in Fig. 2. As can be seen from Fig. 2, a large difference in spectral power density exists at around 10 Hz between the EEG recorded while the subject was thinking UP thoughts as compared to DOWN thoughts. It is interesting that this effect is reversed at the parietal electrodes, which clearly shows that the source of this activity is somewhere underneath central and parietal electrodes.

So far we have been able to train only two subjects to achieve two-dimensional cursor control. One of the subjects is able-bodied person and the other one has post-polio syndrome. The two-dimensional cursor control that these subject can achieve is approximately 80% of targets hit.

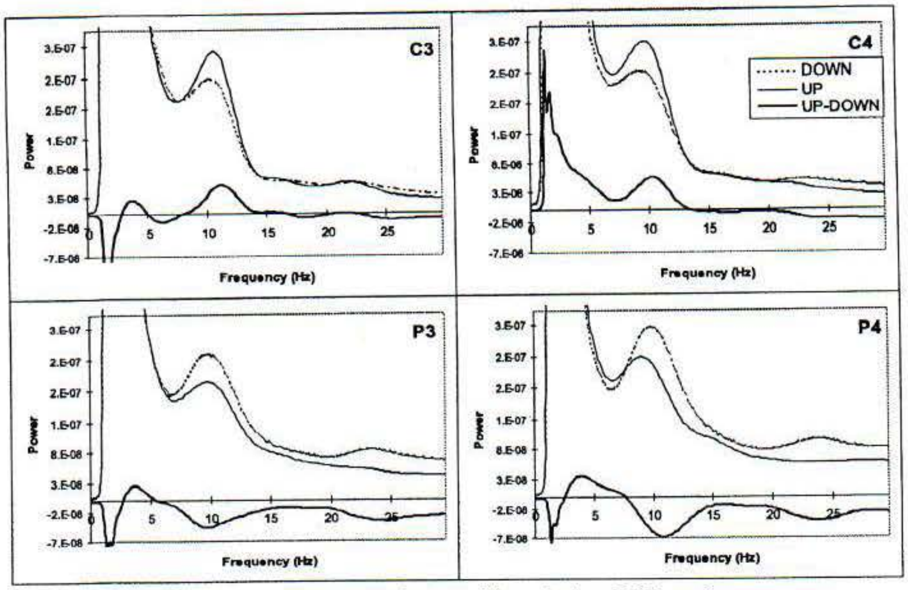

Figure 2. Averaged FFT spectrum of one subject during BCI session

IV. Future Plans

Our short term goals are to train a number of volunteers in two-dimensional cursor movement and positioning, as well as to develop a range of applications for the brain-computer interface.

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A DIRECT BRAIN INTERFACE BASED UPON DETECTION OF EVENT RELATED POTENTIALS IN AN ELECTROCORTICOGRAM

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The goal of this project is the development of a direct brain interface based on detection of event-related potentials (ERPs) within electrocorticogram (ECoG) obtained from the surface of the cortex. The initial study in this effort involved the identification of averaged ERP templates to be used for cross correlation based detection. Ten epilepsy surgery patients, undergoing monitoring with subdural electrode strips and -rid arrays, participated in this study. ECoGs were continuously recorded while subjects performed multiple repetitions for each of several motor actions. ERP templates were identified from action-triggered ECoG averages using amplitude criterion. At least one ERP template was identified for all ten subjects and in 56% of all electrode recording sets resulting from a subject performing an action. These results were obtained even though electrodes were placed solely for clinical purposes and not for research needs. Eighty-two percent of the identified ERPs be-an prior to the trigger, indicating the presence of premovement ERP components. The recording locations for multiple ERPs arising from the performance of a specific action were usually found on close-by electrodes. ERPs associated with different actions were occasionally identified from the same recording site but often had noticeably different characteristics. The ease with which ERP templates were identified for subjects and the differences apparent in the location or shape of valid ERPs related to different actions supported the use of subdurally recorded ERPs as a basis for a direct brain interface

Ongoing, work to develop a direct brain interface is now focused on the detection of individual ERPs within the ECoG using cross-correlation between an averaged ERP template (as described above) and the continuous ECoG from the same electrode recording site. Each point where the cross-correlation value exceeds an experimentally determined detection threshold is considered a detection point. Each detection point is considered to be a valid "hit" if it occurs between one second before and a quarter second after the recorded time of a voluntary action. The difference between the hit and false positive percentages (HF-difference) is used as a metric of detection accuracy. To date, 15 subjects have been studied. HF-differences greater than 75 were found for 8 of the 15 subjects. Four subjects had HF-differences in the range 50 to 75. The subjects with low detection accuracy either performed only one action or had electrode locations not well suited for recording movement-related ERPs. The best HF-differences were 96 (96% hits - 0% false positives), 96 (100%-4%), and 93 (100%-7%).

In all of these studies electrodes were placed solely to meet clinical needs and not for research purposes. The number of subjects for whom accurate detection of ERPs was possible even without custom placement of the electrodes over sensory-motor cortex indicates that a direct brain interface that can accept a command directly from the brain (without requiring any physical movement) and produce a single switch closure is quite feasible. Such an interface would enable people with severe disability (i.e. locked-in syndrome) to communicate and to participate in society. Results further indicate the strong feasibility of multiple control channels using this approach.

The actual provision of this direct brain will require chronic subdural implantation of electrodes, an extremely invasive procedure. Before this step is considered, additional studies are being performed with epilepsy surgery subjects to 1) confirm that improved electrode placement will produce higher percentages of accurately detectable ERPs and 2) demonstrate the use of the direct brain interface for communication or other functional tasks.

Concurrently, other studies are underway which include: 1) improved methods to predict the accuracy possible with a particular ERP template; 2) template optimization through data preprocessing and/or selection of average constituents; 3) methods for ERP detection when there is no associated physical motion, 4) exploration of the ability of subjects to control or modify ERP quality given appropriate feedback; 5) optimization of the detection methods through alternative methods for analysis of the cross-correlelogram; and 6) examination of multiple-electrode detection algorithms.

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BRAIN-COMPUTER INTERFACE TECHNOLOGY: THEORY AND PRACTICE

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Fluctuations in Alertness

In tasks requiring sustained attention, human alertness varies on both sub- and supra-n-finute time scales. This can have serious consequences in occupations ranging from air traffic control to monitoring of nuclear power plants. A method of objectively monitoring human operators for signs of drowsiness would by useful in those working environments. Our previous results confinned that the group averages of task performance in an auditory detection task and a visual compensatory tracking task follow similar trends. Initial near-ideal performance begins to decay after about one minute. Thereafter, group mean error rate rises steadily until I I min into the task, after which it remains more or less stable near 30%. However, individual performance on either monitoring task often tends to fluctuate irregularly with central state, including periods of from near twenty seconds to many rninutes of intermittent or complete unresponsiveness (Makeig & Inlow, 1993; Makeig & Jung, 1995; Makeig & Jung, 1996; Jung et al., 1997).

EEG-Based and Eye-Activity Based Alertness Monitoring

We have reported that changes in the electroencephalographic (EEG) power spectrum (including stable individual differences) accompany these fluctuations in the level of alertness, as assessed by measuring simultaneous changes in EEG and performance on an auditory monitoring task (Makeig & Jung, 1996; Jung et al., 1997). These papers showed that continuous, accurate, noninvasive, and near real-time estimation of an operator's global level of alertness is feasible using EEG spectrum. Our recent work suggested that eye activity (blink frequency and duration, fixation frequency and duration, pupil diameter) can also be used to detect the onset of drowsiness in a visual tracking tasks. Our current work is to compare and contrast these two complementary measurements and to discuss how to fuse multiple streams of psychophysiological information to deliver reliable information about changes in the cognitive state of operators of complex computer-based systems. At the workshop we could present the signal processing methods we have used to derive stable near-real time alertness measures and discuss their possible applications to brain-mediated control.

Spontaneous and Single-Trial EEG Signal Processing

Our recent work has focused on developing signal processing tools and methods for single-trial analysis of EEG signals that combine Independent Component Analysis (ICA) and time/frequency analysis (Makeig et al., 1996-99; Jung et al., 1998-99.). Using these techniques, we have developed methods of extracting the activities of the eyes, scalp muscles and spatially stationary brain activities into independent channels. We foresee many uses for this technology, including online artifact elimination and/or muscle and eye activity measurement. At the workshop we might demonstrate use of these tools on a PC or workstation equipped with Matlab, if one is available. The software tools we would demonstrate are publicly available to all participants through our web site (http://www.cnl.salk.edu/~scott/ica.html).

EEG-Mediated Control

Finally, with Richard Sweringen and Marwan Jabri of the University of Sydney, we have begun to explore the use of new paradigms for EEG-mediated control of a computer cursor. At the workshop we might demonstrate a portable computer and experimental data collection task we are using to gather data on this topic, and could discuss our strategy for incorporating out recent advances in EEG signal processing in this effort.

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BRAIN-COMPUTER INTERFACES
BASED ON THE STEADY-STATE VISUAL EVOKED RESPONSE

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The Alternative Control Technology (ACT) program of the Air Force Research Laboratory, Wright-Patterson AFB, Ohio is engaged in the design and evaluation of a variety of hands-free alternative controls. These include eye, head, speech, electromyographic, and electroencephalographic (EEG) systems that allow communication with computers while the operator's hands remain engaged in other activities. For example, alternative controls may enable maintenance technicians to manually operate test equipment while accessing schematics on a head-mounted display.

Research in the ACT program has harnessed an aspect of the EEG that serves as an effective communication tool for brain-computer interfaces (BCIs). This aspect is the steady-state visual evoked response (SSVER) [1]. Two methods of using the SSVER to control the operation of a physical device or computer program have been employed in this research. In one, operators are trained to exert voluntary control over the strength of their SSVER. In the second, multiple SSVERs are used for control. The latter requires little or no training because the system capitalizes on the naturally occurring responses. The purpose of this paper is to describe the SSVER-based BCIs and to summarize research findings.

BCI Based On Self-regulation Of The SSVER

Communication Task

Communication between the operator and the computer in this BCI is binary in the sense that only two control actions are possible. For example, a device can be turned on or off, moved left or right, etc. It is also appropriate to describe this BCI as a discrete controller. That is, changes in the SSVER result in control actions occurring at fixed intervals of time.

EEG Component

The source of control is the amplitude of the SSVER. The SSVER is elicited using a visual stimulus that is modulated at a fixed frequency. The SSVER is characterized as an increase in EEG activity at the stimulus frequency. Typically, the visual stimulus is generated using white fluorescent tubes modulated at 13.25 Hz and mounted behind a translucent diffusing panel. With biofeedback training, operators learn to willfully increase the amplitude of their SSVER.

Communication Protocol

The EEG is acquired using gold-cup electrodes located over occipital sites O1 and O2 with the left mastoid as ground. The differential signal between O1 and O2 is amplified, filtered, and processed by a hardware-based lock-in amplifier system (LAS), that provides a continuous measure of SSVER amplitude. This information is sampled by a computer for feedback and control purposes. Control logic based on thresholds and duration requirements is used to transform the noisy SSVER amplitude into smooth, stable control. For example, when the SSVER remains above or below an experimenter-specified threshold for 75% of the samples in a one-half second interval, a discrete control action occurs. The threshold and duration parameters are adjustable for individual operators and specific applications. Typically, two thresholds are employed to achieve a binary control signal; raising the SSVER above the upper threshold for the required duration results in one control action and lowering the SSVER below the lower threshold for the required duration results in a different control action.

Assessment of Results

As stated earlier, this BCI provides discrete, binary control; control actions can only be correct or incorrect. Thus, performance data is presented as percent correct and the average time to make a correct control action. Learning curve analyses are used to determine how much training is required to use the BCI. Scalp-wide topographical maps and other time and frequency domain analysis are used to evaluate possible mechanisms of self-regulation.

