BRAIN-COMPUTER INTERFACES FOR COMMUNICATION AND CONTROL

Second International Meeting

Moving Beyond Demonstration

June 12-16, 2002

The Rensselaerville Institute

Rensselaerville, New York

Program and Abstracts

Schedule Quick Reference

Wednesday, June 12, 2002

3:00 - 7:00 pm	Arrival and registration	Guggenheim Lobby
5:30 - 8:00	Opening reception and dinner	Weathervane Restaurant
8:00 on	Panel planning meetings	See program

Thursday, June 13

6:30 - 8:00 am	Breakfast	Weathervane Restaurant
8:15 - 10:30	Welcome and 12 presentations	Guggenheim Auditorium
10:30 - 11:00	Break	Guggenheim Lobby
11:00 - 12:30 pm	9 Presentations	Guggenheim Auditorium
12:30- 2:30	Lunch	Weathervane Restaurant
2:30 - 3:30	7 Presentations	Guggenheim Auditorium
3:30 - 4:00	Break	

		Guggenheim Lobby
4:00 - 5:30	9 Presentations	Guggenheim Auditorium
5:30 - 7:15	Cocktails and dinner	Weathervane Restaurant
7:30 - 8:30	Keynote address	Guggenheim Auditorium
8:30 on	Panel planning meetings	See program

Friday, June 14

6:30 - 8:15 am	Breakfast	Weathervane Restaurant
8:30 - 9:15	Debate I	Guggenheim Auditorium
9:15 - 10:15	Discussion session 1	Guggenheim Auditorium
10:15 - 10:45	Break	Guggenheim Lobby
10:45 - 11:45 am	Discussion session 2	Guggenheim Auditorium
11:45 - 4:00 pm	Packed lunch and field trips	Depart from Weathervane
4:00 - 4:45	Debate II	Guggenheim Auditorium
4:45 - 5:45	Discussion session 3	Guggenheim Auditorium
5:45 - 7:30	Cocktails and dinner	Weathervane Restaurant
7:30 on	Posters and demonstrations	Guggenheim Master Seminar Rm

Saturday, June 15

6:30 - 7:30 am	Birdwatching walk	Depart from Weathervane
7:00 - 8:45	Breakfast	

		Weathervane Restaurant
9:00 - 10:00	Discussion session 4	Guggenheim Auditorium
10:00 - 10:45	Debate III	Guggenheim Auditorium
10:45 - 11:15	Break	Guggenheim Auditorium
11:15 - 12:15 pm	Discussion session 5	Guggenheim Auditorium
12:15 - 3:00	Barbeque	Garden
3:00 - 4:30	Satellite sessions	Guggenheim Auditorium
4:30 - 5:15	Debate IV	Guggenheim Auditorium
5:15 - 6:15	Discussion session 6	Guggenheim Auditorium
6:15 - 8:00	Cocktails and dinner	Weathervane Restaurant
8:00 on	Posters and demonstrations	Guggenheim Master Seminar Rm

Sunday, June 16

9:00 - 11:00 am	Breakfast and summary session	Weathervane Restaurant

Sponsored by:
National Center for Medical Rehabilitation Research, National Institutes of Health
National Institute on Deafness and Other Communication Disorders, National Institutes of Health
Office of Rare Diseases, National Institutes of Health
National Institute of Neurological Disorders and Stroke, National Institutes of Health

Additional support for students and fellows:
Eastern Paralyzed Veterans Association
Department of Defense Advanced Research Project Agency
Whitaker Foundation
Deutsche Forschungsgemeinschaft
Wadsworth Center

Hosted by:
Brain-Computer Interface Project
Wadsworth Center
New York State Department of Health and State University of New York

PROGRAM

Wednesday, June 12, 2002

3:00 - 7:00 pm	**Arrival and registration**	**Guggenheim Lobby**
5:30 - 8:00	**Opening reception and dinner**	**Weathervane Restaurant**
8:30 on	**Discussion panel meetings***	
	Signals I (Heetderks)	Strauss Meeting Room
	Signals II (Trejo)	Ford Lounge
	Methods (Rymer)	Stonecrop Living Room
	Applications I (Moore)	Huyck Library
	Applications II (Weinrich)	Huyck House Board Room
	Standards (Kübler)	Stonecrop Board Room

Thursday, June 13, 2002

6:30 - 8:00 am	**Breakfast**	**Weathervane Restaurant**
8:15 - 10:30 am	**Welcome and presentations**	**Guggenheim Auditorium**

Theresa M. Vaughan and Jonathan R. Wolpaw, Wadsworth Center, NYS Dept Health & SUNY, Albany, NY
Welcome (8:15 am)

Brendan Z. Allison, University of California at San Diego, La Jolla, CA
Think and spell: toward a faster, better P300 BCI (8:30 am)

Florin Amzica, Laval University, Quebec, Canada
Interactions of neurons and glial cells during the genesis of synchronous brain waves

Thursday, June 13, 2002

Charles W. Anderson, Colorado State University, Fort Collins, CO
BCI research at Colorado State University

Jessica D. Bayliss, Rochester Institute of Technology, Rochester, NY
Towards better software components for brain-computer interfaces

Luigi Bianchi, University of Rome "Tor Vergata," Rome, Italy
The bio-feedback systems design approach at the "Tor Vergata" University

Niels Birbaumer, University of Tübingen, Tübingen, Germany
Communication with slow cortical potentials (SCP)

Gary E. Birch and Steven G. Mason, Neil Squire Foundation, Vancouver, Canada
The Neil Squire Foundation brain-computer interface laboratory

Thursday, June 13, 2002

Benjamin Blankertz, Intelligent Data Analysis Group, Fraunhofer-FIRST, Berlin, Germany
Machine-learning for extracting neuronal signatures of natural motor commands from single-trial muti-channel EEG data in untrained subjects

John K. Chapin, SUNY Health Science Center, Brooklyn, NY
Closed loop brain-machine interfaces

Febo Cincotti, Santa Lucia Foundation, Rome, Italy
Development and applications of BCI at Santa Lucia Foundation

Bruce H. Dobkin, Reed Neurologic Research Center, UCLA, Los Angeles, CA
Spinal and cortical plasticity induced by practice after stroke and spinal cord injury

Emanuel Donchin, University of South Florida, Tampa, FL
Unlocking the locked in: progress in brain-computer interfaces

Thursday, June 13, 2002

10:30 - 11:00 am	**Break**	**Guggenheim Lobby**
11:00 - 12:15 pm	**Presentations continue**	**Guggenheim Auditorium**

John P. Donoghue, Brown University, Providence, RI
Intercortical motorneural prosthetic devices

Gyongyi Gaal, Neuroprosthesis Research Organization, Brooklyn, NY
Adaptive control of reaching for neuroprostheses

Shangkai Gao, Tsinghua University, Beijing, China
The SSVEP-based BCI system with high transfer rate

Alan Gevins, San Franciso Brain Research Institute and Sam Technology, Inc., San Francisco, CA
On-line measurement of mental workload

Christoph Guger, Guger Technologies, OEG, Graz, Austria

Biosignal processing environment for an EEG-based brain-computer interface

Thursday, June 13, 2002

William Heetderks, National Institute of Neurological Disorders and Stroke, Bethesda, MD
Brain communication interface research at the NINDS

Jack W. Judy, University of California at Los Angeles, Los Angeles, CA
UCLA Neuroengineering Program

Phillip R. Kennedy, Neural Signals, Inc., Atlanta, GA
The choice of brain-computer interface technique

Daryl R. Kipke, University of Michigan, Ann Arbor, MI
Development of implantable microelectrode arrays at the Neural Engineering Lab (NEL) at the University of Michigan

12:30 - 2:30 pm	**Lunch**	**Weathervane Restaurant**

Thursday, June 13, 2002
2:30 - 3:30 pm **Presentations continue** **Guggenheim Auditorium**

Michael Kositsky, Northwestern University, Chicago, IL
Connecting brain tissue to robots: development of a hybrid system for studying neural plasticity

Simon P. Levine, University of Michigan, Ann Arbor, MI
University of Michigan direct brain interface: 2002 update

José del R. Millán, Joint Research Centre of the EC and Swiss Commission, Fed Inst of Tech, Lausanne
Asynchronous BCI and local neural classifiers

Mohammed M. Mojarradi, California Institute of Technology, Pasadena, CA
Challenges in the development of miniaturized, smart neuro-prostheses suitable for implanting into a brain

Melody M. Moore, Georgia State University, Atlanta, GA
Human-computer interaction research at the GSU Brainlab

Thursday, June 13, 2002

Christa Neuper, Department of Medical Informatics, Graz, Austria
Graz BCI: state of the art and clinical application

Paul Nunez, Tulane University, New Orleans, LA
EEG phase locking during cognitive processing

3:30 - 4:00 pm	**Break**	**Guggenheim Lobby**
4:00 - 5:30 pm	**Presentations continue**	**Guggenheim Auditorium**

Lucas Parra and Paul Sajda, Sarnoff Corporation, Princeton, NJ, Columbia University, New York,NY
Real-time EEG event detection for augmented human machine interaction

José C. Principe, University of Florida, Gainesville, FL
Signal processing methodologies to model the relation between spike trains and hand movements for brain-machine interfaces

Thursday, June 13, 2002

Robert N. Schmidt, Cleveland Medical Devices, Inc., Cleveland, OH
A miniature, wireless two-channel EEG for brain-computer interface

William G. Shain, Wadsworth Center, New York State Department of Health, Albany, NY
Controlling reactive responses around neural prosthetic devices

Mingui Sun, University of Pittsburgh, Pittsburgh, PA
Solving the wireless data communication problem between brain implants and computer

Peter Sykacek, Robotics Research Group, Oxford University, England
The Oxford-Putney BCI system

Dawn Taylor, Arizona State University, AZ
Training cortical cells to produce better directional control signals with and without physical limb movements

Thursday, June 13, 2002

Leonard Trejo, NASA Ames Research Center, Moffett Field, CA
Multimodal neuroelectric human computer interface development

Jonathan R. Wolpaw, Wadsworth Center, New York State Department of Health, and SUNY, Albany, NY
The Wadsworth Center BCI Program

5:30 - 7:15 pm	**Cocktails and Dinner**	**Weathervane Restaurant**
7:30 - 8:30	**Keynote address**	**Guggenheim Auditorium**

Fernando H. Lopes da Silva, Faculty of Sciences, University of Amsterdam, Kruislaan, Amsterdam
EEG features as reflections of brain states

8:30 on	**Discussion panel meetings**	**See page 4**

Friday, June 14, 2002

6:30 - 8:15 am	**Breakfast**	**Weathervane Restaurant**
8:30 - 9:15	**Debate I**	**Guggenheim Auditorium**

Spikes versus Field Potentials in BCI Research and Development
Simon Levine (Moderator), John Donoghue (Spikes), Jon Wolpaw (Field potentials)

Electrophysiological recording can focus on the action potentials (spikes) produced by individual neurons or on the field potentials produced by populations of neurons and synapses. Both methods have a long history in neuroscience research. The discussants will debate the relative advantages and disadvantages of these two approaches for the laboratory development and clinical application of BCI technology.

Friday, June 14, 2002

9:15 - 10:15 am **Discussion session 1** **Guggenheim Auditorium**

Signals I - Discussion: The relative advantages and disadvantages for BCI use of different brain signals and different signal recording technologies

Bill Heetderks (Chair), Daryl Kipke, Thilo Hinterberger, Christoph Guger, Roman Rosipal, Mohammed Mojarradi, Lucas Parra, Florin Amzica, Paul Nunez

10:15 - 10:45 am **Break** **Guggenheim Lobby**

Friday, June 14, 2002
10:45 - 11:45 am **Discussion session 2** **Guggenheim Auditorium**

Signals II - Discussion: The relative advantages and disadvantages for BCI use of different brain signals and different signal recording technologies

Len Trejo (Chair), Xiaorong Gao, Jaime Pineda, José Principe, Febo Cincotti, Michael Rudko, Paul Sajda, David Peterson, Barbara Whilhelm

11:45 - 4:00 pm **Packed lunch and field trips** **Depart from Weathervane**

Friday, June 14, 2002
4:00 - 4:45 pm **Debate II** **Guggenheim Auditorium**

Linear versus Non-linear Methods in BCI Research
Gary Birch (Moderator), Klaus Müller (Linear), Charles Anderson (Non-linear)

Linear methods, such as multiple regression, have traditionally dominated quantitative approaches in science and engineering. Recently, non-linear methods, such as neural networks, have become prominent. The discussants will debate the relative advantages and disadvantages of these two classes of methods in the design, evaluation, and application of BCI technology.

Friday, June 14, 2002

4:45 - 5:45 pm **Discussion session 3** **Guggenheim Auditorium**

Methods: Alternative methods for measuring brain signals and for translating these measurements into communication and control commands

William Zev Rymer (Chair), Gernot Müller, José Millán, Shangkai Gao, Dawn Taylor, Jessica Bayliss, Mingui Sun, Peter Sykacek, Benjamin Blankertz

5:45 - 7:30 pm	**Cocktails and Dinner**	**Weathervane Restaurant**
7:30 on	**Demonstrations/Posters**	**Guggenheim Master Seminar Room**

Saturday, June 15, 2002

7:30 - 8:45 am	**Breakfast**	**Weathervane Restaurant**
9:00 - 10:00	**Discussion session 4**	**Guggenheim Auditorium**

Applications I - Discussion: Identification of those applications of most practical value to users, facilitation of user training, and long-term support of applications

Michael Weinrich (Chair), Christa Neuper, Phil Kennedy, Julie Onton, Theresa Vaughan, Lyndsey Pickup, David Weston, Nicola Neumann

Saturday, June 14, 2002

10:00 - 10:45 am **Debate III** **Guggenheim Auditorium**

Behavioral versus Cognitive Approaches to BCI Research

Alan Gevins (Moderator), Niels Birbaumer (Behavioral), Emanuel Donchin (Cognitive)

For over 100 years, two opposing approaches have dominated the study of mind and behavior: behaviorism, which analyzes behavior without reference to thoughts, emotions, and other mental events; and cognitivism, which incorporates mental events into its analyses of behavior. BCI research presents a new class of mind/behavior phenomena and is thus a new arena for the continuing clash of behavioral and cognitive view-points. The discussions will debate the relative advantages and disadvantages of these two approaches for the understanding of BCI phenomena and for the design, evaluation, and use of BCI technology.

10:45 - 11:15 am **Break** **Guggenheim Lobby**

Saturday, June 15, 2002
11:15 - 12:15 pm **Discussion session 5** **Guggenheim Auditorium**

Applications II - Discussion: Identification of those applications of most practical value to users, facilitation of user training, and long-term support of applications

Melody Moore (Chair), Brendan Allison, Michael Gibbs, Jack Judy, Bob Schmidt, Louis Quatrano, Irina Goncharova, Ahmed Karim, Joseph Green

12:30 - 3:00 pm **Barbeque** **Garden**

Saturday, June 15, 2002
3:00 - 4:30 pm **Satellite sessions** **Guggenheim Auditorium**

Making it real: What the field of Human-Computer Interaction (HCI) has to offer BCI

How do we move beyond demonstrations and ensure that this new interface technology is usable in the real world? Interfacing to common devices using BCI techniques raises many design and evaluation issues. The mature field of Human-Computer Interaction (HCI) already has a wealth of knowledge, metrics and techniques, which could be exploited by our community. The incorporation of HCI theory and methods would significantly impact the efficacy, usability, and therefore the acceptance, of BCI technologies in the general population. We propose to introduce the community to HCI concepts and discuss how these ideas impact the development of real-world applications.