Results

In general, the studies show that all operators perform above chance level. In addition, data analysis has revealed that there are large individual differences between operators. While some operators experience difficulty, others achieve nearly perfect control. These are general observations; specific results are reported in the following discussions of research conducted in the ACT program.

Device Control

Flight simulator roll control. In this task, the BCI is used to control the roll position of a simple flight simulator. A display in the simulator provides SSVER amplitude feedback and presents a series of random commands requiring the operator to roll right or left to specific target angles. The stimulus lamps are located adjacent to the display behind a translucent diffusion panel. As operators increases their SSVER amplitude above one threshold, the simulator rolls to the right. When the SSVER amplitude is decreased below a lower threshold value, the simulator rolls to the left. Although no formal studies were conducted with this system, operators were generally able to roll the simulator in the correct direction 80% of the time after 5-6 training sessions.

Muscle stimulator operation. A functional electrical stimulator (FES), a rehabilitation device designed to exercise paralyzed limbs, was integrated with this BCI. Operators are required to hold their SSVER amplitude above the "on" threshold for one second to activate the FES. This causes the FES to activate at the muscle contraction level and begin increasing the current, gradually recruiting additional muscle fibers to cause knee extension. Decreasing the SSVER magnitude below the "off" threshold results in the reversal of the FES system and subsequent ramp-down of the current and lowering of the limb. The control algorithm parameters are adjusted to emphasize accuracy over speed.

Three able-bodied participants with previous SSVER self-regulation experience participated in 3 to 5 one-hour sessions. A display provided SSVER amplitude feedback, commanded knee angle, actual knee angle and FES status. The visual stimulus was located above the display monitor. Time history data was examined to ensure that a change in current level preceded a change in knee angle to confirm that the able-bodied participants accomplished knee extension by controlling the brain-FES interface. Data from each participant's best session was examined. Participants acquired 95.8% of the commanded knee angles with average FES on and off latencies of 4.28 seconds and 5.93 seconds, respectively [2].

Mechanisms of SSVER self-regulation

The control signal in this BCI is derived as a differential measure of SSVER activity at O1 and O2. As a result, operators can change the amplitude of the control signal by self-regulating: (1) the relative amplitude of the SSVER activity at O1 and O2, (2) the relative timing (phase) of the SSVER activity at the two sites, or (3) a combination of both. In one experiment three participants performed a task that required repeated 2-second periods of SSVER enhancement or suppression. Scalp-wide EEG was recorded. Each participant showed inter-hemispheric shifts of SSVER activity between the enhance and suppress conditions. Data for one participant is shown in Figure 1. These results suggest that modulation of the relative amplitude of the SSVER at O1 and O2 plays a role in SSVER self-regulation. In a separate study with four participants, monopolar O1 and O2 signals were recorded in addition to the bipolar control signal. Phase and amplitude relationships between O1 and O2 were evaluated during periods of sustained SSVER enhancement and suppression. Each of the participants showed evidence of phase-based control. They maintained relative phase synchrony between O1 and O2 during periods of suppression and produced 45-180 degrees of phase asynchrony during enhancement. As in the topographic analysis above, independent regulation of O1 and O2 amplitude was observed as well [3].

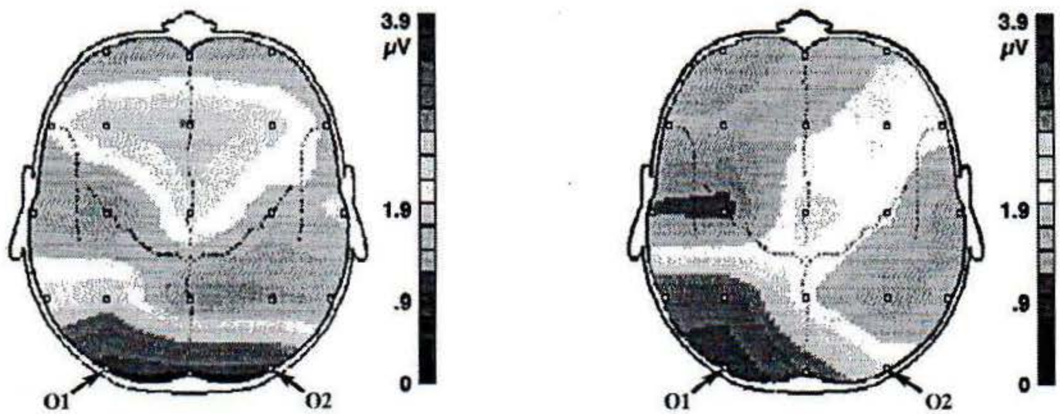

Figure 1 – Topographic maps of 13.5 Hz activity recorded during task-related SSVER enhancement and suppression for Participant 2. Note the evenly distributed activity in the O1 and O2 regions of the left map (suppression) and the asymmetric activity in the right map (enhancement).

Effects of feedback on learning SSVER self-regulation

Eight participants were trained to perform a switch selection task under one of two feedback conditions, discrete or proportional. Three switches were aligned next to three target fields on a computer generated display and the task involved selecting the switch next to the field containing a target. To change which switch was selected, participants increased their SSVER above an experimenter specified threshold to begin cycling through the switches. To stop progression through the switches, the participants decreased the SSVER below threshold. Changes in the border and fill color of the switches indicated whether the SSVER was above or below threshold in the discrete feedback condition. In the proportional feedback condition, a dynamic vertical bar with a threshold mark was displayed. Learning curves for the two groups are shown in Figure 2. Both groups showed significant learning, but there was no overall difference as a result of feedback type.

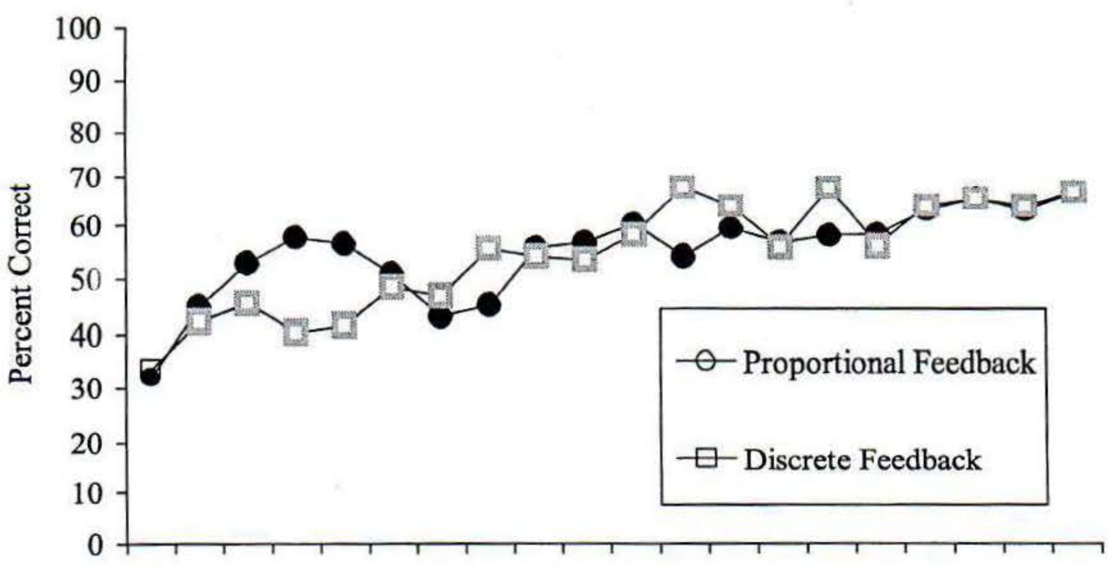

Figure 2 – Learning curves for an SSVER-based switch selection task under two feedback conditions (n = 4 per group). There was no overall difference between the groups. However, the data for sessions 1-5 suggests that the continuous feedback may have supported more rapid initial learning.

BCI Based On Naturally Occurring SSVER

Communication Task

The task is to select virtual buttons on a computer screen. A virtual button is a small area of the screen similar to an icon that can have a control action associated with it. The luminance of the virtual buttons is modulated, each at a different frequency to produce the SSVERs. The operator selects the desired button simply by looking at it. At present, a maximum of two virtual buttons have been displayed at one time. Therefore, the discussion regarding the binary and discrete nature of the first controller is relevant to this BCI.

EEG Component

The SSVER is also the source of control for this system. However, this is a passive system because operators are not actively regulating their SSVER amplitude. This system uses the naturally occurring amplitude of multiple SSVERs. Therefore, little or no training is required.

Communication Protocol

The EEG is acquired using plastic, silver chloride-coated, surface electrodes. A small drop of aloe vera gel is applied to each electrode to improve conductivity. The electrodes are held in place over O1, O2, and Oz (ground) using a headband. The differential (O1-O2) EEG is filtered, amplified, and sampled by a computer. Three software LASs are implemented for each virtual button. One LAS computes amplitude at the stimulus frequency, while the other two compute amplitude at frequencies slightly above (upper frequency) and below (lower frequency) that frequency. The control algorithm monitors the LAS outputs to determine if a selection should be made. The algorithm requires that certain criteria be satisfied for a fixed time duration. First, the amplitude of the center frequency must be above a threshold value. This is intended to prevent an unwanted selection due to natural fluctuations in the EEG. Second, the amplitude of the center frequency must be larger than the average of the lower and upper frequencies by a fixed ratio. The purpose of this is to ensure that broad-band increases in activity do not trigger the system. When these criteria are met, a red border appears around the corresponding virtual button. If these criteria are maintained continuously for 0.3 seconds, then the corresponding button is selected. This BCI system also features an automated software procedure for calibrating operators to set thresholds and other control algorithm parameters.

Assessment of Results

The performance of this system is evaluated in terms of percent correct selections and average time for correct selections

Results

Eight people participated in a formal evaluation of this BCI. Two virtual buttons (2.9 cm wide by 3.8 cm tall) were displayed on the left and right sides of a computer monitor (separated by 10.3 cm) and modulated at 23.42 and 17.56 Hz, respectively. The participants' task was to select the virtual button indicated by a small yellow command box. The participants averaged 92 percent correct selections (range: 83 to 99%) with an average selection time of 2.1 seconds (range: 1.24 to 3.02) [4].

Future Plans

Despite the success demonstrated with the self-regulation based BCI, substantial training is required. For this reason, the ACT program will focus its near-term BCI efforts on approaches that use naturally occurring SSVERs.

The next step with this BCI will be to compare its performance to that of a standard computer mouse. A Fitts' Law paradigm will be employed to compare the speed and accuracy of the two controllers. Other studies will explore the number of virtual buttons that can be simultaneously presented and their spatial separation. Although additional buttons and functions will increase usability, this BCI appears ready for near-term application as an assistive technology.

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EEG-BASED CONTROL OF VIRTUAL BUTTONS

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The Alternative Control Technology program, located in the Air Force Research Laboratory, Wright-Patterson AFB, Ohio, has developed a brain-computer interface (BCI) system that allows operators to select virtual buttons on a computer screen simply by looking at the desired button. A virtual button is a small area of the screen, similar to an icon, that can have a control action associated with it. Control inputs are achieved by modulating the luminance of the virtual buttons at different frequencies, thereby causing a frequency-specific steady-state visual evoked response (SSVER) to appear in the operator's EEG when the operator fixates on a button. Once an SSVER is reliably detected, the corresponding virtual button is selected. Accordingly, the SSVER is the central component of the EEG that enables this technology. At present, a maximum of two virtual buttons can be displayed at one time.

The BCI system being demonstrated consists of a 486 PC operating at 120 MHz with a standard video card, color monitor, and a Scientific Solutions Labmaster AD analog-to-digital (A/D) converter. The software is written in Microsoft™ Visual C 1.5.2 and is run under DOS. The I/O board controls the software timing which is updated at 70.25 Hz.