Organizer: Melody Moore

BCI Data Analysis Competition: Results, Lessons Learned and The Future

To foster development of machine learning techniques and evaluate different algorithms for BCI systems, we announced a data analysis competition at the NIPS*2001 Brain Computer Interface Workshop (December 2001). Three EEG data sets involving separate BCI tasks were provided:

1. EEG self-paced key typing (courtesy of Benjamin Blankertz and Klaus-Robert Mueller, Fraunhofer FIRST, and Gabriel Curio, FU-Berlin). This data set consists of 513 trials of 27 electrode EEG recordings from a single subject. While sitting in a normal chair, relaxed arms resting on the table, fingers in the standard typing position at the computer keyboard (index fingers at 'f','j' and little fingers at 'a',';') the subject was instructed to press the aforementioned keys with the corresponding fingers in a self-chosen order and timing. The task was to classify EEG potentials as being associated with left or right finger movement.
2. EEG synchronized imagined movement task (courtesy of Allen Osman, University of Pennsylvania). The task of each of 9 subjects during the EEG Synchronized Imagined Movement data set was to imagine moving his or her left or right index finger in response to a highly predictable timed visual cue. The goal of competition participants was to classify EEG recordings as belonging to left or right imagined movement. EEG was collected using 59 sensors and there were 90 trials for each subject (45 left and 45 right)
3. Wadsworth BCI Data Set (courtesy of Gerwin Schalk, Wadsworth Center) The data set consists of 64 electrode EEG recordings from 3 subjects. The task of each subject was to move a cursor on a video screen to 1 of 4 predetermined positions. Each target position differed only in vertical location. Horizontal coordinates were identical for each target position. The objective of this contest was to classify EEG recordings as belonging to the correct target position.

We will describe the data sets in further detail, present results from the competition and discuss lessons learned. We will also have an open discussion on the general utility of such competitions for promoting algorithm development in BCI and identify opportunities for a future competitions. More details can be found at http://newton.bme.columbia.edu/competition.htm.

Organizers: Paul Sajda, Lucas Parra and Klaus-Robert Müller

Saturday, June 15, 2002

3:00 - 4:30 pm **Satellite sessions continued** **Guggenheim Auditorium**

Training patients: a challenge for the use of brain-computer interfaces

Brain-computer interfaces are highly developed technical systems. However, the feasibility of BCIs for the target group, for example, severely disabled or brain-damaged patients, has to be considered. Training patients who are diagnosed with intractable neurological diseases to self-regulate their brain potentials poses several difficulties. The following questions will be discussed:

1) Which patients should be selected if there is a choice? Are there any predictors for good performance?
2) How to communicate with locked-in patients? How do they perceive their environment?
3) How to take the patient's social environment into account? Who wants the patient to be able to communicate? Who is going to conduct the training?
4) How to motivate patients for weeks and months of training during which patients have to maintain their effort?
5) Are patients with intractable neurological diseases always depressed?
6) In case of failure: When to stop training?
7) What about burn-out of research associates?

Organizers: Nicola Neumann & Andrea Kübler

Implantable Microelectrodes for BCI Systems

This discussion will focus on various types of microelectrode technologies to function as sensor/actuators for BCI systems that interface directly with the CNS for human applications. Implantable microelectrode systems that are used routinely in animal models for neuroscience research provide a relatively robust technology base for developing human neural implants. We expect this discussion to include both basic microfabricated electrodes, as well as various types of hybrid electrode technologies that involve biologically active agents.

Organizers: Daryl Kipke, Justin Williams, Kevin Otto

Saturday, June 15, 2002
4:30 - 5:15 pm **Debate IV** **Guggenheim Auditorium**

A standard BCI framework: Good or Bad?
Bruce Dobkin (Moderator), Steve Mason (Good), Dennis McFarland (Bad)

BCI researchers use terms for BCI system components, their inputs and outputs, and their functions and interactions. The discussants will debate the advantages and disadvantages of a detailed standard framework for BCI development, evaluation, and application.

Saturday, June 15, 2002

5:15 - 6:15 pm	**Discussion session 6**	**Guggenheim Auditorium**

Standards - Development and adoption of appropriate standards for designing BCI studies and for assessing and comparing their results, both in the laboratory and in actual applications

Andrea Kübler (Chair), Luigi Bianchi, Jane Huggins, Gerwin Schalk, Todd Kirby, Charles Robinson, Steven Helms Tillery, Daniel Moran

6:15 - 8:00 pm	**Cocktails and Dinner**	**Weathervane Restaurant**
8:00 on	**Demonstrations/Posters**	**Guggenheim Master Seminar Room**

Sunday, June 16, 2002

9:00 - 11:00 am	**Breakfast and summary session**	**Weathervane Restaurant**

ABSTRACTS OF PRESENTATIONS
(in order of presentation)

THINK AND SPELL: TOWARD A FASTER, BETTER P300 BCI

B. Z. Allison, J. A. Pineda
Cognitive Science Dept.
UC San Diego, La Jolla, CA

The P300 is a well-studied ERP component present in most adults. It is typically evoked in an "oddball" paradigm in which two types of stimuli, one frequent and one infrequent, are presented to a subject who is asked to pay attention only to the infrequent stimulus. For example, if several areas on a monitor are sequentially flashed and the subject is asked to press a button when one area is illuminated, flashes in the attended area will produce a P300, while unattended flashes will not. This characteristic suggests that users could communicate their interest in events via EEG activity alone through voluntary control of attention. Brain Computer Interface (BCI) systems using this characteristic of the P300 have been demonstrated (Farwell and Donchin 1988, Bayliss and Ballard 2000, Donchin et al. 2000), but many avenues for improving such a system remain unexplored. Two studies were conducted to explore which display parameters were best for a P300 BCI system. In the first study, subjects viewed an 8 x 8 display containing English letters and other characters. Rows or columns of characters were briefly flashed, and subjects were asked to count the flashes of a target character while ignoring other events. Subjects participated in 6 conditions, with three different ISIs (125, 250, 500 ms) and two different approaches to grouping flashed characters (single row or column vs. multiple row or column flashes). As expected, P300 amplitude and area were larger in response to attended vs. unattended flashes. P300 and N1 amplitude were reduced in both flash conditions at faster presentation speeds. Targets which were flashed more frequently in the multiple flash condition produced greatly reduced P300 amplitude; the decline in amplitude was more severe than in previous studies of P300 and target probability. While subjects could reliably count flashes of the target character at all speeds in the single flash condition, many had trouble with the counting task in the multiple flash condition at higher speeds. The second study sought to explore the advantages and drawbacks of different grid sizes. Subjects were asked to count target flashes in three different grid sizes (4x4, 8x8, and 12x12) with the ISI between flashes of 500 ms. Counting accuracy was excellent in all three conditions, and attended flashes again produced a larger P300 in all subjects. Results suggest that improved brain computer interfaces (BCIs) based on attentional differences in the EEG are feasible, and further elucidate the optimal display and analysis parameters for such a system. (These data will also be presented in poster format.)

INTERACTIONS OF NEURONS AND GLIAL CELLS DURING THE GENESIS OF SYNCHRONOUS BRAIN WAVES

Florin Amzica
Laboratory of Neurophysiology, School of Medicine
Laval University, Quebec, Canada, G1K 7P4

The study of the electrophysiological activity of the brain as a whole has acquired a well-established importance. Through experiments that are underway, we have opened a new field of investigation, studying relationships between neurons and glia in intact brain networks during physiological states such as wakefulness and sleep, and during pathological states such as epilepsy. Recent years have brought to attention the unexpected rich anatomical and electrophysiological properties of glial cells (in simple preparations such as cultures and slices). Much of the present neurobiological effort is invested in the further investigation of these properties. The research unit allows a multitude of approaches by investigating the same phenomenon from electrical and ionic angles. One of the major issues in neurosciences is related to the synchrony of cellular activity, especially in fields related to the interpretation of cognitive activity. One of the most straightforward approaches to reach that goal is through the recording of simultaneous intracellular activities at the very site of their occurrence. Experiments are therefore carried out in acute (anesthetized) or chronically implanted cats.

At the same time, I am involved in the study of the mechanisms underlying the genesis of the electroencephalogram (EEG). This research evolves along several lines:

1) Understanding of the cellular mechanisms contributing to the genesis of particular rhythms of the EEG such as spindles, delta, slow (0.1-1 Hz) or fast (beta-gamma) oscillations. As an example, in recent papers we have found that sleep slow (<1 Hz) and paroxysmal oscillations result from complex interactions of neurons and glial cells also involving the extracellular ionic composition [*J Neurophysiol (1999) 82:3108-3122*; *(2001) 85: 1346-1350; J Neurosci (2002) 22: 1042-1053*; *Cereb Cortex (2002) in press*]. Of particular interest for this meeting is the ability of training restricted regions of the brain to produce specific oscillation bursts in the gamma range (~40 Hz) [*PNAS (1997) 94:1985-1989*].

2) More recently, we became interested in the genesis of very slow or steady EEG components, also termed DC potential shifts. The understanding of the electrophysiological bases of these potentials may acquire a particular pertinence for their use in brain-computer interfaces. Preliminary data emphasize that, although brain cells might be involved in their generation, their role is limited to the effect they undergo from paracellular impingements arising in cerebral blood circuits.

These projects are supported by the Canadian Institutes for Health Research and by Fonds de la recherche en santé Québec.

BCI RESEARCH AT COLORADO STATE UNIVERSITY

Charles Anderson[1,4], David Peterson[1,2,4,5], Michael H. Thaut[4,5], Michael Kirby[3]
[1] Department of Computer Science, [2] Department of Psychology
[3] Department of Mathematics, [4] Program in Molecular, Cellular, and Integrative Neuroscience
[5] Center for Biomedical Research in Music
Colorado State University, Fort Collins, CO 80523

Brain-computer interface research at Colorado State University consists of several related efforts. Much of our work is focused on the discovery of low-dimensional characterizations of multi-channel, spontaneous, EEG signals that are reliable discriminators of cognitive activity during common mental tasks, such as mental multiplication, rotation of three-dimensional objects, and mentally writing a letter. To-date, our best results are obtained by modeling signals from each channel with sixth-order, autoregressive (AR) models and classifying the AR coefficients with feedforward neural networks. We trained neural networks to classify half-second segments of six-channel, EEG data into one of five classes corresponding to five mental tasks performed by one subject. Using the AR representation and averaging over consecutive segments, an average of 72% of the test segments are correctly classified; for some test sets 100% are correctly classified.

We are currently investigating several other techniques for dimensionality reduction and classification. Subspace methodologies, such as the Karhunen-Loeve (KL) transform, are generally useful tools for the characterization of high-dimensional data sets. Two approaches that have received considerably less attention than the KL transform are the maximum signal fraction method and canonical correlation analysis. In a comparative study of subspace methods, we find interesting differences in how each method extracts noise and other components that facilitate the discrimination of signals into classes corresponding to mental task. The subspace methods result in linear transformations of the data. Our preliminary results suggest that the combination of these linear transformations with fairly simple classifiers, including linear discriminant analysis (LDA), may be sufficient for solving some BCI classification problems. Careful comparisons of LDA, neural networks, and support vector machines show little statistical significance in the classification performance.

In the work summarized above, analysis is performed off-line after EEG recording. We are currently experimenting with an inexpensive EEG acquisition and analysis system based on the 16-channel, MindSet-1000 EEG amplifier ($2000) connected via a SCSI interface to a laptop computer, and custom software running in a Linux environment. Recently this system was used to acquire 10-channels of EEG from subjects listening to paired tones of varying dissonance. Analysis of the signals identified the electrode pairs whose signals were most coherent at various frequencies and how this differed between the most dissonant and least dissonant tones. This system will be used in biofeedback experiments in which subjects will observe the classification result and confidence in real time, giving subjects the opportunity to modify their cognitive behavior to increase the classification accuracy.

In joint work with Colorado State University's Center for Biomedical Research in Music (CBRM), our lab is also engaged in basic research into the neural dynamics associated with auditory working memory. CBRM has extensive clinical results demonstrating the value of music for rehabilitating impaired motor function; a similar regime may ameliorate cognitive dysfunction. Working memory is our focus because of its critical role in most cognitive functions. Our analysis of the EEG recorded during auditory working memory tasks is based on custom, high-resolution frequency bands that we classify using support vector machines. A genetic algorithm is used to search the high-dimensional feature space for the feature subsets that best dissociate conditions. The genetic algorithm is used in a "wrapper" fashion, searching over feature subsets using the support vector machine's classification accuracy as a “fitness” measure.

TOWARDS BETTER SOFTWARE COMPONENTS FOR BRAIN-COMPUTER INTERFACES

Jessica D. Bayliss
Rochester Institute of Technology
Computer Science Dept.

Most existing Brain-Computer Interfaces (BCIs) are monolithic creations that are designed to run on special hardware. Recently, interest has increased in making BCI systems flexible (see bci2000.org for an example of another flexible system). Flexible systems allow both hardware and software components in the system to be swapped in and out with minimal changes. Using techniques from software engineering, we have created components for data acquisition, communications, signal processing, and user applications. These components have been successfully integrated to form a BCI that has been used for tasks as diverse as on-line P3 recognition and feedback in virtual reality, playing games with eye movement control, and gamma wave experiments. With this system, it is possible to change signal processing without altering the main BCI system program code. We will discuss current work on assuring system reliability as well as the benefits of being able to change user applications easily.

THE BIO-FEEDBACK SYSTEMS DESIGN APPROACH AT THE "TOR VERGATA" UNIVERSITY

Luigi Bianchi[1,4], Fabio Babiloni[2], Marco Arrivas, Patrizio Bollero, Maria Grazia Marciani [1,3]
[1] Dip. Neuroscienze, University of Rome "Tor Vergata", ITALY
[2] Dip. Fisiologia Umana e Farmacologia, University of Rome "La Sapienza", ITALY
[3] IRCCS, Fondazione "S. Lucia", Rome, ITALY
[4] Brainware, Rome, ITALY

The objective of this research was to realize an efficient and scalable C++ Bio-Feedback software framework that could be used in a wide range of pathological situations thus minimizing the time spent to build a completely new system.

One of the main problems encountered in the development of computer-based systems for handicapped people is that it is very difficult to optimize them in a wide range of situations. This generally occurs because every patient has residual capabilities that are specific to his condition and that make him in some way unique. Moreover, very often, different pathologies are treated using different approaches and tools: sometimes the processing power of a PC is required while in some others it is desirable for the whole system to be portable and lightweight. In any case it is necessary to try to use all of the usable biological signals such as EEG, EOG, EMG, voice, etc. simultaneously to maximize the overall "communication bandwidth". It must be noted that different approaches (e.g. EP, EEG, etc) could require targeting different platforms: the Microsoft Windows OS family for example (with the exception of Windows CE/Embedded) does not provide a Real-Time environment and several unpredictable delays (of the order of tenths of milliseconds) can be introduced at different stages. This is probably not a problem in EEG based applications, but it could be in EP ones. Moreover, in general, a Windows based solution could easily provide many features, such as text to speech capabilities, but, on the other side, it still does not allow to build wearable and cheap systems.

However, even if the nature of the utilized signals may vary among different pathological situations, the way in which a biofeedback system works is quite stereotyped: after the data have been acquired, there is a DSP pre-processing stage that performs some basic operations on the biological input signals, then a classification stage in which some features are extracted and manifested in some way to the user and eventually recognized as one of the subject voluntarily controlled activities, and, at the end, a stage in which a task can be executed. Finally it is very frequent that these systems provide different operating modalities such as training, testing, setup, and running.

This is a situation in which an object oriented programming approach reaches his best results: in our case it is possible to describe the operative flow that is common to all the biofeedback applications leaving to be defined only those aspects that are specific to the single implementation, such as the algorithms and the classification rules. Then, in a separate step, several systems can be realized just defining the points that are left unspecified.

It is important to notice that the proposed solution does not make any assumption on both the operating system and the hardware used. For this reason all the formats of the generated files were based on the XML technology (eXtensible Markup Language), that is portable across virtually any OS, and that also allows to extend the file format without loosing backward compatibility. This is a key issue when data files need to be shared across different laboratories or put on the Web.

This framework was used to develop three different BCI systems. Each of them was fully implemented using no more than 40 lines of C++ code. The same source code was compiled under the following operating systems: Windows 98/2000/XP (using Borland C++ Builder 5, Microsoft Visual C 6.0 and GCC 3.1), Windows CE 3.0 (using Microsoft Visual C++ for Embedded Visual Tools) and Linux (using GCC 3.1).

More details and resources can be found at http://www.luigibianchi.com/bci.htm

COMMUNICATION WITH SLOW CORTICAL POTENTIALS (SCP)

Niels Birbaumer[1,2], Thilo Hinterberger[1], Andrea Kuebler[1], Jochen Kaiser[1], Ahmed El Karim[1], Juergen Mellinger[1], Barbara Wilhelm[1], Nicola Neumann[1]
[1]Institute of Medical Psychology and Behavioral Neurobiology, University of Tuebingen, Germany
[2]Center for Cognitive Neuroscience, University of Trento, Italy

The brain-computer interface ("Thought Translation Device", TTD) has been developed to re-establish communication in severely paralyzed patients who operate the device by generating shifts of their slow cortical potentials (SCP) (Birbaumer et al., 1999; Kübler et al., 2001). Ten patients have been trained with the TTD for an extended time period. The research is targeted toward understanding the learning mechanisms of SCP self-regulation. Neuroanatomical structures responsible for physiological control have been investigated in a group of patients with intractable epilepsy using functional magnetic resonance imaging (fMRI). Results indicated that attentional-motor systems were activated during cortical negativity while cortical positivity correlated with the inhibition of motor and thalamoreticular systems. Performance in physiological regulation was predicted with high accuracy by activation of inhibitory basal ganglia structures and deactivation of SMA. The research will be extended to paralyzed patients at the initial stage of amyotrophic lateral sclerosis (ALS). Psychophysical methods as well as questionnaires have been developed to reveal the relationship between successful SCP regulation and the perception of brain waves. Patients who had successfully learnt self-regulation, were able to perceive their brain state correctly (Kotchoubey et al., 2002). Conscious perception occurs after patients have already learned SCP regulation. One paralyzed patient gave a very detailed description of his mental strategy to produce negative and positive SCP shifts that corresponded exactly with his recorded brain activity (Neumann et al., submitted). Mental strategies may play an important role in the patients' perceived self-efficacy.

To assess the cognitive status of locked-in patients, a neuropsychological test system based on event-related potentials was integrated into the TTD. Different psychophysiological paradigms (e.g., oddball paradigm) were applied to completely paralyzed patients and patients in the vegetative state to evaluate their remaining processing capacities. Only patients with intact event-related potentials in at least some of the experimental tests were trained with the TTD.

To measure depression in severely paralyzed patients, a questionnaire has been developed. Existing instruments, such as Beck's depression inventory, are inappropriate, because they contain questions that cannot be answered by severely paralyzed and artificially ventilated patients (e.g., questions concerning sleep, appetite, etc.). Depression scores in a group of 76 ALS patients were significantly higher than in healthy controls (N=93), but significantly lower than in patients with unipolar depression (N=56). Quality of life was rated as satisfactory or good by 63% of the ALS patients.

To enhance the learning process of SCP regulation, transcranial magnetic stimulation (TMS) was used in a group of healthy subjects. A single-pulse was applied before each trial in the TTD self-regulation training. An effect of stimulation on cortical positivity was found, when the coil was rotated in an angle of 90º (Kübler et al., in press). Different stimulation and recording sites are presently investigated.

To increase motivation in severely ill patients, BCIs have to be adapted to individual needs. For the TTD, a special web browser was developed that enables patients to browse the internet with their brain activity. The different options which are usually offered on a web page, are presented successively and patients select the desired option by a downward cursor movement. A patient with restricted writing skills was provided with a fast communication program containing his most relevant needs (Kaiser et al., 2002).

References

Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kübler, A., Perelmouter, J., Taub, E., & Flor, H. (1999). A spelling device for the paralysed. *Nature, 398*, 297-298.

Kaiser, J., Kübler, A., Hinterberger, T., Neumann, N., & Birbaumer, N. (2002). A non-invasive communication device for the paralyzed. *Minimally Invasive Neurosurgery, 45*, 19-23.

Kotchoubey, B., Kübler, A., Strehl, U., Flor, H., & Birbaumer, N. (2002). Can humans perceive their brain states? *Consciousness and Cognition, 11*, 98-113.

Kübler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J., & Birbaumer, N. (2001). Brain-computer communication: Unlocking the locked-in. *Psychological Bulletin, 127(3),* 358-375.

Kübler, A., Schmidt, K., Cohen, L. G., Lotze, M., Winter, S., Hinterberger, T., & Birbaumer, N. (in press). Modulation of slow cortical potentials by transcranial magnetic stimulation in humans. *Neuroscience Letters*.

Neumann, N., Kübler, A., Kaiser, J., Hinterberger, T., & Birbaumer, N. (submitted). Perception of brain states: mental strategies for brain-computer communication.

THE NEIL SQUIRE FOUNDATION BRAIN-COMPUTER INTERFACE LABORATORY

Gary Birch[1], Steven Mason[1,2]
[1]Neil Squire Foundation, Vancouver, B.C. Canada
[2]GF Strong Rehabilitation Center, Vancouver, B.C. Canada

Abstract:

The focus of our research is the development of BCI technologies for intermittent control applications, that is, technology that will work when the User intends control, but also remains neutral when there is no intent to control.

Our BCI laboratory is located in the G.F. Strong Rehabilitation Centre in Vancouver, Canada. This lab is equipped with a computer network running a Matlab/Simulink development environment. Our team of three researchers, an RA and several graduate students conduct a range of studies across the following four streams of research:

Stream I: BCI Technology Development

In this stream of research, our efforts are focused on developing better signal processing methods to convert EEG into reliable control signals. To date, our research team has developed a single-position, switch that responds to specific spatiotemporal patterns in EEG data related to imagined movement. This switch, which we refer to as the Low-Frequency Asynchronous Switch Design (LF-ASD) or more casually, the "brain switch", has demonstrated on-line asynchronous detection accuracies greater than 96% with able-bodied subjects and subjects with high-level quadriplegia (see Stream 2).

Currently our team is working on various statistical signal processing methods to improve the design of our brain switch. For example, we recently added a custom energy normalization transform to the LF-ASD. An off-line study of this new addition has indicated that True Positive or hit rates can be increased by 13-24% for False Positive rates near 1.0%.

In the last year, we began a collaborative project with Dr. Moore and her team at Georgia State University, Atlanta, USA to conduct a comparative evaluation of selected BCI technologies.

In the future we plan to investigate alternative electrode designs, electrode placement (external vs subcutaneous), and the ability to extend our brain switch to recognize multiple brain states.

Stream II: BCI Technology Evaluation and Usability Evaluations

A significant portion of our research is dedicated to on-line studies of the BCI technologies we have developed. These studies are used to determine switch performance and reliability and to determine how well people can adapt to a particular interface technology. For example, we are completing a study involving five able-bodied subject and five subjects with high-level quadriplegia as they dynamically control a simple video game. Preliminary results from seven subjects indicate that the brain switch can be operated at True Positive (TP) rates in the range of 40%-75%, with corresponding False Positive (FP) rates less than 1.0%. This corresponds to an overall switch accuracy greater than 96%. These results verify previous results from an on-line evaluation on a smaller test population.

Stream III: Theoretical Modeling

As a new, multidisciplinary field of research, BCI technology development and evaluation lacks a common vocabulary and formal functional model. As a result it is quite difficult for researchers to objectively compare technology designs and evaluations. Drs. Mason and Birch have proposed a general, theoretical framework to describe BCI System design to address part of this need. This new framework has been submitted to IEEE Tran. Rehab. Eng. for publication.

Stream IV: Consumer Hardware Design

We have started this stream of research to explore what designs and application methods are acceptable to the Users in real-world environments. We feel that we need to start looking at these issues because the acceptable designs for these “wearable” interfaces may significantly constrain electrode type and placement, thus affecting the types of signals available for control.

Our lab continues to grow through the support of the Natural Sciences and Engineering Research Council of Canada (NSERC), the Rick Hansen Neurotrauma Initiative (RHNI-BC), the Government of British Columbia, Ministry of Competition, Science and Enterprise, the National Science Foundation (NSF), and the GF Strong Rehabilitation Centre.

MACHINE-LEARNING FOR EXTRACTING NEURONAL SIGNATURES OF NATURAL MOTOR COMMANDS FROM SINGLE-TRIAL MULTI-CHANNEL EEG DATA IN UNTRAINED SUBJECTS

Benjamin Blankertz, Christin Schaefer, Guido Dornhege, Roman Krepki, Klaus-Robert Mueller
Intelligent Data Analysis Group
Fraunhofer-FIRST, Berlin, Germany

Volker Kunzmann, Florian Losch, Gabriel Curio
Neurophysics Group, Dept. of Neurology
Klinikum Benjamin Franklin, Freie Universitaet, Berlin, Germany

The Leitmotiv of our BCI approach is 'let the machines learn', i.e., we aim to minimize the need for subject training while the major learning load imposed on two coupled adapting systems (human subject and computer) is to be accomplished by the machine. Key ingredients in our approach are (1) a behavioral context in which the subject can use well-established motor competences overlearned in daily life, which (2) are embedded in a 'naturalistic' BCI design, while (3) in the background the algorithmic flow is controlled by state-of-the-art machine learning (ML) techniques that extract relevant information from high-dimensional noisy EEG data. Concerning the selection of brain signals, we presently investigate event-related potentials (ERPs), with a focus on non-oscillatory lateralized pre-movement potentials. Our analyses suggest that here the classification problem of discriminating ERPs characteristic for different intended motor outputs is linear: the use of linear models results in better classification generalization as compared to more complex non-linear models if the number of training samples is limited as it is typically the case in BCI paradigms. Ongoing studies analyse two different ERP types: 1) We predict the laterality of imminent left vs. right hand finger movements in a natural keyboard typing condition: when classification is based on the lateralized Bereitschaftspotenzial, 5 of 10 subjects, who all were untrained for BCI, achieved a theoretical information transfer rate of greater than 15 bits per minute (bpm), and further 4 subjects reached 6-10 bpm. 2) We detect cerebral error potentials from single false-response trials in a forced-choice task (d2-test), reflecting the subject's recognition of an erroneous motor response: based on a tailor-made classification procedure that allows to bound the rate of false positives at 2%, the algorithm manages to detect 85% of error trials in 7/8 subjects. The design here is to concatenate such error detector to the output of a BCI-classification of intended motor actions: the latter, as a 'first-pass' classification, is fed back instantaneously so that the subject's brain can detect eventually erroneous classifications, 'label' them by emitting an error potential and thereby initiate an on-line 'second-pass' BCI-reclassification to raise the BCI bit rate.

These results of our ERP-ML approach constitute an interesting BCI benchmark adding to established techniques working with feedback of slow cortical potentials or brain oscillations.

CLOSED LOOP BRAIN-MACHINE INTERFACES

John K. Chapin[1], Miguel Nicolelis[2]
[1]Dept of Physiology and Pharmacology, SUNY Health Science Center, Brooklyn, NY
[2] Dept of Neurobiology, Duke University Medical Center, Durham, NC

Over the past 5 years, we have demonstrated, for the first time, that simultaneously recorded populations of single neurons in the motor cortices of rats and monkeys can be electronically "decoded" and used to directly control a robot arm. In the first study, populations of up to 46 single neurons were simultaneously recorded in the primary motor cortex of rats initially trained to obtain water by pressing a lever to move a robot arm. Next, electronic techniques were used to transform the movement related information recorded in the motor cortex into an electronic output capable of controlling the robot arm in real time. In experiments, the rats first controlled the robot (and got their water) by moving by moving the lever, but this robot control was then suddenly switched to the brain-derived signal. Most rats were able to routinely use this motor cortex population function to position the robot arm under the water dropper and obtain their water. Over continued trials, the ability of the brain-derived signal to control the robot arm became increasingly independent of the forelimb movement, with which it was normally associated. These results therefore demonstrated the feasibility of using neuronal population activity to control external devices

Next, we demonstrated the feasibility of brain-controlled robotics in monkeys trained either to move a manipulandum or to reach to a target in 3D space. Neural populations were recorded throughout the arm areas of the frontal and parietal cortices. Using multivariate regression techniques to decode the neural population vectors, the animals were able to use their brain signals to move a robot arm in both 1D and 3D spaces with the same trajectory as their hand. Accuracy improved generally with increased numbers of recorded neurons, approximating a slowly saturating hyperbolic curve.

Because these results suggested the feasibility of using brain-derived signals to restore movement in spinal cord injured patients, we are now investigating the possibility of bringing tactile and proprioceptive feedback from a brain-controlled robot back to the brain by stimulating in the somatosensory system through implanted multi-electrodes. Initial studies have shown that stimulation in the somatosensory cortex of rats can be used to deliver virtual conditioned stimulus cues. These animals are trained, using medial forebrain bundle stimulus rewards, to turn in the direction of the part of the body that receives a perceptible virtual stimulus, generally producing an illusion of being touched on the left or right side of the face. When a remote controlled stimulator is attached on the rat's backpack, it can be remotely guided to traverse a wide range of indoor and outdoor terrains, including stairs, ladders, trees and rubble piles. In conclusion, these studies suggest feasibility of using electronic technology to transmit information bi-directionally between the brain and external machines.