EEG signals are acquired with three silver chloride-coated, plastic surface electrodes, that are mounted in a headband and located over occipital sites O1, O2, and Oz. The scalp is cleaned with alcohol to reduce impedance and a small drop of aloe vera gel is placed on each electrode to improve conductivity. Impedance between electrode pairs is typically below 35K ohms. The bipolar EEG signal (O1-O2, with Oz as ground) is amplified and filtered using a S75-01 biological signal amplifier manufactured by Coulbourn Instrumentation, Inc.

EEG signals are processed using lock-in amplifier systems (LAS), that produce an estimate of amplitude at a specified frequency. Three LAS's are implemented for each virtual button - one LAS computes amplitude at the stimulus frequency, while the other two compute amplitude at frequencies slightly above and below that frequency.

The control algorithm monitors the LAS outputs to determine if a selection should be made. The algorithm requires that certain criteria be satisfied for a fixed time duration. First, the amplitude at the stimulus frequency must be above a threshold value (to prevent an unwanted selection due to natural EEG fluctuations). Second, the amplitude at the stimulus frequency must be larger than the average of the lower and upper frequencies by a fixed ratio (to ensure that broad-band increases in activity do not trigger the system). When these criteria are met, a red border appears around the corresponding virtual button. If these criteria are maintained continuously for 0.3 seconds, the button is selected.

In support of the demonstration, we would appreciate two chairs, a small table, and access to a power outlet. Some control over room lighting may be necessary if the ambient light level is very bright. Conference attendees will be invited to try the system.

CURRENT TRENDS IN GRAZ BRAIN-COMPUTER INTERFACE (BCI) RESEARCH

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Index Terms - Brain-computer interface (BCI), common spatial patterns (CSP), event-related desynchronization (ERD), adaptive autoregressive models, EEG feedback

I. Introduction

The Graz Brain Computer Interface (BCI) project is aimed at developing a technical system that can support communication possibilities for patients with severe neuromuscular disabilities, who are in particular need of gaining reliable control via non-muscular devices. This BCI system uses oscillatory EEG signals, recorded during specific mental activity, as input and provides a control option by its output. The obtained output signals are presently evaluated for different purposes, such as cursor control, selection of letters or words, or control of prosthesis.

Between 1991 and 1999, the Graz BCI project moved through various stages of prototypes. In the first years, mainly EEG patterns during willful limb movement were used for classification of single EEG trials [1-4]. In these experiments, a cursor was moved e.g. to the left, right or downwards, depending on planning of left hand, right hand or foot movement. Extensive off-line analyses have shown that classification accuracy improved, when the input features, such as electrode positions and frequency bands, were optimized in each subject [5]. Apart from studies in healthy volunteers, BCI experiments were also performed in patients e.g. with an amputated upper limb [6]. From the preliminary results of the patients' study, we could expect that spatiotemporal EEG patterns related not only to planning but also to imagination of a specific movement, can be classified on-line and therefore used for cursor control.

As mentioned before, scalp-recorded rhythmic EEG components are used as input signal. Several studies have shown that EEG responses during voluntary movement can involve both, "event-related desynchronization" (ERD), and "event-related synchronization" (ERS) of different frequency components [7]. During preparation of a voluntary hand or finger movement, for example, a circumscribed ERD can be found over the contralateral hand area with respect to the side of the movement being planned [8]. Of special interest is that such an asymmetrical ERD distribution could also be demonstrated, when subjects only imagine performing such movements [9]. This fact is exploited by the Graz BCI system using left-right differences in the sensorimotor EEG to provide a control option in one dimension [10].

II. Methods

A. EEG Preprocessing

For the analysis of oscillatory EEG components, we investigated the following preprocessing methods:

(i) Calculation of band power in predefined, subject-specific frequency bands in intervals of 250 (500) ms [10],
(ii) Adaptive autoregressive (AAR) parameters estimated with each iteration [11],
(iii) Calculation of common spatial filters (CSP) [12].

When band power data are used for classification, first the reactive frequency bands must be selected for each subject. This means that data from an initial experiment without feedback are required. Based on these training data, the most relevant frequency components can be determined by using the distinction sensitive learning vector quantization (DSLVQ) algorithm [5, 13]. This method uses a weighted distance function and adjusts the influence of different input features (e.g. frequency components) through supervised learning. When DSLVQ is applied to spectral components of the EEG signals (e.g. in the range of 5 to 30 Hz), weight values of individual frequency components according to their relevance for the classification task are obtained.

The AAR parameters, in contrast, are estimated from the EEG signals limited only by the cut-off frequencies, providing a description of the whole EEG signal. Thus, an important advantage of the AAR method is that no a priori information about the frequency bands is necessary [14].
For both approaches, two closely spaced bipolar recordings from the left and right sensorimotor cortex were used. In further studies, spatial information from a dense array of electrodes located over central areas was considered to improve the classification accuracy. For this purpose, the CSP method was used to extract a series of spatial filters with decreasing discriminatory power [15]. These spatial filters can be seen as a representation of spatial EEG patterns associated with the different mental states (e.g. left and right motor imagery).

B. Classification Procedures

An important step towards real-time processing and feedback presentation is the setup of a subject-specific classifier. For this, two different approaches have been investigated in more detail:

(i) Neural network based classification, e.g. a learning vector quantization (LVQ) [2], and
(ii) Linear discriminant analysis (LDA) [16, 17].

LVQ was mainly applied to on-line experiments with delayed feedback presentation. In these experiments, the input features were extracted from a 1-s epoch of EEG recorded during motor imagery. The EEG was filtered in one or two subject-specific frequency bands before calculating four band power estimates, each representing a time interval of 250 ms, per EEG channel and frequency range. Based on these features, the LVQ classifier derived a classification and a measure describing the certainty of this classification, which in turn was provided to the subject as a feedback symbol at the end of each trial [10].

In experiments with continuous feedback based on AAR parameter estimation, a linear discriminant classifier has usually been applied for on-line classification. The AAR parameters of two EEG channels are linearly combined and a time-varying signed distance (TSD) function is calculated [11, 14, 18]. With this method it is possible to indicate the result and the certainty of classification, e.g. by a continuously moving feedback bar.

The different methods of EEG preprocessing and classification have been compared in extended on-line experiments and data analyses [18, 19]. These experiments were carried out using a new developed BCI system running in real-time under Windows with an 8 or 64 channel EEG amplifier [20]. The installation of this system, based on a rapid prototyping environment, includes a software package that supports the real-time implementation and testing of different EEG parameter estimation and classification algorithms [18].

III. Experiments

A. Experimental Task

All experiments are based on the same basic imagination paradigm (training session without feedback): At the beginning of each trial (t= 0.0 s), a fixation cross appears at the center of a monitor. At 2.0 s a short warning tone ("beep") is delivered and at 3.0 s, an arrow pointing either to the right or to the left (cue stimulus) is presented for 1.25 s indicating the target side of this trial. The subject's task is to imagine a movement of the right or the left hand, depending on the direction of the arrow. One experimental session consists of 4 experimental runs of 40 trials, providing a total of 160 trials per session.

Further experimental sessions differ mainly with regard to the setup and presentation of feedback. In experiments with delayed feedback, the success of discrimination between imagination of left and right hand movement is provided at the end of each trial (t= 6.0 s). In particular, feedback consists of 5 different symbols, indicating how well the subject-specific classifier could recognize the selected EEG features [10].

In the case of an experiment with continuous feedback, a horizontal bar moving to the right or left boundary of the screen is shown for a period of 4.0 s (Figure 1). The subject is instructed to imagine the experience of moving the right hand, in order to extend the bar toward the right side. Concentration on moving the left hand, in contrast, would extend the bar to the left. The length of the bar directly corresponds to the linear distance function obtained by on-line analysis [21].

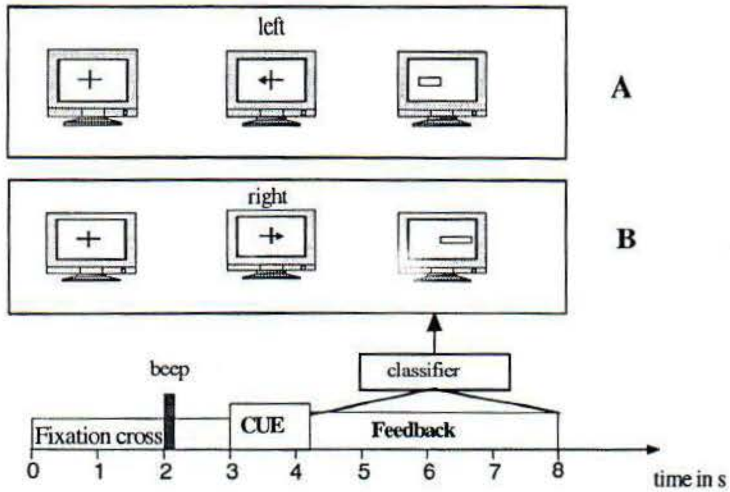

Figure 1: Paradigm for experiments with continuous feedback. A: the arrow is pointing to the left side and therefore the subject has the task to extend the horizontal bar to the left. B: the arrow is pointing and the bar extending to the right (correct classification assumed).

B. Protocol

The basic idea of the Graz BCI is to train the computer to recognize and classify certain subject-specific EEG patterns generated by motor imagery. Based on training sessions without feedback, the acquired data are applied off-line to the (i) bandpower, (ii) recursive least squares (RLS) or (iii) common spatial filters (CSP) algorithms, to calculate the appropriate coefficients for each iteration. In other words, a subject-specific classifier is created and then applied to provide feedback in the following sessions. During these feedback sessions, the coefficients are calculated and classified in real-time e.g. to show the feedback bar on the screen. As soon as feedback is provided, however, changes of the EEG patterns can be expected, that require again adaptation of classification methods. There is evidence from several experiments that it is favorable to update the classifier after a few feedback sessions [2, 14, 18, 19].

IV. Results

A. Experiments with Delayed Feedback

Long-term experimental series, using feedback computed with the bandpower and LVQ approach, were carried out with 4 subjects. This type of feedback yielded to minimum on-line classification errors of around 10 %, 13 %, 14 % and 17 % after several sessions [14].

B. Experiments with Continuous Feedback

In these experiments, the horizontal feedback bar was continuously updated in real-time by using either the CSP or AAR together with LDA approach. After 6 or 7 sessions with several updates of the weight vectors, the lowest on-line errors for three subjects were 1.8 %, 6.8 %, and 12.5 % for the CSP method [19] and, around 5%, 9% and 9% for the AAR method [18].

To compare the classification results obtained with different preprocessing methods, namely bandpower, RLS, and CSP algorithm, the time courses of error rates were computed with a 10 times 10 fold cross validation of a linear discriminant. Figure 2 shows the error time courses for one experimental session of a trained subject. On-line feedback was given with the CSP method. After cue presentation, the error rate decreases significantly for all three algorithms. The lowest error rate for the CSP method (1 %) was observed at second 5.5, the lowest error rate for the RLS (3 %) at second 6 and for bandpower (6 %) at second 6.5.