DEVELOPMENT AND APPLICATIONS OF BCI AT SANTA LUCIA FOUNDATION

Febo Cincotti, Fabio Babiloni, Donatella Mattia, Maria Grazia Marciani
Fondazione Santa Lucia - I.R.C.C.S., Roma, Italy

The Santa Lucia Foundation is a renowned hospital for the neuro-motor rehabilitation of patients suffering from different diseases (stroke, amputation, paraplegia, etc). Since the beginning of its activities, in addition to the clinical routine a great deal of scientific research work on the themes of neuroscience was carried out, also in cooperation with Italian and foreign Universities. For the last 10 years, the Santa Lucia Foundation was recognized “IRCCS” (Scientific Institute for Research, Hospitalization and Health Care) by the Italian Government.

As for clinical activity, the center admits about 2000 patients per year, mostly affected by neurological diseases, caused by either cerebrovascular or degenerative or post-traumatic injuries. The treatment of these patients comprises motor rehabilitation (functional recovery and development of compensation strategies) or cognitive rehabilitation.

As a research center, the scientific interest is focused on themes regarding neurological and motor rehabilitation, spanning from neurophysiology and neuroimages to experimental neuropharmacology and kinematics of movement. The scientific productivity benefits from the cooperations that the Santa Lucia Foundation has with national and international centers. This effort produces about 100 publications per year on scientific journals.

In this context, the research on Brain-Computer Interfaces is supported by a group of researchers with different skills, both on the neurological side and on the bioengineering side. All researchers have previous experience in the field of EEG acquisition and analysis in the framework of neurophysiological research.

During the years 1998-2001, the group participated in an important project funded by the European Commission named ABI (Adaptive Brain Interfaces). The main achievements of the project were: (i) the development of effective EEG classification algorithms, which brought to several publications on scientific papers and presentations at international meetings; (ii) the availability of a prototype of portable BCI; (iii) a large resonance in the media (e.g. more than 100 interviews and articles on newspapers and magazines) and in the European Commission (e.g. selection of the project as finalist of the Descartes Project, the major European science prize for outstanding collaborative research in any scientific field).

The current version of our Brain Computer Interface is based on: (i) the acquisition of eight EEG channels placed on the fronto-centro-parietal regions of the scalp; (ii) the extraction (twice a second) of spectral features, in the band 8-30 Hz; (iii) the classification through a local neural classifier, based on the Mahalanobis distance of incoming features vectors from given prototypes. The prototypes were obtained using the expectation maximization framework on samples of the features vector used as training set.

The current research efforts are aimed at three objectives:

(i) improving portability and effectiveness of the working prototype. This research benefits from the collaboration with the group at Tor Vergata University (Rome) with its engineering competence and has already produced a new promising type of quadratic classifier;

(ii) adaptation and development of applications to use the current prototype as an aid for disabled people. This research line is funded by the Italian National Research Council and is carried on in cooperation with other groups from the Universities of Rome. In this research line we benefit from the environment provided by the hospital and the established competence in the care-giving of the many patients;

(iii) application of the technologies developed in the BCI research to the studies on cerebral plasticity. We expect to provide evidence for a potential application of the BCI area into the cognitive/motor retraining processes after focal brain injury, to implement future rehabilitation strategy.

SPINAL AND CORTICAL PLASTICITY INDUCED BY PRACTICE AFTER STROKE AND SPINAL CORD INJURY

Bruce Dobkin
Reed Neurological Research Center
University of California Los Angeles

Brain-computer neural communication to drive functional neuromuscular stimulation and robotic devices have become feasible as neural network modeling and computer algorithms for translating thought into action evolve. Adaptive algorithms will better decode neural signals and provide more physiologic feedback for multijoint movements. Multiple cortical motor representations are tuned to aspects of movement, observation, and imitation. A neuroprosthesis that draws these regions will interact with mechanisms of CNS plasticity in ways that aid or in ways that may interfere with success. Functional neuroimaging techniques can be used as physiologic markers of representational plasticity during skills learning in patients with stroke or spinal cord injury. Similarly, these techniques can provide information about where to place cortical stimulators or sensors and how training and activations over time alter functional neuroanatomy.

Hemiparetic subjects were trained with a specific technique called body weight-supported treadmill training to try to improve overground walking ability. This physical therapy intervention optimizes sensory feedback related to the step cycle at walking speeds that are greater than subjects can achieve with over ground, conventional training. Training is associated with an evolution of changes in the primary sensorimotor cortex and supplementary motor areas that parallel gains in motor control and behaviors. Greater intensity of locomotor training further alters these representational changes when such changes would not be expected clinically.Such CNS changes may be derived from interactions within the distributed motor network. The effects of repetitive locomotor-related sensory inputs during the practice of a skill such as walking provides insights into how functional neuroimaging may be employed in developing neuroprostheses and in designing training paradigms for subjects.

UNLOCKING THE LOCKED-IN: PROGRESS IN BRAIN-COMPUTER INTERFACE

Emanuel Donchin
Department of Psychology
University of South Florida, Tampa, FL

Brain-Computer Interfaces come in two flavors, the "Control" model and the "Keyboard" model. Systems adopting the Control model aim to provide the user with continuous control over a device. The control is initiated by the subject. In such a system the controlling element is conceptualized as a switch, or a cursor, that can be applied to a large number of control situations. In general, most such 'control' systems utilize bio-feedback techniques to train the user to control the spectral composition of the EEG. The Keyboard model, on the other hand presents the subject with a structured environment, no different in the level of imposed structure than the standard keyboard. The simulated keyboard generates systematic stimuli and the subject choice of keys is inferred from the pattern of brain activity triggered by these stimuli. In most of these systems the selection is based on an analysis of Event Related Brain Potentials elicited by keyboard elements. In this report we describe a Keyboard model first described by Farwell & Donchin (EEG Journal, 1988, 70:510-523). The system employs the "oddball paradigm" generated by presenting the subject with a 6 by 6 matrix of cells. The cells contain the letters of the alphabet and a few symbols. The user focuses attention on the cell containing the character to be communicated. An "odd ball" paradigm is generated by intensifying, every 125 msec, in a random order each of the rows and columns of the matrix. Thus the subject is presented with a sequence of stimuli 16% of which contain the attended row and column. As can be expected from all we know about the oddball paradigm and P300, the row, and the column, containing the attended cell elicit a P300 component. The system examines the 600 msec epoch following each intensification and if the P300 can be detected, the selected cell can be identified. The detection of P300 required, in our original study, the averaging of at least 17.3 trials, so that the system could communicate only 2.3 characters per minute at 95% accuracy. In a subsequent study using a modified approach to the detection algorithm, including use of the discrete wavelet transform (Donchin, E., Spencer, K. M., & Wijesinghe, R, IEEE Trans. Rehab. Engineering, 2000,8, 174-179) 10 able-bodied subjects, and 5 subjects who used wheel chairs, the number of trials required for detection, increasing the transmission rate to 4.1 characters per minute at 95% accuracy for the able bodied subjects and 3.2 characters per minute for the disabled subjects. One of the major advantages of the Keyboard model is that subjects can use it without requiring prior training. The P300 is elicited in virtually all subjects who are exposed to an oddball sequence. We are currently planning to test the system with ALS patients.

INTRACORTICAL MOTOR NEURAL PROSTHETIC DEVICES

John Donoghue
Department of Neuroscience
Brown Medical School, Providence RI 02912

Our laboratory is developing a neural motor prosthetic (NMP) to restore the ability for paralyzed humans to interact with their environment. We are developing three basic components of an NMP system: an implantable recording array, neural decoding hardware and software, and an interface with real world devices. The recording device, which serves as a brain machine interface (BMI), is a Bionic Technologies silicon 100 electrode array which includes a percutaneous connector for external communication. We have demonstrated that this array can be used to record multiple neurons for years when implanted in the motor cortex (MI) of macaque monkeys, suggesting that it is a reasonable prototype for a human BMI. We are developing decoding algorithms that transform neural activity into useful control signals. Using linear correlation methods we are able to reconstruct intended hand trajectories based upon the activity of small numbers (~6-40) of MI neurons. Such signals can be used to drive robot arms and computer cursors. Finally, we have created a real time system which successfully decodes MI neural activity and translates it into cursor motion on a computer monitor. Using this system monkeys are able to perform visually guided tracking tasks when the cursor is driven by MI neural activity. This decoding nearly as fast, and is about 70% as accurate as the actual hand motion required to perform this task. Further, cursor control does not require that the actual hand tracking motions be performed. These results demonstrate that an NMP should be able to provide rapid, real time control signals for humans. Intended hand motions can be transformed into the motion of other physical or virtual instruments or potentially of paralyzed muscles. Importantly, single neuron based NMPs can provide motions that resemble natural hand trajectories in their speed and accuracy.

Financial Disclosure: JD is a founder and stockholder in Cyberkinetics, Inc, a company that is developing neural prosthetic devices

ADAPTIVE CONTROL OF REACHING FOR NEUROPROSTHESIS

Gyongyi Gaal
Neuroprosthesis Research Organization
GPO Station PO Box 20350
Brooklyn NY 11202-0350

Various authors proposed linear models to reconstruct monkey arm movement trajectories from neural activities. Nevertheless, I would like to reintroduce here the notion of estimating the elements of the movement outcome phase space dependent Jacobian matrix of neural activity - movement outcome nonlinear functions with a view to develop a cortical control scheme of artificial robot arms with high number of nonlinear sensors and actuators. The method uses local linearization. It is equivalent to multivariate fitting of time derivatives of time-shifted neural activities and movement outcomes (e.g. velocities if the arm movement is modeled simply as the movement of the endpoint along a movement trajectory). The fitting is performed at each and every point in movement outcome phase space. The estimated matrix elements can then be used for trajectory and velocity reconstruction even with few recording sites if consecutive movement outcomes and neural activities are reproducible. The model can also be extended to include configurations and forces. I will then present a hybrid software hardware model to illustrate how nonlinear functions can be learnt by systems whose task is to control robotic arms which have high number of sensors and actuators with correlated activities. Finally, I propose a method to calculate weight patterns, which are needed to transform high dimensional, but arbitrarily selected spatiotemporal motor outcome related activities into desired movement outcome either for a robot arm or functional electrical stimulation of primate muscles. Such weight patterns will then be ideal in a least square sense to later predict and implement desired movement even when the desired movement is known only to the primate subject. Supported by NIH.

Gaal, G. (2001) Nonlinear models for cortical control of robotic arms, submitted.

Freeman, WJ. and Gaal, G. (2001) The role of entorhinal cortex in multisensory integration based on epidural EEG recordings from olfactory bulb, somatomotor, auditory, visual and entorhinal cortices of awake cats. submitted to J. Neurophysiology.

THE SSVEP-BASED BCI SYSTEM WITH HIGH TRANSFER RATE

Shangkai Gao
Lab of Medical Information Engineering
Department of Biomedical Engineering
School of Medicine, Tsinghua University, Beijing, China

The Lab of Medical Information Engineering is a research division under the Department of Biomedical Engineering, School of Medicine, Tsinghua University, Beijing, China. Our research scopes include the detection, processing, analysis, recognition, transmission and management of medical information in various biomedical signals and images. Currently, the most active research areas in the lab are: (1) Brain and neural information engineering; (2) Medical Imaging and image processing. In addition, the general theory of biomedical signal processing is also a subject of our long-term research.

In the area of brain and neural information engineering, our interests fall mainly around ***3D dynamic imaging of brain electrical activities*** and ***brain-computer interface***. The research projects cover the extraction of transients in EEG, single trial and dynamic analysis of EP and ERP, dipole localization in the brain, high- resolution EEG, independent component analysis (ICA) of EP and ERP nonlinear dynamics, and approximate entropy (ApEn) analysis of EEG. In addition, to develop novel signal processing methods, some applied software has also been developed, such as the epileptic discharge wave detection, brain-computer interface (BCI), sleep analysis, perception and cognition analysis.

Since 1999, we have been engaged in brain computer interface research. We have developed a BCI system based on steady state visual evoked potentials (SSVEPs). Our first paper published in this area is in the first joint meeting of BMES and EMBS, in Atlanta, 1999. The title of the paper is “An EEG-based cursor control system”.

To develop a practicable EEG based BCI system, we seriously consider the following problems:

(1) The information transfer rate.
The information transfer rates of current BCI devices are rather low. If this rate could be increased, BCIs might become a useful tool for people to interact with their environment.

(2) Requirements for training.
Long time training is always not expected. BCIs based on evoked potentials may require less training.

(3) The medical invasiveness.
The less invasive the technique is, the more likely it can be used in a wide range of applications.

(4) Least number of electrodes for data acquisition.
To mount a large number of electrodes on scalp will be time consuming and tiresome. The strategy of using a small number of electrodes in the system will be welcome in practice.

(5) System should be easy to carry and easy to use.

Based on the above considerations, we have developed a SSVEP-based BCI system which bears the advantages of high transfer rate, minimal training and noninvasiveness. The system focuses on EEG activity that occurs at a specific frequency and specific location of cortex. These characteristics simplify the feature extraction procedures and the necessary training.

We have applied our SSVEP-based BCI prototype system to control cursor movements, home electrical appliances and to make phone calls. The main features of our system are:

(1) Larger number of inputs. One can pick up a specific target out of as many as 40 candidates.
(2) Fewer electrodes for data acquisition. Only two active electrodes are used in a wireless EEG system.
(3) Higher transfer rate: the average transfer rate over all testees was 27.15 bits/min, the higher one is over 50 bits/min.

Future work will seek to develop a compact and portable system and put it to practical use. Also, increasing the input accuracy and the applicability to a larger range of users are necessary.

ON-LINE MEASURMENT OF MENTAL WORKLOAD

Alan Gevins
San Francisco Brain Research Institute & SAM Technology
San Francisco, CA

Perhaps the most basic issue in the study of cognitive workload is the problem of how to actually measure it. Here, we review our long-term program of research aimed at developing cognitive workload monitoring methods based on EEG measures. This research program began with basic studies of the way neuroelectric signals change in response to highly controlled variations in task demands. The results yielded from such studies provided a basis on which to develop appropriate signal processing methodologies to automatically differentiate mental effort-related changes in brain activity from artifactual contaminants, and for gauging relative magnitudes of mental effort in different task conditions. These methods were then evaluated in the context of more naturalistic computer-based work. The results obtained from these studies provide initial evidence for the scientific and technical feasibility of using EEG-based methods for monitoring cognitive load during human-computer interaction.

Research supported by the National Institutes of Health, the Air Force, and the National Aeronautics and Space Agency.

BIOSIGNAL PROCESSING ENVIRONMENT FOR AN EEG-BASED BRAIN-COMPUTER INTERFACE

C. Guger, G. Edlinger
g.tec – GUGER Technologies OEG
Graz, Austria

Biosignal Processing Environment

g.tec offers a complete biosignal processing platform under MATLAB which allows the fast and easy realization of an EEG-based brain-computer interface (BCI). This platform facilitates the multi-modal acquisition and analysis of biosignals such as EEG, ECoG, EMG, EOG and ECG. After amplification (g.BSamp) the signals are passed to a PC/notebook data acquisition system for visualization and storage. g.STIMunit controls experimental paradigms while g.RTsys performs the data acquisition and real-time parameter extraction and classification of the EEG.

The system provides algorithms for off-line analysis and allows integratation the same algorithms for real-time processing. A key feature is the rapid prototyping environment which enables fast and easy implementation of different processing algorithms and classification methods for optimal BCI performance. The system enables to achieve reliable results in an early stage of development and to perform rapid iterations of the design. The environment allows the integration of user-specific hardware and processing modules and gives access to MATLAB-Toolboxes to accelerate the BCI research and to encourage the creativity.

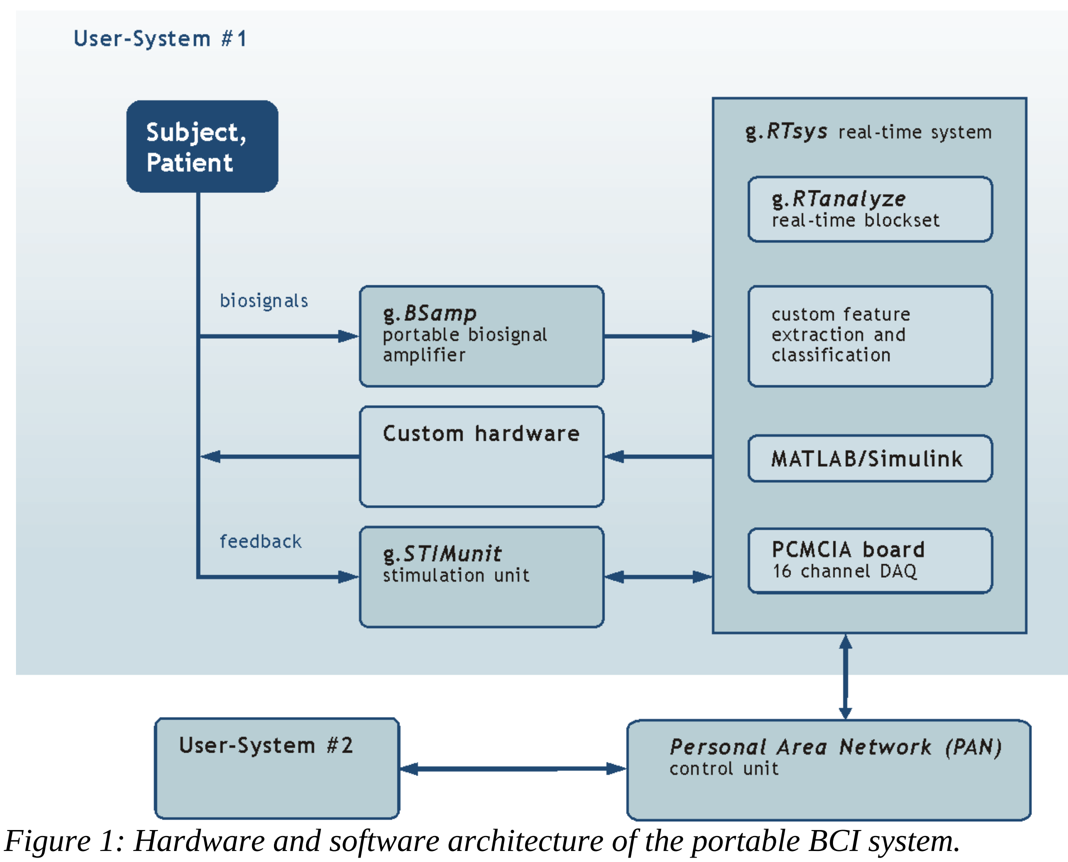


Figure 1: Hardware and software architecture of the portable BCI system.

To give BCI professionals the opportunity to acquire and analyse data of multiple patients/subjects a Personal Area Network gives access to a network of BCI systems (User-Systems #1, #2,...). A remote control unit allows to access multiple systems.

Development Process and Tests of the Brain-Computer Interface

Step1: Selection of parameter estimation and classification algorithms

The selection of the correct and best suited parameter estimation and classification algorithms is one of the most important tasks when setting up a new BCI system. Therefore, a specific algorithm selected from an EEG parameter estimation blockset can be plugged into the Simulink model as shown in Figure 2. In this case the brain-computer interface uses two bipolar EEG recordings (C3 and C4 of the international 10/20 system). Of each channel bandpower parameters are estimated and classified on-line with a linear-discriminant analysis. The classification result can be used to control, e.g., a cursor on the computer screen .

Step2: Implementation of the parameter estimation and classification algorithms with Simulink

Custom algorithms can easily be integrated in the analysis model.

Step3: Off-line simulations and tests of the Simulink block diagrams

Step4: Connection of the Simulink model to the real world

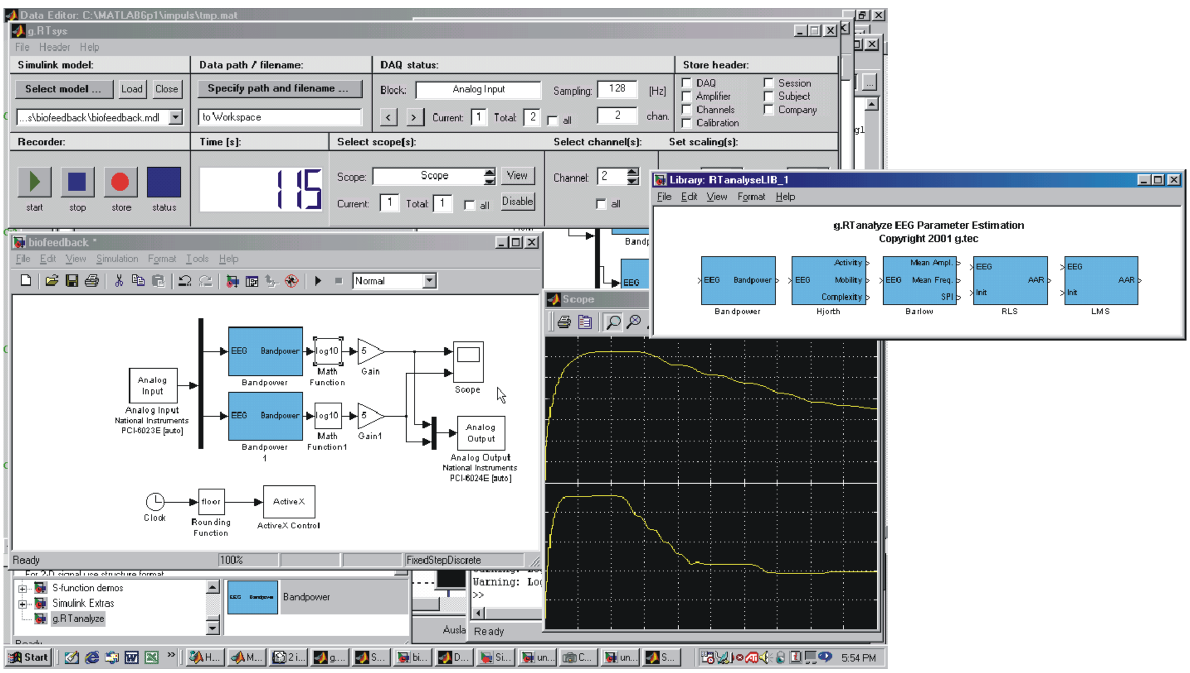


Figure 2: Real-time bandpower estimation of 2 EEG channels.

Step 5: Real-time code generation

Step 6: Development of an experimental paradigm under g.STIMunit

The brain-computer interface can be controlled by e.g. motor imagery of left/right hand movement. Therefore, a program converts a left hand imagination into a left movement of a horizontal bar on a computer screen and a right imagination into a right movement.

Step 7: Real-time tests

The BCI system was tested on about 150 subjects/patients [1, 2, 3, 4]. Three subjects reached a classification accuracy of 100 % [3].

Future developments

In order to make BCI systems accessible to patients it is necessary to minimise the size and the costs. g.tec is currently developing a Pocket-PC brain-computer interface consisting of an EEG-amplifier, and a Pocket-PC.

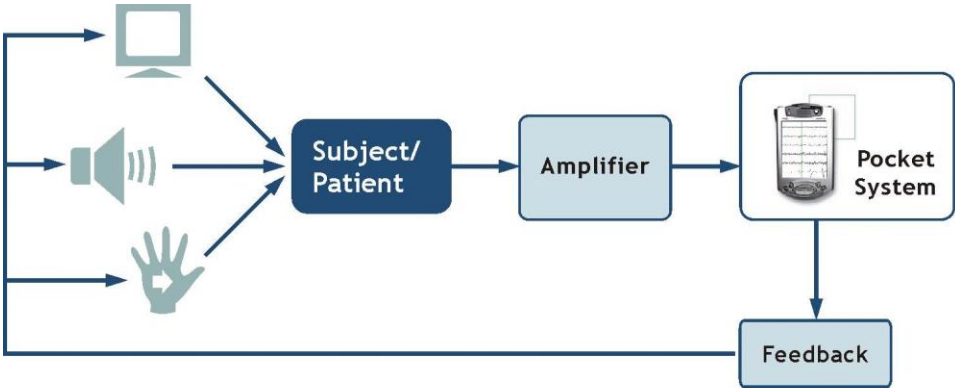


Figure 3: Pocket-PC BCI system.

The system is running Windows CE and allows the visualization, the quality check and storage of data. Parameters are extracted in real-time and are used for visual, auditory or tactile feedback to the patient/subject.

References

[1] C. Guger, W. Harkam, C. Hertnaes and G. Pfurtscheller, “Prosthetic control by an EEG-based brain-computer interface (BCI),” in Proc. AAATE '99, 1999, pp. 590-595.

[2] C. Guger, A. Schlögl, C. Neuper, D. Walterspacher, T. Strein and G. Pfurtscheller, “Rapid prototyping of an EEG-based brain-computer interface (BCI),” IEEE Trans. Rehab. Engng., vol. 9, pp. 49-58, 2001.

[3] Pfurtscheller G, Neuper C, Guger C, Harkam W, Ramoser H, Schlogl A, Obermaier B, Pregenzer M.: “Current trends in Graz Brain-Computer Interface (BCI) research,” IEEE Trans Rehabil Eng., vol. 8, pp. 216-9, 2000.

[4] Pfurtscheller G, Guger C, Müller G, Krausz G, Neuper C. Brain oscillations control hand orthosis in a tetraplegic. Neurosci. Lett., vol. 292(3), pp. 211-4, 2000.

BRAIN COMMUNICATION INTERFACE RESEARCH AT THE NINDS

William Heetderks, M.D., Ph.D.
Neural Prosthesis Program
NINDS, NIH

The mission of the National Institute on Neurological Disorders and Stroke (NINDS) is to reduce the burden of neurological disease. Loss of the ability to communicate with others and with the environment represents a significant burden in many neurological disorders including neurodegenerative disorders and trauma to the central nervous system. Our research is focused on developing integrated systems to restore function and provide significant functional benefit to affected individuals.

The Neural Prosthesis Program supports the development of direct interfaces with the intact parts of an injured nervous system for the purpose of getting information into and out of the brain. A major focus over the past several years has been the development of arrays of microelectrodes that can chronically record the activity of single cells or multi-unit activity from small clusters of cells. To make devices clinically useful a system that includes detection of microvolt potentials within the brain and transmission of these signals from the brain to appropriate processing systems is needed.

NINDS primarily supports research by providing grants and contracts to investigators at universities and research centers within the US and to a lesser degree internationally. Projects can be initiated by the NINDS or by extramural researchers. For the conduct of translational research a third research strategy is being developed that will involve collaborative activity between extramural researchers and the NINDS program staff. Plans for the future are to utilize multiple mechanisms including grants, contracts and cooperative agreements with investigators around the country to further this research effort. We also anticipate additional collaboration with other government agencies in pursuing these goals.

UCLA NEUROENGINEERING PROGRAM

Jack Judy
Department of NeuroEngineering
UCLA
Los Angeles, CA

The UCLA NeuroEngineering Research Laboratory is focused on several efforts to make use of state-of-the-art engineering technology to develop and execute projects that address problems that have a neuroscientific base. The following three projects are examples of the type of research in this laboratory.

UCLA Neuroengineering Project 1: Transcutaneous RF-Powered Neural Recording Device (a collaboration with Dr. Istvan Mody, Neurology, UCLA). The study of complex neuroscientific phenomena, such as fear, epilepsy, and aggressive behavior, is currently being limited by the physical and psychological effect of the test environment itself. In such studies it is necessary to have a means of observing electrophysiological activity, without interfering with its environment, so the test subject does not know that it is being studied. Examples include the dynamic electrophysiological features of emotion, the behavioral interactions of multiple interacting animals in their natural environment, and the real-time continuous monitoring of brain activity in epileptic animals enabling the analysis of seizure activity during awake and sleep periods. This research effort has designed, fabricated, and is testing a miniature, implantable, remotely powered, and wirelessly transmitting recording device. Specifically, an inductively powered single-channel
neural recording device has been designed, fabricated, and tested. This device amplifies the recorded signal, which is then used to regulate a voltage-controlled oscillator about a 3.1 GHz carrier wave. This FM wave is sent through a power amplifier that drives a 50 W antenna load and transmits the signal into free space. The signal is picked up by a similar antenna and demodulated using off-the-shelf equipment. The demodulated signal has a high degree of correlation with the original input signal for inputs as small as 5 mV and as great as 1.5 mV. The device has a 0.5 m transmit range allowing for continuous recordings from animals in their
natural environments.

UCLA Neuroengineering Project 2: Multielectrode Microprobes to Deep-Brain Stimulation (a collaboration with Dr. Marie-Françoise Chesselet, Neurology, UCLA). Although deep-brain stimulation (DBS) can be used to eliminate the severe side effects of Parkinson's disease (e.g., muscle tremors), it does not prevent neurodegeneration that leads to dementia or death. A combination of DBS and drug treatment might be capable of halting these degenerative processes by altering the response of neural tissue to drugs. In order to fully investigate this hypothesis, a comprehensive long-term stimulation study in an animal model is needed. We have designed, fabricated, and tested a novel micromachined probe that is able to accurately stimulate the subthalamic nucleus (STN) while minimizing damage to the surrounding tissue. The probe is coated with gold and insulated with silicon nitride for biocompatibility, has four platinum electrodes to provide a variety of stimulus patterns, and is formed in a novel 3-D plating process that results in a microwire-like geometry (i.e., smoothly tapering diameter) with a corresponding mechanically stable shank.

UCLA Neuroengineering Project 3: Development of High Density Electrode Arrays for Retinal Prostheses (a collaboration with Dr. Bob Greenberg, Second Sight, LLC). Electrically stimulating the retinas of blind patients suffering from macular degeneration can illicit visual perceptions. High-density arrays of electrodes can induce increasingly higher resolution images. However, the area of the retina to be simulated
is small (3×imes;3 mm2) and each electrode must be capable of delivering sufficient charge to activate deep

retinal neurons. Simple flat electrodes cannot supply the required current density reliably without electrode corrosion. Our approach is to enhance the effective electrode area by micromachining the electrode surface, and investigating materials with higher charge injection density capability.