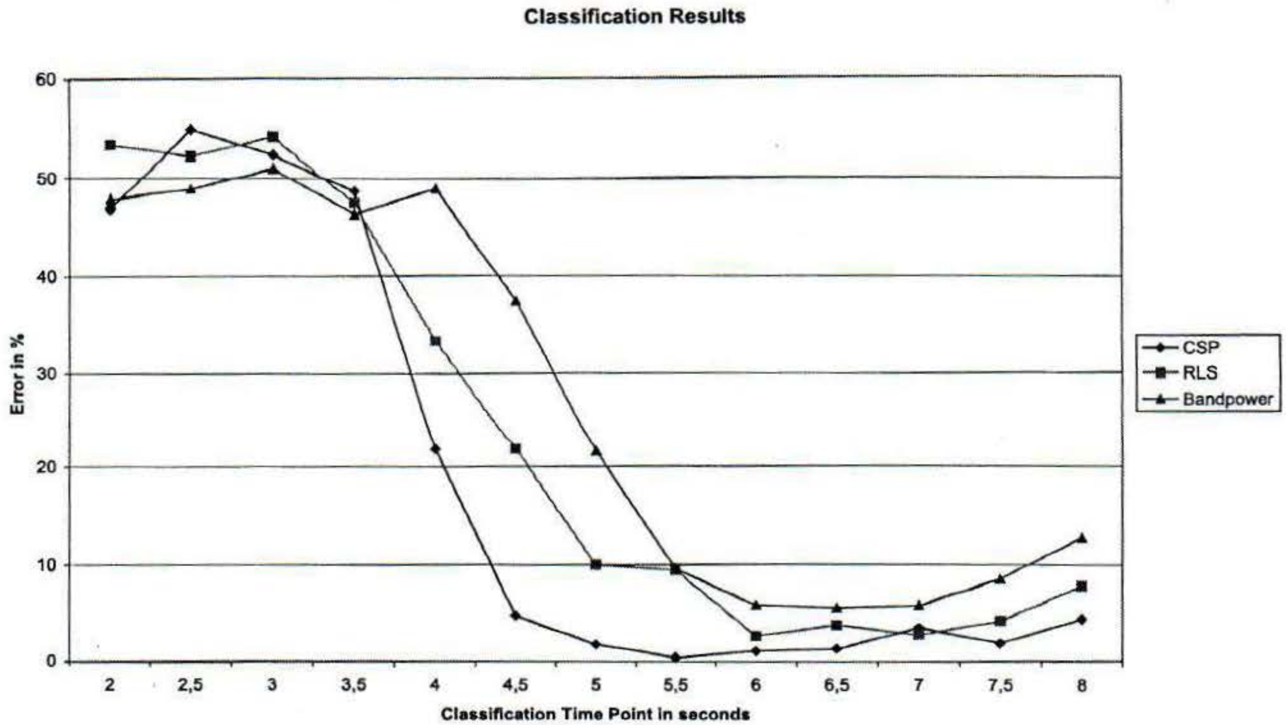

Figure 2: Classification results for one subject and session for three different algorithms: (i) CSP, (ii) RLS and (iii) Bandpower. The error rates were obtained with a 10 times 10 fold cross validation of a linear discriminant. The arrow was presented at second 3.

V. Discussion

Recent experiments were carried out to optimize the BCI training procedure. For example, we investigated the impact of feedback presentation on sensorimotor rhythms [22]. Although a direct comparison of experiments with delayed vs. continuous feedback is not possible, it appears that instantaneous feedback information improves the left-right differentiation of EEG patterns [6, 21].

The classification results show that all methods used, (i) bandpower, (ii) AAR and (iii) CSP, result in low classification error rates after some sessions. At this time, the standard method used at our lab is AAR parameter estimation with the RLS, combined with the LDA algorithm. AAR models have the advantage that it is not necessary to specify the reactive frequency band, as it is for the bandpower method.

The linear discriminant analysis has the advantage that, compared to the LVQ, a smaller amount of training trials is needed to set up a suitable classifier for on-line experiments. Therefore, the next experiment can be performed immediately after a session which was used to calculate the classifier.

First investigations with the CSP method reveal promising results. However, one has to consider that this method requires a larger number of electrodes than the other procedures and that it shows some sensitivity to the electrode montage. The CSP method might be an interesting approach for special applications, as e.g. to process signals from implanted electrode arrays.

An important feature of the new Graz-BCI is, that it is equipped with a remote control that allows controlling the system over an analog dial up, LAN or Internet connection. Beside on a normal PC, the system also runs on a notebook or embedded computer. That means a patient's system can be remotely updated, to change the weight vector, the analysis method or to install improved software. Furthermore, EEG data recorded during the training sessions at the patient's home can be transmitted to the BCI developer for off-line processing. At this time a prototype system is tested for opening and closing a hand-orthesis in a patient with a C5 lesion. The system is installed in the patient's home and remote controlled from our lab.

Another goal of the Graz BCI project is to implement EEG-based control of prosthetic devices to investigate how the feedback (e.g. moving hand prosthesis) affects the overall accuracy of the system. It can be expected that providing feedback by a moving hand prosthesis is more efficient than a cursor moving on a computer monitor.

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RAPID BCI PROTOTYPING: RESULTS WITH ADAPTIVE AUTOREGRESSIVE PARAMETERS AND COMMON SPATIAL PATTERNS

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A BCI system that uses Rapid Prototyping to enable a fast transition of various types of parameter estimation and classification algorithms to real-time implementation and testing is described. The system is able to process multiple EEG channels on-line and operates under Windows 95 in real-time on a standard PC. The BCI can be controlled over the Internet, LAN or modem. For assistive applications an embedded computer can be used. Matlab controls the data acquisition and the presentation of the experimental paradigm, while Simulink is used to describe the current state of the EEG in real-time. Results are presented for two different parameter estimation methods: calculation of adaptive autoregressive (AAR) parameters and common spatial patterns (CSP). In the first case the recursive least square algorithm is utilized to control a prosthesis. In the second case a horizontal bar is controlled on a computer screen by utilizing subject-specific spatial patterns that weight each electrode according to their importance to the discrimination task and allow to achieve a high classification accuracy. Experiments with three subjects resulted in 86,95 and 98% accuracy during on-line discrimination of left and right motor imagery.

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AN EEG-BASED CONTROLLER FOR THE HAND GRASP NEUROPROSTHESIS

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Background

Functional neuromuscular stimulation (FNS) has been effectively used to restore hand grasp in individuals who have sustained a spinal cord injury at the fifth or sixth cervical level. The current hand grasp neuroprosthesis, developed at Case Western Reserve University and the Cleveland VA [1], uses an implanted stimulator that electrically excites paralyzed muscles of the forearm and hand to restore both palmar and lateral grasp. Either an external [2] or implanted [3] transducer mounted at the shoulder or wrist provides the control over hand opening and closing. As the neuroprosthesis continues to develop to allow its implementation in both arms or implantation in persons with a higher cervical level injury, the reliance upon existing voluntary movement for a control signal becomes increasingly difficult. Therefore, alternative methods for controlling hand function must be investigated.

There are currently several alternatives that have been investigated for the control of the neuroprosthesis. These include the use of electromyographic (EMG) signals [3], head movement [4], respiration control [5], and voice control [6]. Another method that has been proposed is the use of signals recorded through the use of intracortical electrodes. One study has demonstrated that an electrode could be implanted into the cortex to record neuron firing patterns, which were then used to operate a computer cursor [7]. These signals might have future applications in controlling electrically stimulated muscles. Other investigators [8,9,10] have also studied the firing patterns of the neurons in the motor cortex to predict extremity movement. One goal of this research would be to use this signal to operate a neuroprosthesis to restore function to the entire upper extremity.

The use of intracortical signals to operate the neuroprosthesis is attractive since it would allow for the restoration of the link between the brain and hand movements. Another possible method of using the brain signals to operate the neuroprosthesis would be to use the electroencephalogram (EEG). Several investigators have demonstrated that subjects can be trained to voluntarily control the amplitude of a specific frequency component of the EEG [11,12] or the slow cortical potential [13]. This signal has been used to move a cursor on a computer screen, which is the basis of an assistive communication device for those persons with severe physical disabilities (i.e. ALS and stroke). These signals could also have potential application to the field of neuroprosthetics.

Specific Aim

The objective of this study was to develop and examine the feasibility of an EEG-based controller for use with the neuroprosthesis. During the course of this investigation, there were two studies that were conducted. The first study was the examination of the use of the frontal beta rhythm to operate a neuroprosthesis. The frontal beta rhythm was selected as the control signal since there would be little interference from electrical stimulation upon the recording of the signal, and, since we were recording from areas not directly related to extremity movement, little interference of remaining voluntary movement upon EEG control was expected. The second study was focused on the development of the EEG-based controller for the neuroprosthesis. This study is still in progress, although preliminary findings indicate that the EEG signal can be used to control hand grasp. However, the effectiveness of this signal has yet to be defined.

Methods

A total of six subjects (four able-bodied and two neuroprosthesis users) have participated in this investigation. For the first study, Dr. Jonathan Wolpaw and colleagues provided the instrumentation and protocols used to train subjects to control the amplitude of the EEG. The brain-computer interface (BCI) and the protocols have been described extensively elsewhere [11], so only a brief synopsis is provided. For training in the control of the frontal beta, each subject was seated in front of a monitor, upon which appeared a cursor in the middle and a target at either the top or bottom. Subjects were trained to identify mental states that would achieve cursor movement toward the target. The EEG signal was recorded from all areas of the brain using 64 electrodes arranged in a modified 10-20 format. For cursor control, only the 25-29 Hz component of the EEG recorded from the FP1, FP2 or F3 sites were used. Training for each subject involved one to three sessions per week. Each session consisted of 8 runs, 3 minutes in length, with anywhere from 30 to 35 targets per run.

Once subjects had attained a high accuracy rate (> 90%), additional studies were performed to determine if EEG control could be maintained under conditions of neuroprosthetic use. To evaluate the effect of movement upon EEG control, the following experiment was performed. The subject was seated in front of a table upon which was placed the computer monitor, a 0.5-kg weight, and a divider. The subject was instructed for the first run to move the cursor as they normally would. In the next run, the subject was then instructed to move the cursor while moving the weight with their right hand over the divider. The next run involved the subject repeating the movement with their left hand. The series of non-movement, right movement, and left movement was then repeated twice, for a total of 9 runs. For the neuroprosthesis users, this protocol was modified in that the subject was asked only to move their hand to the weight. All other aspects were the same. To address the issue as to whether the electrical stimulation would interfere with the control of cursor movement, the neuroprosthesis users were asked to turn their systems on, and then proceeded with a normal session. The system was turned off between runs to prevent fatigue of the muscles due to continuous stimulation.

A final experiment that was conducted as part of the examination on the use of the frontal beta was an examination of the EMG contamination of the signal. Since we were recording from the frontal areas, there was a great deal of concern as to whether subjects were activating the muscles of facial expression to generate cursor movement or if this was a "true" EEG signal. To address this, the BCI was modified so that the sampling rate for the signal was increased to 3 kHz and the LPF was adjusted up to 1 kHz. This allowed for a full examination of the spectra that not only included the EEG signal, but the EMG signal as well. The EMG signal has different signal characteristics, such as a peak amplitude in the spectral analysis between 80 to 100 Hz and a large energy component in all frequencies up to 1 kHz, which would make identification of the EMG in the signal straightforward. Subjects were instructed to move the cursor as they normally would, and then to activate specific muscles to generate cursor movement. The voltages recorded from the entire scalp (represented by head topographies) and the spectra at the recording site were then compared under the different conditions.

The study on the development and assessing the feasibility of an EEG-based controller has only been performed with one neuroprosthesis user. To achieve EEG control of hand grasp, the BCI system was modified to provide an output signal, which could then be converted into a command to control hand grasp. The movement of the cursor up generated a command to close the hand, while down movement opened the hand. The subject was given 30 minutes to adapt to the new controller, and was then asked to use this new controller to manipulate a fork, a cup, and a weight.