THE CHOICE OF BRAIN COMPUTER INTERFACE TECHNIQUE

Philip R. Kennedy
Neural Signals, Inc.
Atlanta, GA

It is difficult to decide which communication system is optimal for a specific patient. This decision is not made easier by the various devices available and their capabilities. Nor is the decision made any easier by the patient's diagnosis. We suggest here that when deciding on the most suitable device, we should make a functional diagnosis and use this as the basis for the decision. This is a valid approach except when the underlying disorder is quickly worsening (as in some ALS patients) or improving (as in some brainstem strokes). In static or slowly progressive conditions, which are the majority, the following schematic is proposed.

The key step to making a functional diagnosis is to focus on what the patient can do. Do not focus on what the patient cannot do.

If the patient has movement, an assistive or augmentative communication device may be adequate. At this meeting we are mainly concerned about BCI devices for patients who have minimal movements. Six decision points appear as the patient's function deteriorates.

1] If there is visible movement involving three distinct muscles, then use the Muscle Communicator (MC) or Mouse Mover. If there are two muscles, use the MC with Dwell time enter command, or Dual Scan, or Morse Code with switches. If only one muscle effects a movement, use MC as a switch, or use a single switch (for scanning or Morse Code).

2] If there is no discernible movement, but EMG activity can be detected from three muscles, use the MC. If two muscles, use the MC with dwell. If one muscle, use MC with switch.

3] If there is no discernible movement or EMG activity, but the patient has coordinated eye movements, use an eye gaze system.

4] If there is inadequate eye control, use EEG systems.

5] If EEG is inadequate and an invasive system is acceptable to the patient, use local field potentials (LFP) recording systems from extradural or subdural locations provided these can be implanted before the patient loses all movement.

6] If EEG is inadequate, an invasive system is acceptable and the patient has reached the stage of total paralysis, then use implanted electrodes.

Let us take the ALS patient as an example. There are 30,000 ALS patients in the USA, with an annual incidence of about 6,000 per year, and a life expectancy of five years from time of diagnosis. Over 90% chose to die without a ventilator. Those with bulbar ALS (moving limbs but paralyzed respiration, speech and swallowing) more often accept a ventilator though the percentage is not known. ALS is not a terminal disease. Patients have been kept alive on a ventilator for decades. Stephen Hawking is an example.

The decision regarding the communication device for an ALS patient is as follows:

1. While the patient can still move, an augmentative device is used.
2. At this time the patient needs to decide for or against a ventilator.
3. If the decision is against, a device like the MC will suffice until death.
4. If the patient decides in favor of a ventilator, a non-invasive EEG system should be initiated if adequate and available for the patient's needs.
5. If an EEG system is not desired or available, a system for recording LFPs is implanted extra- or sub-durally while movements remain available for correlation with the LFPs.
6. If the patient is fully paralyzed, LFPs probably can not be adequately set up. An implanted electrode such as the Neurotrophic Electrode will then provide communication channels.

DEVELOPMENT OF IMPLANTABLE MICROELECTRODE ARRAYS AT THE NEURAL ENGINEERING LAB (NEL) AT THE UNIVERSITY OF MICHIGAN

Daryl R. Kipke, Justin C. Williams, Kevin J. Otto, David S. Pellinen, Jamille F. Hetke
Department of Biomedical Engineering
University of Michigan, Ann Arbor, MI

Researchers in the Neural Engineering Laboratory (NEL) are working to develop and refine several types of microdevices to provide long-term, high-density, two-way communication channels to highly specific areas of the brain. This has recently resulted in a new class of thin-film polymer implantable microelectrodes for neural recording and electrical stimulation. These devices are notable for their flexibility and their surfaces that can be modified to receive specially engineered bioactive coatings. The NEL is also actively involved in the continued development of the class of silicon-based implantable microelectrode arrays that have been a hallmark of Michigan Biomedical Engineering and Electrical Engineering for many years (http://www.engin.umich.edu/center/cnct/). Several projects are working to extend these base MEMS technologies to include micro-drug delivery functionality. These neural implant technologies provide the means to create reliable neural interfaces that enable the investigation and development of sophisticated brain-machine interface systems. The NEL is conducting several experimental studies to investigate sensory augmentation, neural control, and neural plasticity, each within the context of neuroprosthetic systems and brain-machine interfaces. Electrically induced and naturally evoked stimulus discrimination behavior are being investigated in animals using paradigms that combine natural sound stimulation and cortical microstimulation. The NEL website provides more information on these projects (http://www.eecs.umich.edu/NELab).

CONNECTING BRAIN TISSUE TO ROBOTS: DEVELOPMENT OF A HYBRID SYSTEM FOR STUDYING OF NEURAL PLASTICITY

M. Kositsky, A. Karniel, K.M. Fleming, V. Sanguineti, S.T. Alford, F.A. Mussa-Ivaldi
Department of Physiology
Northwestern University Medical School, Chicago, IL

The declared goal of early pioneers of computer science was to create a machine capable of imitating the human brain. Many researchers have adopted the reference to biology as a source of inspiration for creating artificial devices, particularly in the last two decades. More recently, a new perspective has emerged: the perspective of including biological elements within hybrid integrated systems. The idea of using "neurobiology as a technology" is rooted on the simple observation that the nervous systems of the simplest organisms still outperform the most advanced digital computers. In addition, there have been important advances in the techniques for delivering stimulations to brain tissue and for recording the activity of large neuronal populations. These advances allow us to think of neural nets not just as simulations of biological properties as possible operational descriptions of neural tissue.

At the moment, the major obstacle toward the development of systems that incorporate neural elements is our own ignorance of how the brain tissue operates. But this limit should not prevent us from moving along this direction as, the creation of systems in which biological neurons interact with computers and artificial machines provides us with new tools for investigating the neurobiological underpinnings of computation.

We have developed one such hybrid system establishing a bi-directional communication between the brainstem of a lamprey and a small mobile robot. The neural tissue is maintained alive and in working conditions by immersing it in a constantly refrigerated and oxygenated Ringer's solution. The mobile robot acts as an artificial body that delivers sensory information to the neural tissue and receives command signals from it. The sensory information encodes the intensity of light generated by a fixed source. The closed-loop interaction between brain and robot generates autonomous behaviors whose features are strictly related to the structure and operation of the neural preparation. The comparison between the behaviors generated by this system and the behaviors generated by a model of its neural component is a tool for investigating the role of synaptic plasticity in sensory motor learning.

In particular, we are interested in exploring the possibility of inducing controlled long-lasting changes in synaptic efficacy so as to effectively "program" a desired response of the robot to the light. If neural tissue can be considered as a biological computer and if we have an understanding of the mechanisms of neural plasticity, this goal should be within reach. Our ability to establish bi-directional communications with neural tissue and to control the mechanisms of synaptic plasticity would have a great impact on the development of new powerful prosthetic devices and, at the same time, would provide us with a deeper insight on the processing of information within the central nervous system.

UNIVERSITY OF MICHIGAN DIRECT BRAIN INTERFACE: 2002 UPDATE

S.P. Levine, J.E. Huggins, J.A. Fessler, W.M. Sowers, R.K.Kushwaha, S.L.BeMent, D.N. Minecan, O. Sagher, K.J. Leneway, J.J.Choi, S.J. Grikschat
The University of Michigan, Ann Arbor, Michigan USA
L.A. Schuh, B.J. Smith, K.V. ElisevichHenry Ford Hospital, Detroit, Michigan, USA

A direct brain interface (DBI) is a human computer interface that accepts commands directly from the brain without requiring physical movement. The University of Michigan Direct Brain Interface (UM-DBI) project seeks to detect voluntarily produced event-related potentials (ERPs) in human electrocorticogram (ECoG) as the basis for a DBI.

Research subjects are patients in one of two epilepsy surgery programs who have had subdural macro electrodes implanted for clinical purposes unrelated to the research objectives. The electrodes are 4 mm in diameter and arranged in grids or strips at distance of 1 cm center to center. Each subject has up to 126 subdural electrodes.

Subjects perform simple voluntary movements in a self-paced (non-prompted) manner with at least 4 seconds separating each repetition of the movement. Each dataset contains ECoG related to approximately 50 repetitions of the same action from each recording electrode. An ECoG database with data from 29 subjects has been compiled. Most previous work relied on off-line processing which necessitated the use of movement-related ERPs (instead of preferable motor imagery ERPs) so that movement onset (the trigger point) could be determined from muscle activity or another similar indicator and used to determine detection accuracy. A limited number of on-line experiments employing feedback protocols have also been performed and are reported separately (see Huggins et al., 2002 in these proceedings).

The basic detection method used by the UM-DBI has been a cross-correlation based template matching method. Triggered averaging of the ECoG from the first half of a dataset is used to create templates of the ECoG corresponding to the action. A template showing a distinct ERP is then selected and cross-correlation is performed with the ECoG from the second half of the dataset (the test data). Detections are defined when the cross-correlation value exceeds an experimentally determined threshold. Valid detections (hits) are defined to be within 1 second before and 0.25 seconds after a trigger point. Detections outside this time interval are considered false positives. Detection accuracy is quantified by the hit percentage, which is the percentage of trigger points in the test data that were detected, and the false positive percentage, which is the percentage of the detections which are false positives.

The most accurate off-line single channel detections have been 96% hits with 0% false positives and 100% hits with 4% false positives. Multiple channel detection methods have resulted in a detection accuracy of 100% with 0% false positives in some trials. In preliminary feedback experiments, 3 of 6 subjects were able to significantly improve the SNR of the selected ERP with the best subject also improving detection accuracy from 79% hits with 22% false positives to 100% hits and 0% false positives.

Current work is focused in two general areas, improved signal processing techniques and feedback experiments, both aimed at increased detection accuracy. Work on signal processing techniques is being addressed by analyzing the underlying assumptions about ECoG signal characteristics in the current detection model and exploring means for improvement (see Sowers et al., 2002 in these proceedings). Additionally, detection methods based on event-related desynchronization and event-related synchronization are being explored and the implications of combining these methods with the cross-correlation based template matching method are being evaluated (see Graimann et al., 2002 in these proceedings). A new experimental feedback system is being designed which will provide feedback based on the cross-correlation value instead of on the SNR. This feedback system will include a range of feedback programs that will start by providing the subject with basic feedback on the cross-correlation value and progress through several training steps to simulated operation of a communication system.

ASYNCHRONOUS BCI AND LOCAL NEURAL CLASSIFIERS

José del R. Millán
Joint Research Centre of the EC & Swiss Federal Institute of Technology Lausanne

Over the last years we have developed a portable BCI, called Adaptive Brain Interface (ABI), based on the on-line analysis of spontaneous EEG signals measured with a few scalp electrodes (6 to 9, normally 8) from which a local neural network classifier recognizes 3 different mental tasks. We have demonstrated publicly ABI on a number of occasions while subjects operated different brain-actuated applications, namely a virtual keyboard, a video game and a mobile platform (similar to a wheelchair).

ABI relies on an asynchronous protocol where the subject makes voluntary self-paced decisions on when to stop doing a mental task and start immediately the next one. This make the system very flexible and natural to operate, and yields rapid response times -- ABI tries to recognize what mental task the subject is concentrated on every 1/2 second. In this respect, every user chooses the mental tasks that he or she finds easier, and the preferred strategies to accomplish them. Subjects select three out of the following mental tasks "relax", imagination of "left" and "right" hand (or arm) movements, "cube rotation", "subtraction", and "word association".

Another characteristic of our approach is a mutual learning process where the user and the brain interface are coupled and adapt to each other. This accelerates the training process. The local neural classifier achieves error rates below 5% for 3 mental tasks, while correct recognition is 70% (or higher). In the remaining cases (around 20-25%), the classifier doesn't respond, since it considers the EEG samples as uncertain. The incorporation of rejection criteria to avoid making risky decisions is an important concern in BCI. From a practical point of view, a low classification error is a critical performance criterion for a BCI, for otherwise users would be frustrated and stop utilizing the interface. These classification rates (accuracy and error), together with the number of recognizable tasks and duration of the trials, yield a maximum transmission rate of approximately 2.0 bits/second. Normally, people reach the above-mentioned performances at the end of several days of moderate training (around 1/2 hour daily). But other subjects have also reached them in a single day of intense training. It is worth noting that one of these latter subjects is a physically impaired person suffering from spinal muscular atrophy. In total, we have worked with around 15 different subjects in a variety of conditions.

ABI has a simple local neural classifier where every unit represents an EEG prototype of one of the mental tasks to be recognized. We have found that this local network performs better than more sophisticated approaches such as support vector machines and temporal-processing neural networks (TDNN and Elman-like). This performance is achieved by simply averaging the outputs of the network for 8 consecutive EEG samples. The input to this classifier is the power spectrum in the band 8-30 Hz of each channel (standard fronto-centro-parietal locations) over the last second.

ABI is used to select letters from a virtual keyboard on a computer screen and write a message. For our trained subjects, it takes 22.0 seconds on average to select a letter. This time includes recovering from eventual errors. ABI also makes possible the continuous control of a mobile robot generating non-trivial trajectories among different rooms in a house-like environment. A key idea to control the robot with just 3 mental commands is to associate the user's mental tasks to high-level commands that the robot executes autonomously using the readings of its on-board sensors. Another critical aspect is that subjects can issue mental commands at any moment as ABI uses an asynchronous protocol. Experimental results show that mental control of the robot is only 35% longer than manual control.

CHALLENGES IN THE DEVELOPMENT OF A MINIATURIZED, SMART NEURO-PROSTHESIS SUITABLE FOR IMPLANTING INTO A BRAIN

Mohammad Mojarradi[1],David Binkley[2], Benjamin Blalock[3], Richard Andersen[4], Norbert Ulshoefer[2], Travis Johnson[1], Linda Del Castillo[1]
[1] Jet Propulsion Laboratory, Californian Institute of Technology
[2] Department Electrical and Computer Engineering, University of North Carolina at Charlotte
[3] Department of Electrical and computer Engineering, University of Tennessee Knoxville
[4] Division of Biology, California Institute of Technology

Passive microelectrode arrays have been widely used by researchers as a neuro-prosthetic tool to extract electrical signals from the brain. The microelectrode arrays are directly connected to measurement instruments through a large bundle of wires and are placed into the brain using surgical techniques. The large number of wires connected to current passive microelectrode arrays limits their widespread use as permanent neuro-prosthetic devices. In addition, there is an increasing demand for deploying microelectronics to develop a more sophisticated generation of neuro-prosthetic devices, capable of producing high quality electrical signals while significantly reducing the number of wires, or potentially eliminating wires entirely using an RF system.

To achieve this goal, a multiplexing electronic chip can be designed to multiplex the signal from each electrode in the array into a single channel; hence minimizing the number of wires exiting the electrode array. However, prior to multiplexing, individual amplifiers need to be added to each electrode at the array to enhance its signal to noise ratio. To that end, the chip can be designed with amplifiers arranged in geometrical patterns corresponding exactly with the electrodes of the array. Advanced assembly techniques can, in turn, be used to directly attach the chip to the passive microelectrode device. A wireless transmitter can be attached to the multiplex line, to transmit the signal from the brain through an RF link. The same RF link can also be used for powering the chip.

Features offered by a miniaturized device that combines analog electronics with the microelectrode array will come at a price. For one thing, power consumed by the active electronics will raise the temperature of the neuro-prosthetic device and could potentially destroy the neighboring biological tissue. And secondly, energy absorbed by the tissue because of the wireless features of the device (wireless coupling of power and wireless transmission of the signals to and from the implanted prosthesis) can be a potential source of long-term tissue damage.

The design of the electronics for the smart neuro-prosthesis is therefore constrained by micro-power levels that would prevent the excessive temperature rise (less than 1 deg centigrade) of the device and the choice of transmission frequencies that would minimize the absorption of radio frequency energy by the tissue. The signal to noise performance of traditional analog circuits is directly proportional to their operating power. To produce a high signal to noise ratio, non-traditional analog circuits solutions need to be developed.

The absorption of RF energy by the tissue is directly proportional to the increase in RF frequency. Minimizing the RF transmission frequency to reduce the energy absorption by the tissue will impact the transmission data rate. Hence, chip signal processing and data compression will need to be deployed to enhance the signal quality. Employing these functions in turn impacts the already small power budget and makes it even more difficult to develop a perfect neuro-prosthesis solution.

HUMAN-COMPUTER INTERACTION RESEARCH AT THE GSU BRAINLAB

Melody M. Moore, M. Todd Kirby
Georgia State University, Atlanta, GA

The overall goal of the GSU BrainLab is to determine the most effective paradigms of human-computer interaction for direct control of a computer using brain signals. Our central research focus is on applying brain-computer interface (BCI) technologies to real-world problems. We aim to provide significant quality-of-life improvement to users with severe disabilities as well as studying ways of utilizing brain-computer interfaces for everyone. The BrainLab currently has ongoing projects in several BCI and assistive technology areas:

New User Interface Control Paradigms

The aim of this research is to explore the human-computer interaction field to determine possibilities for alternate paradigms of brain signal control (in addition to proportional 2-D spatial navigation such as a mouse emulator). We are studying several approaches, including hysteretic ("nudge and shove" thresholding) control, which allows several control signals to be generated from a continuous neural signal. We have also collaborated with researchers from Georgia Tech to adapt 2-D spatial interfaces to serialized interfaces, which can be then neurally controlled. We adapted several applications, including a web browser, for serialized access. We are also studying logical vs. proportional control to improve speed and accuracy of BCI control.

BrainTrainer - Subject Training

The BrainTrainer project is researching the most effective ways of teaching a person to control brain signals in order to interact with a device. The BrainTrainer toolset allows trials to be composed, providing simple tasks such as targeting, navigation, selection, and timing that can be combined to produce an appropriate-level task for a particular subject. It also allows the researcher to incorporate different forms of biofeedback (visual, auditory, and haptic). BrainTrainer automatically instruments the resulting application for data recording such as error rates, speed, and accuracy of task performance. We are working with Neil Squire Foundation to determine the atomic tasks, benchmarks, and standardized data formats that BrainTrainer will support.

Neural Art - Biofeedback

The Neural Art project is exploring different methods of representing brain signals, both for biofeedback and training purposes, and for creative expression and recreation. The Neural Music program we have developed translates brain signal and brain signal patterns directly to MIDI, allowing for a tonal representation of the signal. This has been tested in offline analysis with brain signal recordings and is currently being ported to allow real-time presentation of the auditory data. We also implemented a signal visualizer, which allows the signal to be represented graphically according to configurable signal characteristics.

Quality of Life Applications

· Neural Internet - We have developed a neurally-controlled web browser that serializes the spatial internet interface and allows logical control of a web application. We have also developed a neurally-controlled email program that accompanies the web browser, allowing neural signals patients to send and receive written communications from the internet.

· Aware 'Chair **-** The "Aware 'Chair" is a context-aware intelligent power wheelchair which integrates environmental control, communication, and multilevel prediction based on context and user history. The communication and environmental control systems are informed by environmental sensors, user history, time of day, medical status and other information in order to predictively narrow the selection space, thereby improving user performance. We are currently adapting the Aware 'Chair for neural control, working with UC Berkeley to incorporate their prediction algorithms.

Collaborations

The GSU BrainLab currently enjoys active collaborations with researchers at the Wadsworth Center, Neil Squire Foundation, Georgia Institute of Technology, and the University of California at Berkeley. Our funding sponsors include the National Science Foundation, the National Institutes of Health, DARPA, and Georgia State University.

GRAZ-BCI: STATE OF THE ART AND CLINICAL APPLICATION

C. Neuper, G. Müller, G. Pfurtscheller
Dept. of Medical Informatics, Institute for Biomedical Engineering,
University of Technology Graz, Austria

In the last decade the work on the Graz-BCI was dedicated to differentiate between two or more brain states and EEG patterns, respectively, related to motor imagery in predefined time windows (synchronous BCI). On the one hand, different methods of parameter estimation were investigated, on the other hand, a number of classifiers were tested. It has been demonstrated that the discrimination of oscillatory EEG components, associated, for example, to two different types of motor imagery, is possible with a high classification accuracy (Pfurtscheller and Neuper, 2001).

An unlikely harder task is the asynchronous classification of one specific transient brain state in the ongoing EEG. In this approach, a continuous analysis of brain signals is performed to detect transient changes in oscillatory EEG components. In some preliminary experiments investigating EEG data recorded during self-paced finger and foot movements, we obtained very promising results that show that movement performance can be predicted not only by analyzing the MRPs (Birch and Mason, 2000), but also by considering the dynamics of oscillatory brain activity.

Besides this, further projects, which are presented below, were dedicated to investigate the application of the standard Graz-BCI system in patients. Since most of the previous studies were performed on healthy volunteers, there was a need to evaluate the performance and acceptance of such a classifier-based BCI system in severely paralyzed patients. In detail, two projects are reported: (i) BCI training to operate a 'Virtual Keyboard' and (ii) BCI-based operation of a hand orthosis.

(i) BCI training to operate a 'Virtual Keyboard'

This project (done in cooperation with N. Birbaumer and A. Kübler, Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Germany) aimed at training a patient diagnosed a severe cerebral palsy to use the Graz-BCI for verbal communication. Over a period of several months EEG feedback training was performed at the patient's home (clinic), supervised by the distant laboratory with the help of a 'telemonitoring system' (Müller et al., 2002). On-line feedback computation was based on single-trial analysis and classification of specific band power features of the spontaneous EEG. The patient learned to 'produce' two distinct EEG patterns and to use this skill for BCI-controlled spelling. Significant learning progress was found as a function of training session, resulting in an average accuracy level of 70% (correct responses) for letter selection. 'Copy spelling' was performed with a rate of approximately 5 decisions per minute (Neuper et al., 2002).

(ii) BCI-based operation of a hand orthosis

In a further project, an electrical hand orthosis in a tetraplegic patient was controlled by EEG activity using a synchronous BCI design and 2 types of motor imagery. After a number of training sessions with variations of the motor imagery strategy over a time period of several months, imaginations of foot movement versus imagination of right hand movement achieved a classification accuracy of close to 100% (Pfurtscheller et al., 2001). Inspecting the EEG signals, it was found that foot motor imagery induced long trains of 17- Hz beta oscillations focused on the electrode position on the vertex. Based on these induced 17-Hz oscillations a simple brain switch was constructed and used to operate the hand orthosis asynchronously. The patient was able to perform an opening and closing operation in about 11 seconds.

References:

Birch, G. E., and Mason, S.G. Brain-computer interface research at the Neil Squire foundation. IEEE Trans. Rehab. Eng., vol. 8, no.2, pp. 193-195, 2000.

Müller GR, Neuper C, Pfurtscheller G, Implementation of a Telemonitoring system for the Control of an EEG-Based Brain Computer Interface. 2001; submitted.

Neuper C, Müller G, Kübler A, Birbaumer N, Pfurtscheller G. Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment. 2002; submitted.

Pfurtscheller G, Guger C, Müller G, Krausz G, Neuper C. Brain oscillations control hand orthosis in a tetraplegic. Neurosci Lett 2000; 292(3):211-4

Pfurtscheller, G. and Neuper, C. Motor Imagery and Direct Brain-Computer Communication. IEEE Trans. Rehab. Eng., vol. 89, no.7, pp. 0018-9219, 2001.

EEG PHASE LOCKING DURING COGNITIVE PROCESSING

Paul Nunez
Brain Physics Group, Dept of Biomedical Engineering
Tulane University, New Orleans, LA

The physiological mechanisms at cellular levels underlying EEG are outlined. A single conceptual framework in which to view EEG, ERP, MEG, fMRI and PET is proposed. Neocortical dynamics and behavior/cognition are viewed in the context of *cell assemblies* (or neural networks) embedded within *synaptic action fields*. These so-called synaptic action fields are simply the numbers of active synapses per unit volume, independent of their functions. The introduction of such *fields* to neuroscience has two complementary motivations: 1) To provide a direct link between synaptic or action potential activity and scalp potentials 2) To suggest the importance of top-down interactions between the synaptic fields and network activity, analogous to top-down cultural influences on social networks. Complex dynamical systems are typically characterized by both top-down and bottom-up interactions, called *circular causality* in the field of *Synergetics*, for example. A similar picture is proposed for neocortex in which the so-called localized functional regions obtained with fMRI and PET are viewed as *hubs* in the various networks.

Brains apparently operate at various intermediate dynamic states between the extremes of *global coherence* (widespread neural masses acting together) and *functional localization* (regional tissue acting independently). Differences in this local-global "balance" are associated with different cognitive or behavioral states. In this context, several similar measures of neocortical dynamics are discussed, *covariance*, *coherence*, *phase synchronization* and *bicoherence*.

Every *cognitive brain state* may be identified with some combination of dynamic measures, the *dynamic brain state*, including the above measures of local versus global dominance. For example, the coherence or covariance between every electrode pair (2016) in a 64-channel recording might be used to define *dynamic brain state*. With the covariance measure, normally applied to transient ERP's as in the work of Alan Gevins and colleagues, spatial covariance patterns are obtained at different latencies from the stimulus. With the coherence measure, applicable to spontaneous EEG or steady-state evoked potentials as in the works of Petsche, Thatcher, Silberstein, Pfurtscheller, Lopes da Silva, Schack, Nunez and others, spatial coherence patterns are obtained in specific frequency bands.

Any such analyses of *spatial patterns* are limited by the distortions of volume conduction and reference electrode. *High-resolution EEG* provides estimates of dura surface potential independently of assumptions about the nature of brain sources. The accuracy of high-resolution EEG is discussed briefly. High-resolution EEG data showing various measures of phase locking in the theta and upper alpha bands during mental calculations is presented in the context of the proposed conceptual framework

REAL-TIME EEG EVENT DETECTION FOR AUGMENTED HUMAN MACHINE INTERACTION

Lucas Parra[1], Paul Sajda[2]
[1]Adaptive Image and Signal Processing, Sarnoff Corporation
[2]Department of Biomedical Engineering, Columbia University

Recent research in neuroimaging has identified electroencephalography (EEG) signals that are correlated with cognitive processing states such as attention, memory encoding and recall, perceived reaction errors, and motor intent. We envision that real-time monitoring of EEG brain activity has the potential to revolutionize human-machine interaction by making interfaces adaptive to such mental states.

We are developing, in this context, a robust non-invasive brain-computer interface (BCI) that measures individual cognitive events in real-time and maps brain activity to generate a feedback signal used for monitoring and interface control.

We aim to demonstrate, using three different candidate EEG signals, the utility of the BCI for improving subject performance in the following scenarios:

(1) Perceived error and conflict. Error related negativity (ERN) in EEG has been linked to perceived response errors and conflicts in decision making. We are developing a BCI system to measure the ERN and predict task-related errors. The system is being evaluated as an automated real-time decision checker for time-sensitive control tasks. Detected reaction errors will be corrected or "flagged," requiring additional confirmation before execution of critical commands.

(2) Working memory encoding. Transient modulation of oscillations in the theta (4-8 Hz) and gamma (20-30 Hz) bands, recorded using EEG and magnetoencephalography (MEG), have been implicated in the encoding and retrieval of semantic information in working memory. We are developing a system which exploits these neural correlates of semantic processing to construct an automated "tutor" that will re-enforce semantics in memory intensive tasks. When the tutor detects problems with semantic information processing it can alert the subject of anticipated memory recall deficits, repeat portions of the training sequence, etc.

(3) Motor imagery. A number of neural signals have been shown to correlate with motor intent, including lateralized alpha (10-12 Hz) band activity in EEG and short transient pulses in MEG over the motor cortex. We are developing a system to predict, on a single trial basis, motor intent through robust and differential classification of motor imagery generated by a subject. This will enable an intuitive, hands-free, communication channel that bypasses the motor system.

We will report initial results for ERN detection/error correction and prediction of motor intent via motor imagery.

SIGNAL PROCESSING METHODOLOGIES TO MODEL THE RELATION BETWEEN SPIKE TRAINS AND HAND MOVEMENTS FOR BRAIN MACHINE INTERFACES

José C. Principe
University of Florida, Gainesville, FL

The University of Florida Computational NeuroEngineering Laboratory (CNEL) is part of a five members consortium (Duke, MIT, SUNY, Plexon Inc.) lead by Duke University that is developing closed-loop brain machine interfaces (BMI). The ultimate goal is to allow patients suffering from paralysis or other neurological disorders to control robotic prosthetic limbs through thought.

One of the issues for the feasibility of BMIs is the bandwidth/accuracy achievable with EEG scalp recordings. Unlike these approaches, we are using invasive recording techniques pioneered by Nicolelis et al at Duke [1] to test their suitability to build BMIs. Spike trains from large arrays of microwire electrodes implanted in the pre motor, primary motor and posterior parietal cortices of nonhuman primates are recorded at Duke University while the primates performed 3-D reaching tasks. These recordings of large neuronal assemblies provide mesoscopic information while maintaining high temporal and spatial resolution. Electrode outputs processed by spike detection and sorting techniques yield firing patterns of up to 104 single neurons. For real-time processing of the data, neuronal firing counts in 100ms windows are used as inputs from which control signals are derived.

The translation of these signals into control commands is approached both from an input-output (I/O) modeling framework and from a state estimation perspective. We assume there exists an unknown system that maps the firing counts to hand position in 3-D space, and by observing the inputs and outputs we can optimally adapt the model to approximate the desired relationship. The CNEL lab has investigated three I/O models: Wiener filtering, switching local linear models, and nonlinear recurrent neural networks (RNN). The Wiener filter assumes a linear relationship between the neuronal firing counts and hand position. The filter output is simply a weighted sum of delayed versions of the firing counts achieved by optimal projection to a linear space. The multiple linear model method assumes that the firing counts that produce a desired hand trajectory are piecewise stationary. Multiple linear FIR filters are trained in parallel and compete to become specialized for each piecewise stationary segment. The RNN adapts a nonlinear model to map firing counts to hand position. This model is a modified version of the multilayer perceptron (MLP) and contains feedback connections in its hidden layer. State feedback allows for continuous representations on multiple timescales and is a powerful method to extract temporal information from neuronal firing counts. The state estimation approach uses a Kalman filter to model the hand position, speed and acceleration as states given the spike trains as noisy observations.