Results

The ability of the subjects to control the amplitude of the beta rhythm, as measured in the accuracy rate, is shown in Figure 1. The subjects have participated in anywhere from 10 to 25 training sessions during an eight-month period. The able-bodied subjects are given the designations AB-1 through AB-4, and the two neuroprosthesis users are given the designations NP-1 and NP-2. Five out of the six subjects were able to achieve excellent control, achieving accuracy rates well above 90%. One subject (AB-4) did not do as well as the other subjects, achieving only an 80% accuracy rate. The reason for this is believed to be due to the erratic training schedule of this subject. Subject AB-4 would participate in one session, and then due to scheduling conflicts, would be unavailable for training for another 2 weeks. Although long periods of time between sessions can be done once control is learned (4 of our subjects have gone a period of 60 to 75 days between sessions with no effect upon control), this cannot be done during the initial training phase (first 7 – 9 sessions). Because of these scheduling conflicts, subject AB-4 was excluded from participation in the other studies.

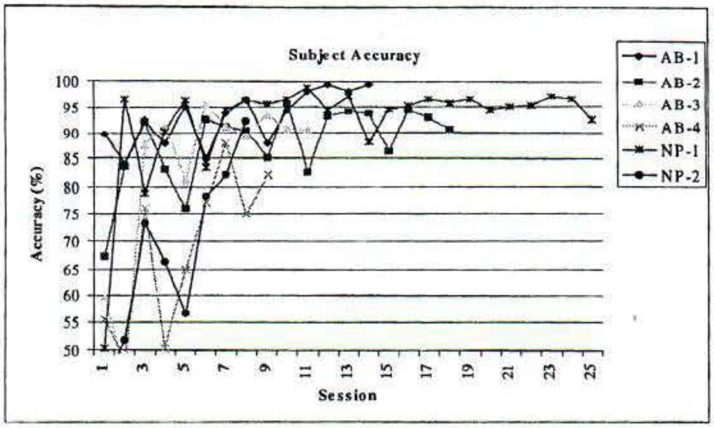

Figure 1 - Subject Accuracy

Movement had little effect upon the subject's ability to control the EEG signal. From these data, it was concluded that the effect of extremity movement was insignificant ($p > 0.5$, repeated measures ANOVA using arcsine transformation of success rates). Neuroprosthesis operation also did not effect beta rhythm control. The overall accuracy rate for subject NP-1 when the neuroprosthesis was active was 93.5%, which was only 0.7% lower than the subjects average accuracy rate without the neuroprosthesis.

Figure 2 shows the results from one of the subjects where the EMG contamination of the signal was investigated. Only two subjects (AB-1 and NP-1) have participated in this study to date. From the figure, it can be seen that subjects are using the EEG signal to operate cursor movement. In the normal condition, the energy in the spectra is restricted to between 0 and 45 Hz, and the voltage difference between the up and the down cursor movements are quite small in the beta band (between 0.2 and 0.5 microvolts). In comparison, the EMG exhibits energy in the entire frequency band up to 1 kHz, with a peak occurring between 80 and 100 Hz. The topographies in the figure, showing the voltages at the control frequency (27 Hz) of this subject also demonstrate that the EEG control is unilateral, focused only over a few sites, and of a low intensity. The EMG is bilateral, involving most of the scalp, and of much higher voltage intensity. The results seen in this subject are identical to those observed with the second subject.

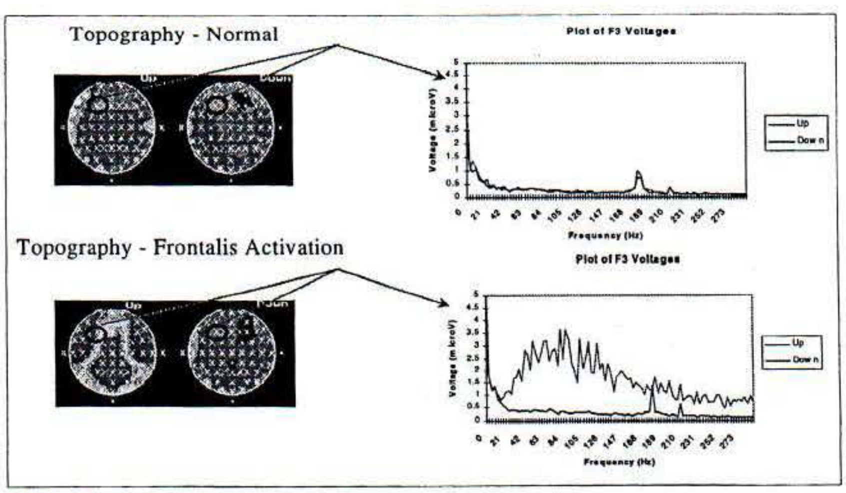

Figure 2 - EMG Analysis

In the final study, the one neuroprosthesis user was able to effectively manipulate all three objects using the EEG-based controller with his current neuroprosthesis. However, the controller only allowed the subject to open and close the hand and not lock it in any one position. To maintain his grip upon an object, the subject had to maintain a high amplitude signal (up cursor movement) continuously, which became harder to do as the subject became tired.

Conclusions

The analysis of the data indicated that the use of the beta rhythm would be ideal for operation of the neuroprosthesis. Subjects have effectively demonstrated that they can achieve a high degree of accuracy with the signal, and can maintain this level of accuracy while generating voluntary movements or while the neuroprosthesis is in operation. The answers to these questions were critical in determining if the EEG signal was feasible as a control source for the neuroprosthesis. The subsequent investigations into the contamination of the EEG signal by muscle activity would indicate that subjects are controlling the amplitude of the frontal beta rhythm and are not contracting the muscles of facial expression to control cursor movement. These findings only apply to two of the subjects to date, although it is expected to hold true once all of the remaining subjects participate in this study. The results from the initial attempt to operate hand grasp using the EEG signal demonstrates that this is a feasible option for controlling the neuroprosthesis. Further work is underway to allow for direct access to the EEG voltages and to develop algorithms to covert the EEG signal into neuroprosthetic control. This would allow subjects to maintain their hold upon an object for a long period of time, as well as to provide finer control over the amount of hand opening and closing (i.e. to achieve positions between fully open and fully closed). This controller will then be evaluated through a matched pairs comparison of performance in manipulating six standardized objects in a controlled environment (Grasp and Release Test), as well as through a more subjective measure of performance (user survey).

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EEG-BASED COMMUNICATION: A PATTERN RECOGNITION APPROACH

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Abstract

The overall aim of this research is to develop an EEG-based computer interface for use by people with severe physical disabilities. The work comprises an 'offline' study and an 'online' study, the offline study establishing principles of interfacce design and the online study putting those principles into practice. The work focuses on using EEG signals to drive one-dimensional cursor movements on a computer screen and our approach is characterised by our emphasis on pattern recognition methods rather than on biofeedback training. Two key technical features further define our approach: firstly, we use dynamic rather than static pattern recognition algorithms and, secondly, we infer not just the parameters of our classifier but also the uncertainty on those parameters. Both of these features result in more robust cursor control.

1 Introduction

The ultimate aim of this research is to develop an EEG-based computer interface for use by people with severe physical disabilities. This would, for example, facilitate interaction with a wordprocessor package or manipulation of various environmental controls. Our work is inspired by the programme of research at the Wadsworth centre. In particular, the work reported by Wolpaw et al. [18] who used fixed features of the EEG (8-13Hz activity) to drive one-dimensional cursor movements on a computer screen. Subjects learn to drive cursor movements via a biofeedback process. Though successful, the process is rather long, taking up to several weeks before users can achieve the accuracy required for a practical communication device. Our approach relies less on biofeedback training and more on the use of pattern recognition methods, the idea being that the burden of communication be met by the user adapting to the computer and the computer adapting to the user. In this type of scheme, cursor movements are generated by the output of a pattern classifier such as a neural network.

The approach is somewhat similar to that used in the Graz BCI [14] but is different in two important technical respects. Firstly, we infer not just the parameters of our classifiers (eg. weights in a neural net) but also the uncertainty on those parameters. This allows us to estimate the uncertainty associated with each subsequent classification. If the cursor is then allowed to move only for high confidence classifications the system has some ability to perform automatic rejection of muscle artifacts and automatic rejection of trials containing irrelevant cognitive components (eg. during lapses of concentration). Secondly, we use dynamic classifiers such that the cursor movement at a given time step is dependent on cursor movements at previous time steps. Both of these features lead to more robust cursor control [13, 16].

A further aspect of our work is an exploration of the cognitive tasks used to provide a starting point for communication. To date, we have looked at motor imagery and mental arithmetic tasks. This aspect of our work is similar to that of the Colorado group [6, 1] but is different both in the pattern recognition approach and in the particular choice of tasks.

2 Offline studies

Our research into EEG-based communication began in 1996. At that time, whilst there was some anecdotal evidence from biofeedback experiments [18, 14] to suggest that motor imagery can be identified from the background EEG, there were no formal experiments to suggest that this is indeed the case. Or indeed, any information on what proportion of subjects these patterns could be detected in or with what accuracy.

To clarify the situation we recorded EEG from seven subjects performing cued imagined hand movements [13]. Control recordings were also made to ensure we were not picking up stimulus-related activity. The EEG was recorded from a single reference electrode and two 11-electrode arrays placed over left and right sensorimotor cortex (a total of 23 electrodes).

Laplacian operators were applied to estimate local activity at three sites over each sensorimotor cortex. Analysis of mu-rhythm power in the resulting signals showed that imagined hand movements could be identified in six out of seven subjects with a typical accuracy of 70%. The most discriminative electrode positions were found to be 3cm posterior to C3 and C4. Extraction of complexity features [15] showed that, in four out of seven subjects, imagined hand movements could be discriminated from background EEG activity with a typical accuracy of 80%. A comparison of classification accuracy using neural network versus logistic classifiers showed no benefit in using neural nets; logistic regression was sufficient [13].

This research was useful in concretely establishing that motor imagery signals could be picked up by spectral features and that, in principle, they could be used to drive cursor movements. It also identified the best position to place a smaller number of electrodes. Similar findings have also been made in recent research by McFarland et al. [8].

3 Online system

Whilst the above research established possible principles of EEG-based communication a number of practical issues remained. Firstly, the pattern recognition must be implemented online. But due to the yearly doubling of computer speed this is one of the lesser problems. Secondly, we would like to use a small number of electrodes and thirdly we would like to have a free-running communication protocol (self-paced movements) rather than communicating in response to a cue (although this last point is something of an open issue).

These factors have influenced the design of our EEG-based interface. It uses only three electrodes, a single isolation amplifier and a 266Mhz PC. The electrodes are placed at C3' - C4' (3cm behind C3 and C4 in the 10/20 system) and a reference electrode is placed over the right mastoid.

In experiments with the interface the communication protocol is as follows. Subjects move a cursor up or down a computer screen in order to hit targets that appear either at the top or at the bottom. The number of discrete cursor positions and other details are identical to that described in [18]. These details are not important, however, as to date, we choose to analyse the data on a segment-by-segment basis (see later).

Subjects move the cursor by performing different cognitive tasks and are given a maximum of ten seconds to hit each target. We have also carried out experiments where the cursor does not move. We have tried two different pairs of cognitive tasks; (i) motor imagery versus a baseline task and (ii) motor imagery versus a maths task. For the motor imagery tasks subjects were asked to imagine opening and closing their hand (right or left according to handedness), and for the maths tasks subjects were asked to serially subtract seven from a large number. Further experimental details are available in [12].

Cursor movements were generated by extracting autoregressive (AR) features from the EEG and classifying them using a logistic regression model. Specifically, a 'lagged- autoregressive' (LAR) model was applied to short-overlapping windows of data. LAR models can pick up relevant changes in EEG signals in whatever frequency band they occur and, in our experience, are superior to AR models in being less sensitive to noise [12].

3.1 Handling uncertainty

The LAR features are classified using a logistic regression model trained using the Bayesian evidence framework [7]. This procedure estimates both the classifier weights and the distribution of those weights. The distribution captures the fact that the classifier is not entirely certain as to how to classify some inputs. If this uncertainty is taken into account when making a new prediction (as it should be) then the correct predictive output to use is the 'moderated' output. Moderation in a two-class problem changes the output to a value nearer to 0.5 (the class prior) by an amount which is proportional to the uncertainty on the weights. Moderated outputs are typically better than unmoderated outputs in terms of the likelihood of predictions [7]. It is possible to make even more robust cursor movements by choosing to not move the cursor if the classifier output is not sufficiently different to 0.5. This is known as 'rejection'.

3.2 Dynamic models

For EEG data, averaging classifier outputs over a number of consecutive data segments is known to significantly increase classification accuracy [1]. This is known as 'temporal smoothing'. One approach to temporal smoothing is to average classifier responses not in the output space, but in the space of activations, or the 'latent' space. This scheme arises from considerations of how to make optimal decisions in a 'committee' of classifiers [9] where each committee member makes a prediction from a different time point. Optimal smoothing periods can be established via cross-validation; a typical period is two seconds.

Temporal smoothing can also be achieved with a Hidden Markov Model (HMM) [10]. HMMs have a number of discrete states (eg. one for cursor up and one for cursor down) each of which is associated with particular characteristics of the data. In our case, these would be spectral characteristics as captured by an LAR model. Transition from the current state, i, to a new state, j is determined by (i) the state transition probability p_{ij} and (ii) the characteristics of the new data point (eg. LAR vector). The amount of temporal smoothing is determined implicitly by the matrix of state transition probabilities and, importantly, these can be learnt from the data set.

3.3 Results

We report results from online experiments by analysing the EEG data on a segment-by-segment basis (we could measure the proportion of targets hit but this would tie the results rather strongly to the details of the particular communication protocol which is yet to be optimised). Figure 1 shows classification accuracies on seven subjects for (a) stationary cursor recordings and (b) moving cursor recordings for two pairs of cognitive tasks. In the moving cursor trials four out of seven subjects achieved at least 75% accuracy.

Once we have trained a classifier to discriminate between two different cognitive tasks on the basis of LAR features it is interesting to then go back and look at what are the typical LAR features and corresponding spectra associated with each task. This is equivalent to the enhanced averaging method described by Gevins and Morgan [5].

Figure 2 shows enhanced spectra for subject 5 performing the imagery versus maths pairing. This is quite representative of all the subjects with the majority of differential activity in the mu-band (8-13 Hz). Some subjects also showed differences in the theta (4-7 Hz) and beta (14-20 Hz) bands.

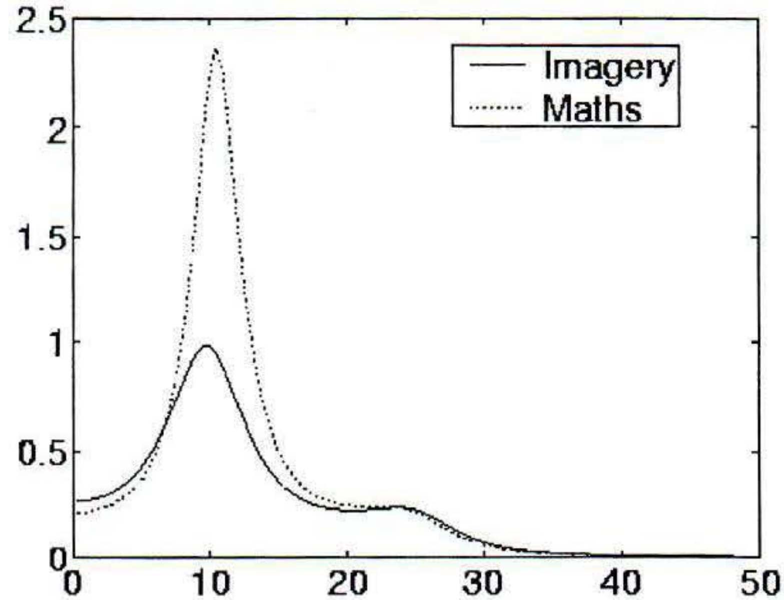

Figure 2: Enhanced spectra for subject five performing motor imagery and maths tasks.

4 Discussion and future plans

We note that four out of the seven subjects achieved at least 75% accuracy in the moving cursor trials. They would therefore be able to immediately use a wordprocessor package via our EEG-based interface using, for example, the protocol developed by Birbaumer et al. [4]. Two of these subjects would use an imagery versus baseline strategy and the other two imagery versus maths.

But what of the other three subjects and what of interfacing with other devices (wheelchair control, for example, may require much better than 75% accuracy) ? As the present technology stands they would not be able to use the interface but we can see the technology improving by following one of two distinct research paths.

Firstly, we could persevere with methods involving little or no biofeedback training and focus on other ways of improving classification accuracy. One method might be to also use 'readiness' potentials (RPs) [2] or 'slow cortical potentials' [4]. Recent research shows that RPs and spectral changes (mu-rhythm desynchronization) are uncorrelated [17]. The RPs would therefore provide an additional source of information. A second method is to look at using additional features such as complexity [15] or to pre-process the signals in more adventurous ways eg. using an Independent Component Analysis embedding [3]. A third method is to use HMMs. HMMs have not, as yet, been applied to the whole database but qualitative results on one subject suggest the approach is promising. The main strength of HMMs is in analysing sequences of data (via Viterbi decoding). We therefore envisage that HMMs can best be utilised by retrospectively analysing sequences of intended cursor movements in order to better decode the transmitted message. Use can also be made of error-correcting codes.

Secondly, we could train subjects using a biofeedback approach. This involves the interaction of two adaptive controllers; the user and the computer. One promising approach for handling this is to use nonstationary classification algorithms [11] which acknowledge that the statistics of each class (ie. how the user moves the cursor up or down) can change with time.

We plan to incorporate all of the more recent technical developments into a new version of the recognition software and to test the resulting system on a large number of normal subjects. The interface will then be tested on patients having severe neurological disabilities but known to be cognitively aware.

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Cognitive Tasks for use with Brain-computer Interface Systems

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The current project in EEG-based brain-computer interface aims at both reducing the training time of subjects and developing protocols that can be used by a wider group. Recent studies in the US (Wolpaw et. al.), have shown that subjects can be trained to achieve control of a cursor on a screen by adapting their thoughts to alter the mu rhythm in appropriate ways. The current study trains subjects to achieve cursor control by performing two types of cognitive task; one associated with movement planning and imagery and the other with mental arithmetic. The aim of this study is to assess whether refining and improving instructions for the subjects re: the cognitive tasks, would contribute to the achievement of more efficient cursor control.

The subjects are required to perform cognitive tasks that demand both concentration and clarity of thought. This assumes a high level of control of mental states and processes on the part of the subject. The subjects' training time may be reduced if we can find ways to make the control of the cognitive tasks easier to achieve. There is support in the literature covering previous studies for making the instructions on cognitive tasks more specific in order to help the subjects to move the cursor (Wolpaw et. al., 1991).

One way of making the instructions more specific would be to break down the cognitive tasks into components and test them separately to see:

a. which components or combinations of components are most effective in producing discernible EEG signals and

b. which mental states and processes are easiest for subjects to control.

In the 'imagined hand movement' task, where motor imagery is used to generate the EEG signals, it is possible to describe the task in at least the following ways:

1. imagine hand moving
2. remember the feeling of hand moving
3. plan to move hand
4. intend to move hand (while at the same time ensuring that it does not move)
5. picture a hand moving

There is some evidence for drawing a distinction between the use of a first person perspective (2.) and the use of a third person perspective (5.) (Decety 1996). The literature on this and other possible distinctions will be explored at this review stage.

There are also other mental states that may be relevant to achieving cursor control. These include notions, used by philosophers in discussions of voluntary action, such as 'will' and 'intention', (Decety and Ingvar 1990, Decety 1996).

Following the literature, the cognitive tasks will be investigated further and ways of improving them will be explored in preparation for the 'hands-on' study.

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1.0 Goals

Our initial interest in BCI-related work is to record movement-related electrophysiology (Mμ Rhythm, Readiness Potentials) and develop real-time recognition of EEG patterns in order to interface with machines and do practical work.

2.0 Current Work

2.1 Study 1: Effects of Self-movement, Observation, and Imagination on Mμ Rhythm

2.1.1 Introduction

The human mμ EEG rhythm is recorded in the 8-13 Hz range from the central region of the scalp overlying the motor cortices. This rhythm is large when a subject is at rest, and is well-known to be blocked or attenuated by self-generated movement. Indeed, the mμ wave is hypothesized to represent an "idling" rhythm of motor cortex that is interrupted when movement occurs. In this study, we show that the mμ wave is also attenuated when a subject observes a movement or when the subject imagines making the same, self-generated movement. According to Rizzolatti and colleagues, the responsiveness of the mμ wave to visual input may be the human electrophysiologic analog of a population of neurons in area F5 of the monkey premotor cortex (Fadiga et al., 1995). These cells respond both when the monkey performs an action and when the monkey observes a similar action made by another monkey or by an experimenter. Older studies have reported that a mμ-like wave is blocked by thinking about moving. For example, individuals with amputated limbs can block this rhythm by thinking about moving the amputated limb. The blocking of the mμ rhythm by visual and imagery input may have implications for understanding movement-related responses and for the rehabilitation of movement-related neurological conditions.

2.1.2 Methods

Subjects were 17 healthy volunteers (10 men, 7 women; age range 19-58 with a mean of 27.7 years). Most subjects were students or employees at the University of California, San Diego and naive to the purposes of the experiment. Only 10 subjects were used for statistical analysis because of problems with noise.

EEG signals were recorded from 6 electrodes placed over frontal (F3, F4), central (C3, C4), and occipital (O1, O2) sites according to the standard 10-20 International Electrode Placement System. Blinks and eye movements were monitored with an electrode in the bony orbit dorsolateral to the right eye. EEG was amplified by a Grass model 7D polygraph using 7P5B pre-amplifiers with bandpass at 1 and 35 Hz. EEG was digitized on-line for two minutes at a sampling rate of 256 Hz.

Subjects participated in four conditions: 1) *rest*: in which no particular task was required; 2) *self-generated movement*: subjects were asked to move their opposing thumb to middle fingers of the right hand ("duck" movement); 3) *observation*: subjects watched a confederate of the experimenter perform the "duck" movement; and 4) *imagination*: subjects were instructed to imagine performing the self-generated "duck" movement. The confederate faced the subject who was seated approximately four feet away throughout all conditions of the experiment.

2.1.3 Results/Discussion

During the rest condition, subjects exhibited significant power in the 8-13 Hz frequency range. This rhythm showed statistically significant changes during the various conditions ($F(3,27)=4.98$, $P<0.01$). Pairwise comparisons showed that the main differences were a reduction in power during the self-generated movement and the observation conditions. Post-hoc analysis of the data showed that during the imagination condition, mμ power decreased at frontal sites but was less affected at central and occipital sites (site x condition, ($F(15,135)=2.22$, $P< 0.01$).

2.1.4 Literature Cited

Fadiga, L.; Fogassi, L.; Pavesi, G.; Rizzolatti, G. (1995) Motor facilitation during action observation: A magnetic stimulation study. Journal of Neurophysiology, 73 (6): 2608-2611.

2.2 Study 2: Readiness Potentials (RPs) and Mμ Rhythm Changes to Spontaneous Overt Single and Multiple Limb Movements

2.2.1. Introduction

The imagination or performance of a movement is generally accompanied by a readiness potential (RP; also called Bereitshaftspotential or BP) which is most prevalent over cortical motor areas. The free running EEG also shows characteristic changes in mμ activity which are unique for movements of different limbs. These findings have proven useful in the construction of BCI systems based on movement related changes in mμ activity.

Numerous studies have explored the RPs and mμ changes associated with single movements of the finger and hand. However, the electrophysiology of left and right foot movement, and those preceding the voluntary simultaneous movement of multiple limbs, have not been thoroughly explored. This information is necessary to better understand how the brain's activity gives rise to different movements, and also expands the range of input signals which could be used in a BCI.

This study recorded EEGs from human subjects performing voluntary movements of either one limb or two limbs at self paced intervals. Results confirmed that each type of movement is associated with unique EEG characteristics which could be categorized artificially.

2.2.2 Methods

A total of 18 subjects (mean age 23.7 +/- 2.8) were run in this experiment. Seven subjects were female and 3 of the female subjects and two males were left handed. Most were undergraduate students at UC San Diego and were compensated with either credit toward an undergraduate course or monetary payment. All subjects were native English speakers with no sensory or motor deficits and no history of psychological disorder. Subjects signed a consent form and research was approved by the Human Subjects Committee at UC San Diego.

EEG activity was recorded monopolarly with Ag/AgCl electrodes over nine sites: F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4 (according to the International 10-20 system of electrode placement), referenced to linked mastoids. All scalp sites had were amplified 10,000 times and bandpass was .1-100 Hz. EOG activity was recorded through an electrode placed over the right orbital bone. Eye activity was magnified 5,000 times and filtered from .3-100 Hz. All electrode sites had an impedance of less than 5 kOhms. Subjects' hand movements were detected through two joysticks (Gravis), while a foot pedal device (CH Products) recorded foot movements. All data (subjects' movements and electrode data) were sampled at 256 Hz and were recorded using the ADAPT software package.

In single movement trials, subjects performed 10 minute long trial blocks during which they made voluntary movements of either hand or foot with at least a five second delay between movements. The movements could be of any one limb, and they were instructed not to worry about randomizing which limb was moved or ensuring a fair distribution of different limb movements. Instructions were identical for multiple movement trials except that subjects were asked to move any two limbs simultaneously.

2.2.3 Results

The data obtained in this study remain under investigation. It is clear that the RPs preceding 2 types of combined movement (left foot/right hand movement and right foot/left hand movement) have a significantly larger peak amplitude than any other single or combined movement. In addition, each of the four single movement types show unique RP and mμ rhythm characteristics. Research is currently directed toward further data analysis and toward exploration of different mechanisms of artificially categorizing the different movement types.

3.0 Future Work

3.0 Classification of RPs using Thoughform (a proprietary software) and other techniques (e.g., PCA, ICA).

3.1 RPs to imagined single and multiple movements.

3.2 Classification of signals using neural networks.

3.3 Detect changes in biorhythm signals, e.g., sleep-wake cycles.

BRAIN-COMPUTER INTERFACE RESEARCH AT THE WADSWORTH CENTER

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Limitations of Conventional Augmentative Communication and Control Technologies

People who are paralyzed or have other severe movement disorders need alternative methods for communication and control. Currently available augmentative communication methods require some muscle control. Whether they use one muscle group to supply the function normally provided by another (e.g., use extraocular muscles to drive a speech synthesizer) or detour around interruptions in normal pathways (e.g., use shoulder muscles to control activation of hand and forearm muscles (7)), they all require a measure of voluntary muscle function. Thus, they may not be useful for those who are totally paralyzed (e.g., by amyotrophic lateral sclerosis (ALS) or brainstem stroke) or have other severe motor disabilities. These individuals need an alternative communication channel that does not depend on muscle control. They need a method to express their wishes that does not rely on the brain's normal output pathways of peripheral nerves and muscles.

Possible Direct Modalities

A variety of non-invasive methods are now available to monitor brain function. These include electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI). PET, fMRI, and MEG are technically demanding and expensive. At present, only EEG, which is easily recorded with simple equipment and reflects changes in function at rates of 5-10 Hz or higher, appears to offer the practical possibility of a new non-muscular communication channel.

Using EEG for Communication

The EEG is an extremely complex signal, reflecting the electrical fields produced by many trillions of individual synaptic connections in the cortex and in subcortical structures. It is also an extremely degraded signal, due to the complex anatomy and electrical characteristics of the cranium. Most important, it is an extremely variable signal. While the brain can produce a given motor performance again and again with very little apparent variation, the brain activity underlying that output, the activity in the many different groups of neurons that contribute to it, varies substantially from performance to performance. As a result, the EEG associated with a given output also varies from performance to performance. The combined effect of these factors is that any effort to determine the brain's intentions from the EEG in a detailed fashion is probably unrealistic and doomed to failure. While relatively gross categories of brain function may be differentiated, detailed analysis is probably not possible in the foreseeable future.

A variety of studies over the past 60 years prompted an alternative approach (25). These studies indicated that people can learn to control certain components of the EEG. They suggested that it might be possible to change the normal relationship between brain function and EEG. Normally, EEG signals reflect brain function, but are not thought to be necessary for that function; they are essentially noise produced by the brain in the course of its operations. However, if people could learn rapid and accurate control of EEG components, the EEG could be converted from noise into a new output signal, a signal that could communicate a person's wishes to an external device.

Possible Methods for EEG-based Communication

EEG activity recorded at the scalp consists of voltage changes of tens of microvolts at frequencies ranging from below 1 Hz to about 50 Hz. It can be analyzed and quantified in the time domain, as voltage versus time, or in the frequency domain, as voltage or power versus frequency. Both forms of analysis can be used for EEG-based communication. In the time domain, the form or magnitude of the voltage change evoked by a stereotyped stimulus, referred to as an evoked potential or evoked response, can serve as a command. For example, the evoked potential produced by the flash of a certain letter can indicate whether the user wants to select that letter (3,18). In the frequency domain, the amplitude of the EEG in a particular frequency band, referred to as a rhythm, can function as a command. For example, that amplitude can be used to control movement of a cursor on a computer screen (4,11,14,22,24-26).

Mu and beta rhythms

The brain-computer interface (BCI) laboratory at the Wadsworth Center has focused on using 8-12 Hz mu and 13-28 Hz beta rhythms in the scalp-recorded EEG for communication (11-13,24-26). These rhythms are produced in sensorimotor cortex and associated areas. We chose them because they are produced in those areas most directly related to movement, and because previous studies suggested that people could learn to control their amplitude (11,25).

In our standard protocol, people with or without motor disabilities learn to control mu or beta rhythm amplitude and use that control to move a cursor in one or two dimensions to targets on a computer screen. Figure 1 summarizes the protocol. Users learn over a series of sessions to control cursor movement. Various kinds of mental imagery are helpful in the initial stages. As training proceeds, imagery usually becomes less important. Figure 2 illustrates the control achieved by a user. While EEG from only one or two scalp locations is used to control cursor movement online, we gather data from 64 locations for later offline analysis (i.e., Figures 3 and 4). This analysis defines the full topography of EEG changes associated with target position and helps develop improvements in online operation.

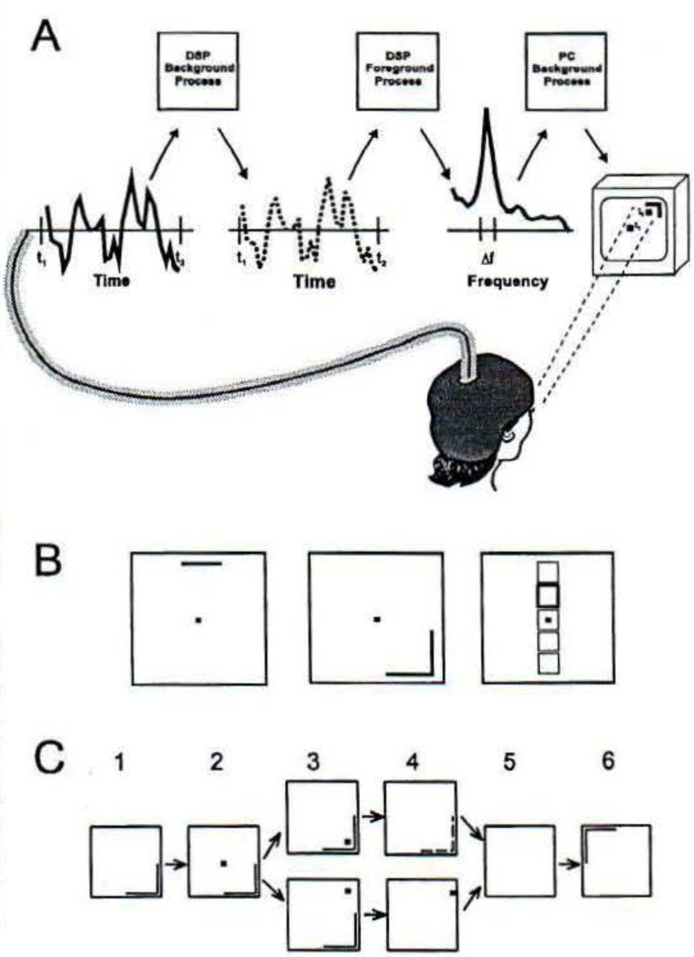


Fig. 1. A: BCI operation. For simplicity, only one EEG channel is shown. Scalp voltage is amplified, digitized, spatially filtered, and frequency analyzed 10 times/sec. Amplitude in a specific frequency band is translated into cursor movement. This is performed by foreground and background processes on the digital signal processing (DSP) board and the PC.
B: Three different control modes. On the left is the basic one-dimensional mode in which the target is on the top or bottom edge and the cursor, which begins in the middle, moves vertically controlled by the EEG until it reaches the top or bottom edge. In the middle is the two-dimensional mode, in which the target is at one of four or more positions on the periphery of the screen and the cursor moves both vertically and horizontally controlled by the EEG until it reaches the periphery. On the right is the graded one-dimensional mode, in which the target is the highlighted box of a series of boxes arranged vertically on the screen and the cursor begins in the middle and moves vertically controlled by the EEG until it stays in one box for a defined period (e.g., one sec) and thereby selects it.
C: Sequence of events during a trial. 1: The trial begins when a target appears in one corner. 2: After a brief period (e.g., one sec) that allows the subject to see the location of the target and initiate the proper EEG, the cursor appears in the center. 3: The cursor moves controlled by the EEG until it reaches the periphery. 4: If it reaches the part occupied by the target, a hit is registered, the cursor disappears, and the target flashes for one sec as a reward. If it reaches another part, a miss is registered, the target disappears, and the cursor remains fixed on the screen for one sec. 5: The screen is blank for one sec. 6: The next target appears.

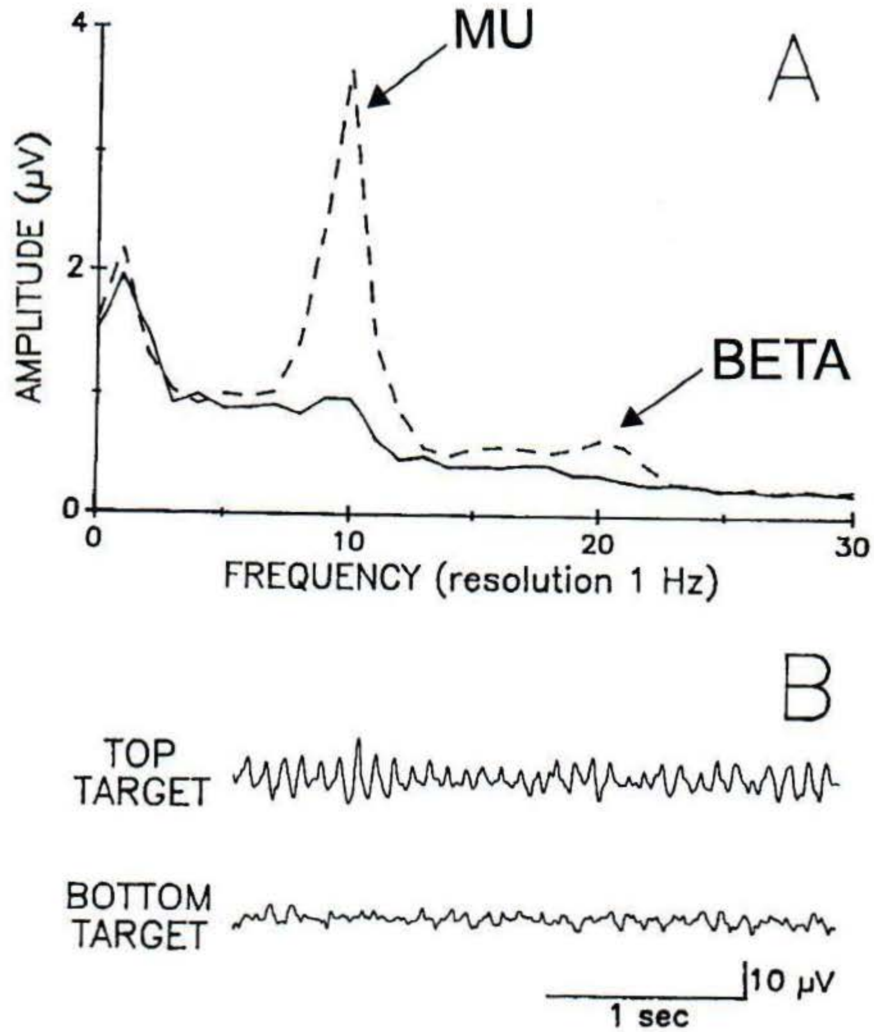


Fig. 2. A: Frequency spectra of EEG recorded over sensorimotor cortex of a trained subject when the target is at the bottom (solid) or at the top (dashed) of the video screen. The main difference between the two spectra is in the 8-12 Hz mu rhythm band (and, to a lesser extent, in an 18-23 Hz beta rhythm band). Differences at other frequencies are absent or minimal. B: Sample EEG traces accompanying top or bottom targets. The mu rhythm is prominent with the top target, and minimal with the bottom target. (From Ref. 25.)

Figure 4 illustrates the topographic and spectral specificity achieved by two representative users (r^2 is the proportion of the total variance of the signal accounted for by target position, and thus indicates the user's level of EEG control). Control is sharply focused over sensorimotor cortex and in the mu and/or beta rhythm frequency bands. With this control, users can move the cursor to answer spoken yes/no questions with accuracies greater than 95% (13). Users can also achieve independent control of two different mu or beta rhythm channels and use that control to move a cursor in two dimensions (26).

Recent studies

Our recent work has focused on realization of a general purpose EEG-based BCI system suited for developing and studying EEG control and for determining the best methods for translating it into device control (11,23). The key feature of this system is recognition and use of the principle that EEG-based communication depends on successful interaction of two adaptive controllers: the system user who produces EEG control and the BCI system which translates that control into device control.

With this laboratory system, we have also sought to delineate the topographical, spectral, and temporal characteristics of the 8-12 Hz mu rhythms used in our initial BCI studies. These rhythms are usually focused near the midpoint of the central sulcus bilaterally. In trained users, they respond to command within 0.5 sec (22), and are associated with 18-25 Hz beta rhythms which in some users may be better control signals (e.g., Figure 4A). The locations and frequencies that provide optimal control may vary within days and between days, particularly early in training.

Another objective has been improvement in the algorithm that translates EEG control into device control. These improvements include: spatial filters that match the spatial frequencies of the user's mu or beta rhythms, autoregressive frequency analysis which gives higher resolution for short time segments and thus permits more rapid device control, and better selection of the intercepts and gains in the equations that translate EEG control into device control (11,12,15).

In ongoing studies, we are seeking additional frequency-domain EEG rhythms that are susceptible to control. Topographically distinct rhythms may be controlled simultaneously, so that one increases when the other decreases (20). Of particular interest is a rhythm recorded over parietooccipital cortex (10). This rhythm might be combined with mu or beta rhythms to provide several independent control channels.

We have also conducted studies indicating that EEG-based communication is not associated with and does not depend on peripheral muscle activity (19). This demonstration is an important step in establishing EEG-based communication as a new communication channel for those who lack voluntary muscle control.

Most recently, we have begun to evaluate the possible contributions to control of time-domain EEG components. Mu and beta rhythm control may be associated with slow cortical potential activity comparable to that which Birbaumer and his colleagues have shown to be useful for communication (1,2,8). A collaborative effort with these investigators is focused on determining whether frequency-domain control based on mu and beta rhythms can be combined with time-domain control based on slow potentials to yield better EEG-based communication. Another time-domain component might provide a method for detecting errors in communication.

Finally we are exploring several practical applications for EEG-based communication and control. The Wadsworth BCI system can be used to answer simple questions and to select items from a screen menu, and appears capable of operating the "Freehand" neuroprosthesis which provides hand-grasp control to people with cervical spinal cord injuries (7,9,13,27).

Present goals

Over the next several years, we will evaluate three hypotheses: 1) that increasing the adaptibility of the online algorithm will increase the accuracy and speed of communication, 2) that time-domain EEG components can supplement and improve the control now provided by frequency-domain components, and 3) that the EEG-based

Fig. 3. The standard 64 scalp electrodes (from Ref. 17) used by the laboratory BCI system. The subject's nose is at the top. While only a few electrodes control cursor movement online, activity from all 64 is stored for later analysis. All electrodes are recorded versus an ear reference so that spatial filters can be applied after digitization.

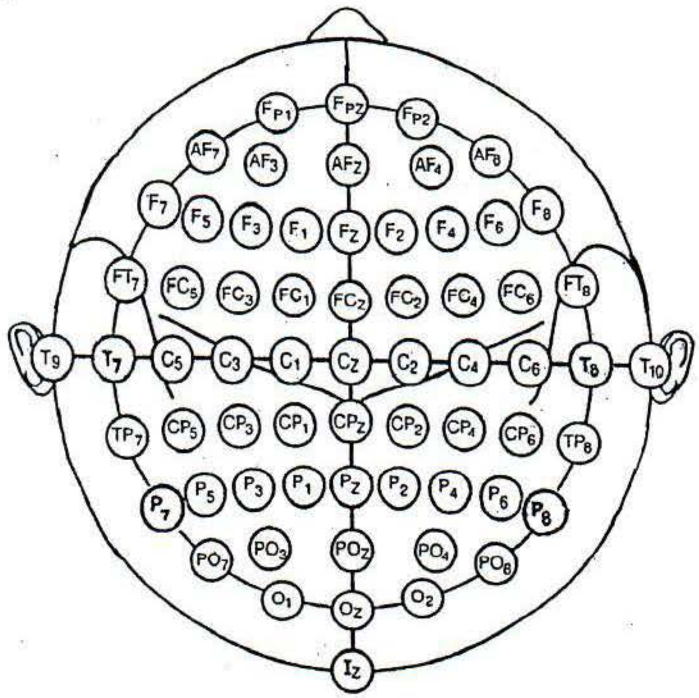
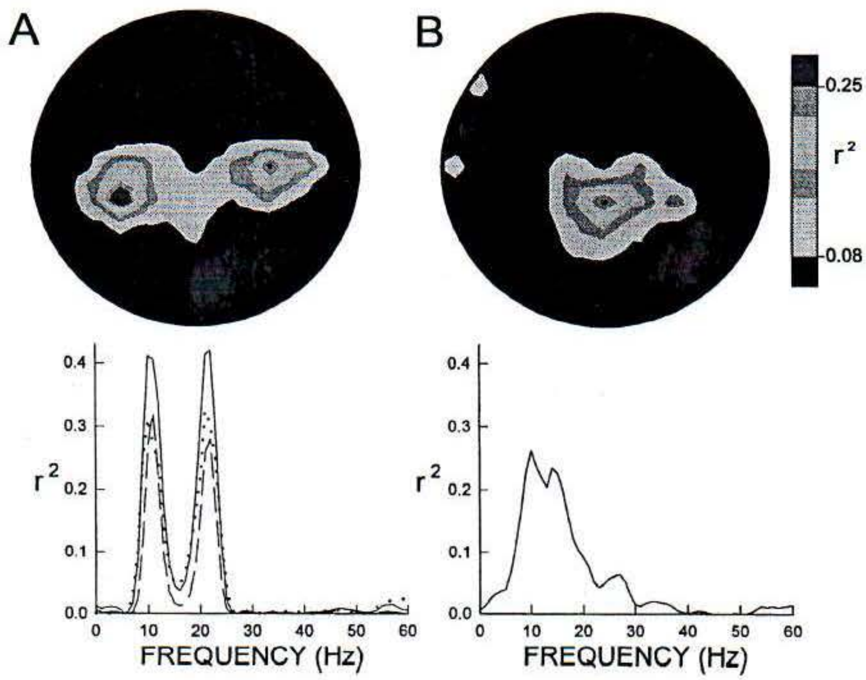


Fig. 4. Topographical and spectral foci of control in two subjects. The r^2 color topography in A is for the beta frequency band and that in B is for the mu band. Subject A has bilateral foci near the midpoint of the central sulci. The r^2 spectra show that the sum (solid) of the right (dashed) and left (dotted) beta rhythm amplitudes, which controlled the cursor, has a higher r^2 value than either amplitude alone, and thus is a better control signal. (Note that the subject also has control in the mu rhythm band.) In contrast, Subject B, who is a 25 year-old man with severe cerebral palsy who now communicates very slowly with a touch-talker, controls the cursor with a mu rhythm focused in the midline just posterior to the vertex.



BCI can provide cursor-based menu selection and operate a neuroprosthesis. In accord with these hypotheses, we plan three sets of studies.

First, we will expand the online algorithm to include automatic selection of optimal EEG components, optimal electrode locations and frequencies for these components, optimal spatial filters, and optimal gain; and will assess the benefits of these modifications. We expect that these changes will improve translation of the user's EEG control into device control, and will also facilitate user training and thereby increase the level of EEG control achieved. The goal is to incorporate into the online algorithm important aspects of analyses previously performed offline.

Second, we will try to supplement the control provided by mu and beta rhythms with that provided by other frequency-domain components and by time-domain components such as slow cortical potentials and error-related potentials. This aim combines the two prevailing methods of EEG-based communication, use of frequency-domain components and use of time-domain components. We expect that this combination will improve the system's detection of the user's commands.

Third, we will try to demonstrate the practicality and usefulness of EEG-based communication. We will evaluate several different methods by which the BCI can support cursor-based letter or icon selection. One method uses simultaneous control of horizontal and vertical cursor movements; the other uses sequential control (i.e., vertical movement to select a row followed by horizontal movement to select a column). We will also continue to contribute to application of the interface to operation of the "Freehand" neuroprosthesis that provides hand grasp function to people with cervical spinal cord injuries (7). We expect that this commercially available prosthesis, which is presently controlled by shoulder muscles, can also be controlled by EEG (9). This demonstration would expand the population of potential users.

In summary, we plan to improve the reliability, speed, and versatility of the current EEG-based BCI by increasing the adaptibility of the online algorithm and incorporating additional frequency-domain and time-domain control signals. We also plan to demonstrate its applicability to several important communication and control tasks.

Conclusions

The continued development of EEG-based communication depends on progress in three crucial areas. First, the EEG components, whether time-domain or frequency-domain, that people are best able to control must be fully characterized and improved methods for detecting and measuring them must be developed (e.g., (12)). Second, the methods used to translate these measurements into device control, e.g., movement of a cursor, prosthesis activation, or letter selection, must be optimized. Third, the fact that EEG-based communication inevitably involves the interaction of two adaptive controllers – the system and the user – must be recognized and accomodated. Improvements in training methods and delineation of reliable techniques for maintaining stable interaction beyond initial training are essential.

Acknowledgements

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