The framework for assessing the results of a BMI is not yet fully established. Model performance to predict hand position from neuronal firing counts is evaluated with three different measures: correlation coefficient, signal to error ratio (SER), and target acquisition plots. The correlation coefficient computed over sliding windows quantifies how well the actual and predicted hand trajectories are linearly related. The SER, defined as the square of the desired signal divided by the square of the estimation error, gives a measure of the accuracy of estimated position in terms of the error variance. The third measure is a graphical technique which places the target location at the center of a 3-D coordinate system. The error associated with each direction (x, y, z) is plotted on its respective axis. Errors that form a tight cluster of points around the target indicate successful target acquisition.

In this presentation I will present comparisons among all these models and raise some of the important signal processing problems in this approach.

[1] Wessberg, J., C. R. Stambaugh, J. D. Kralik, P. D. Beck, M. Laubach, J. K. Chapin, J. Kim, S. J. Biggs, M. A. Srinivasan and M. Nicolelis (2000). "Real-time prediction of hand trajectory by ensembles

of cortical neurons in primates." *Nature* 408(6810): 361-365.

A MINIATURE, WIRELESS TWO-CHANNEL EEG FOR BRAIN COMPUTER INTERFACE

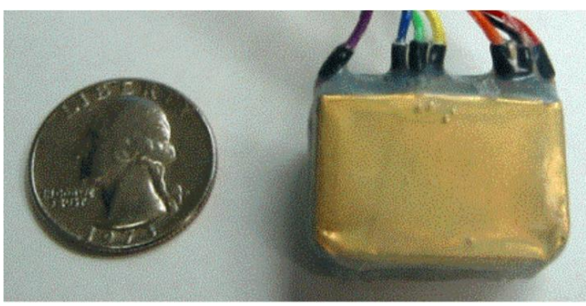
Robert N. Schmidt, PE
Cleveland Medical Devices Inc.

A new, low noise, two-channel wireless data acquisition system used to monitor electroencephalogram (EEG), on humans for research purposes has been developed by Cleveland Medical Devices Inc. It is called the BioRadio® Jr.

The system consists of a small compact integrated transmitter with a form factor that can be used on a headband, or mounted on a hairpin. The device includes, two preamplifiers, two amplifiers, a state-of-the-art analog to digital (A/D) converter, a microprocessor, and a MicroSynth™ RF radio transmitter. It weighs less than one-half ounce, is 1.3" x 0.9" x 0.3" in size, and can transmit digital EEG signals to a nearby receiver to a distance of about 50 feet through walls. This 50-foot range allows users to be untethered, allowing them to move freely about the bed, home, lab, or ward without entangling wires.

The receiver attaches to the serial port of any personal computer (PC). The data stream format at the serial port is available to users to be interfaced with other Brain Computer Interface (BCI) software. Data can also be viewed in real-time using BioCapture software and simultaneously saved to the PC hard drive. ASCII conversion tools allow data analysis in software packages such as MATLAB®, LabVIEW™, Excel, and .edf sleep software.

Contact: Robert N. Schmidt, President, Cleveland Medical Devices Inc., 11000 Cedar Ave. Cleveland, OH 44106, rschmidt@CleveMed.com, 216-619-5925, cell: 216-374-7237, www.CleveMed.com.



CONTROLLING REACTIVE RESPONSES AROUND NEURAL PROSTHETIC DEVICES

W. Shain[1], L. Spataro[1], J. Dilgen[1], K. Haverstick[2], S. Retterer[3],M. Saltzman[2],
M. Isaacson[3], J.N. Turner[1],
[1]Wadsworth Center and Dept of Biomedical Sciences
School of Public Health, Albany NY
[2]Dept of Chemical Engineering or [3]School of Applied and Engineering Physics,
Cornell University, Ithaca NY

Reliable use of neural prosthetic devices is compromised by reactive responses that result in electrical isolation. Early reactive responses initiated by device insertion have many hallmarks of an inflammatory response and may be initiated by the process of device insertion, including unavoidable damage to the brain's microvasculature. Sustained responses develop as early responses wane. We have observed that sustained responses appear to result from tissue-device interactions and have been observed as long as three months following device insertions. To determine if altering inflammatory mechanisms can affect these reactive responses, we have examined the effects of peripheral and local applications of dexamethasone. This synthetic glucocorticoid activates specific receptors found in a variety of cells causing changes in gene regulation. Peripheral injections were made as subcutaneous injections in ethanol (200 µg/kg) and administered either as a single injection on the day of device insertion or for a total of six daily injections. Several limitations of this method are that long-term treatment requires repeated injections, drug exposure is episodic; and treatment does not specifically target the CNS. Local drug delivery, achieved by microfluidics or slow release of compounds from polymers, can overcome these shortcomings. In a first step to demonstrate the effectiveness of local, long-term release, ribbons of poly(ethylene-co-vinyl acetate) (EVAc) (~ 400 x 400 μm^2 and 2 mm long) containing dexamethasone (35% by weight) were inserted into premotor cortex of anesthetized 100-g rats using a 30-gauge needle. Immunohistochemistry and laser-scanning confocal microscopy were used to describe changes in astrocytes (GFAP), microglia (CD11b), and cells of the microvasculature (laminin) in 100 µm thick tissue slices. Samples were prepared one and six weeks following device insertions, representing the early and sustained responses, respectively. In general, reactive responses around control ribbons were similar to those observed around silicon devices with robust responses and accumulation of extracellular material immediately around inserted devices. Responses around control EVAc ribbons differed from those observed around silicon devices by the presence of large cavities. Dexamethasone treatment modified both early and sustained reactive responses. Peripheral injects resulted in greatly reduced astroglial responses, while microglial and vascular responses were either unaffected or increased. Local drug delivery using ribbons containing dexamethasone greatly attenuated all cellular responses of both early and sustained responses. At both times tissue closely packed around the ribbons, though relatively few cells were observed attached to ribbons. Dexamethasone release from EVAc ribbons decreased over time with significant amounts of release measured 40 days after initiation of measured release into physiological saline. Calculated drug concentrations drop off exponentially in the region immediately around insertion sites with initial areas of significant drug concentrations extending as far as several millimeters into the surrounding brain tissue. These results demonstrate that while peripheral injections of anti-inflammatory drugs can produce moderate effects on both early and sustained reactive responses following insertion of microfabricated prosthetic devices, local drug release may provide more complete and long-term control of cellular responses. Thus coating of devices with slow release materials or provisions for long-term drug infusion through microfluidic channels may provide a means to insure the chronic function of neural prosthetic devices.

Support: Supported in part by NINDS and NIBIB (R01-EB000359).

SOLVING THE WIRELESS DATA COMMUNICATION PROBLEM BETWEEN BRAIN IMPLANTS AND COMPUTER

Mingui Sun
Laboratory for Computational Neuroscience
Departments of Neurosurgery, Electrical Engineering, and Bioengineering
University of Pittsburgh, Pittsburgh, PA

There have been a number of previous or ongoing research studies on brain-computer interface. This research mainly target the access/delivery of meaningful signals from/to the human cortex so that the information in the bioelectric form can be converted to/from the information in the digital form. As a result, sophisticated electrodes and implantable chips performing such a conversion have been investigated and several prototypes of these devices have been demonstrated. However, one extremely important, but difficult, problem has not yet been addressed: Suppose that we have successfully converted the information, how do we pass this information between the implanted brain chip and the computer? In the current experimental settings, wires are utilized. This type of connection is clearly unacceptable in the outside world where reduction in mobility and high risk of infection rule out its feasibility. Wireless radio frequency (RF) connection provides an alternative. However, its feasibility is in serious question due to the following limitations: 1) RF antenna and certain circuit elements (e.g., induction coils) increase the size and the mass of the implantable device; 2) the conversion between signal and RF waves requires a considerable amount of energy which is drained from the internal battery within the implantable device, and this battery is difficult to recharge or replace; and 3) the ionic fluid of biological tissues, such as the cerebrospinal fluid (CSF), is highly conductive. As a result, transmitting an RF signal within the head is similar to transmitting a radio wave through an electrically shielded room. Such transmission is possible only when the RF signal is strong and its frequency is relatively low, which requires more energy consumption and larger capacitors and inductors, compounding the first two problems, and promoting adverse biological consequences due to the strong internal emission which generates heat and other effects. Currently, the RF data link has been limited to applications where the device size is large and the implantation time is short.

There exists a natural passageway of information which has been overlooked. The ionic fluid in the biological body conducts electrical current which, when intentionally manipulated, is capable of passing information. This conduction is called volume conduction. Electrostatic laws of physics state that a current source within a volume conductor results in an electrical potential distribution within and on the surface of the conductor. This potential can be easily measured by affixing a pair of stick-on electrodes on the scalp. We have been investigating this volume conduction based data communication method for several years. Our experiments on theoretical models, physically constructed models, and animal experiments have received encouraging results. We found that the volume conduction based system has the following advantages: 1) The strong shielding effect of ionic fluid in the body is no longer a problem. Instead, it is now employed as the information carrier. 2) The volume conduction link is simpler than the RF link, allowing an aggressive reduction in size and weight. 3) It does not require signal conversions to/from RF, thus this approach is highly energy-efficient, potentially enabling a battery that lasts for a life time.

Acknowledgment: The following individuals have made significant contributions to this research: Robert J. Sclabassi, M.D., Ph.D., Marlin Mickle, Ph.D., Chung-Ching Li, Ph.D., Donnald J. Crammond, Ph.D., Ellizbath Tyler-Kabara, M.D., Wendy Fellows, Brian L. Wessel, Paul A. Roche, Qiang Liu, Erxiong Lu, and Wei Liang.
This work has been supported in part by National Institutes of Health grant No. NS43791.

THE OXFORD-PUTNEY BCI SYSTEM

P. Sykacek[1], S. Roberts[1], M. Stokes[2], M. Gibbs[1], L. Pickup[1]
[1] Department of Engineering Science, University of Oxford, Oxford, UK
[2] Research Department, Royal Hospital for Neurodisability, Putney, London, UK

Abstract

Recent BCI research carried out in our groups has focused on two aspects. The main BCI contributions focus on improving standard machine learning approaches by utilizing probabilistic principles. We also design experimental settings which can be used for reliable user-machine communication and user assistance.

Probabilistic models for BCI systems

Probabilistic models can be used to describe many models that have been applied to offline and adaptive BCI systems. Examples are Hidden Markov models, that have been successfully applied to BCI systems ([OGNP01]). Probabilistic models have also been quite popular tools in the machine learning and statistics community. Recently these communities have, in particular, come up with algorithms that allow inference of very complex models. Hence we can benefit from those findings that allow us to extend these classical time series models. We have recently evaluated two such generalizations in the context of BCI systems. Coupled HMM's are generalizations of ordinary HMM's, where two hidden state sequences are probabilistically coupled using arbitrary lags. In ([RGR02]) these models have been applied to movement planning and shown to outperform classical HMM's.

Another modification of HMM's was proposed in [SR02]. Probabilistic principles suggest that classifications based on extracted features have to regard those as *latent variables*. Hence inference and predictions are required to marginalize over this latent space. We applied this model to classification of different cognitive tasks. These experiments have shown that integrating out feature uncertainty significantly outperforms classifications obtained when conditioning on feature estimates.

Probabilistic models can also be used to describe algorithms for adaptive BCI systems. A method which proposes such an approach is shown in [SRS], this workshop. The method uses variational Kalman filtering to infer an adaptive *nonlinear* BCI-classifier. Variational methods are attractive for BCI systems because compared with Laplace approximations (as e.g. used by [PR99]), they allow for more flexibility and, as opposed to particle filters, they still provide a parametric form of the posterior. A parametric form of the posterior is important since it allows efficient implementations. Results with the variational Kalman filter classifier suggest that it significantly outperforms the corresponding offline method. Consequently, our current research direction aims to obtain adaptive methods that implement the ideas we found to be useful for offline BCI systems.

BCI-Applications and experimental issues

We are currently working on two different applications. On one hand we are interested in the classical man machine communication channel. Experiments reported in [CSS + 01] compare the communication bandwidth that can be achieved using different cognitive tasks. It was found that other task pairings result in slightly better correct classification rates as the classical imagined motor task. The main conclusion is that we might significantly increase the bit rate of the BCI system by using more than two cognitive tasks.

Our second project's aim is to develop an immediately effective brain computer interface. Using adaptive inference techniques, we obtain a system that does not require training before the system can be applied. To achieve this we detect and classify *state changes* in the motor cortex areas of the brain which are associated with movement planning. Another major focus of this project is to investigate the effect of different biofeedback mechanisms. As part of this study we look at audio and tactile as well as visual forms of feedback and evaluate the effect on the overall system performance.

References

[CSS + 01] E. Curran, P. Sykacek, M. Stokes, S. Roberts, W. Penny, I. Johnsrude, and A. Owen. Cognitive tasks for driving a brain computer interfacing system: p pilot study. Technical Report PARG-01-07, University of Oxford, 2001.

[OGNP01] B. Obermeier, C. Guger, C. Neuper, and G. Pfurtscheller. Hidden Markov models for online classification of single trial EEG. *Pattern Recognition Letters*, pages 1299-1309, 2001.

[PR99] W. Penny and S. J. Roberts. Non stationary logistic regression. In *Proceedings of the IJCNN 1999*, 1999.

[RGR02] I.A. Rezek, M. Gibbs, and S. Roberts. Maximum a posteriori estimation of coupled hidden markov models. *Advances in Neural Networks for Signal Processing*, page to appear, 2002.

[SR02] P. Sykacek and S. Roberts. Bayesian time series classification. In T.G. Dietterich, S. Becker, and Z. Gharamani, editors, *Advances in Neural Processing Systems 14*, page to appear. MIT Press, 2002.

[SRS] P. Sykacek, S. Roberts, and M. Stokes. Adaptive BCI based on variational inference. In *Proceedings of the BCI Workshop 2002, Albany NY*.

TRAINING CORTICAL CELLS TO PRODUCE BETTER DIRECTIONAL CONTROL SIGNALS WITH AND WITHOUT PHYSICAL LIMB MOVEMENTS

D.M. Taylor[1], S.I. Helms Tillery[1], A.B. Schwartz[1,2]
[1] Bioengineering, Arizona State University, Tempe, AZ
[2] The Neurosciences Institute, San Diego, CA

We have recorded cortical units on implanted microwire electrode arrays in the motor and premotor cortical areas in macaques. Some channels have recorded units stably for over two years. The animals used these signals in real-time to move a virtual reality cursor to targets in 3D space. Two monkeys controlled the 3D cursor movements with their cortical activity while their arms were free to move, and two monkeys did this with both arms restrained.

In the arms-free experiments, a modified population vector was used to translate cortical activity into cursor movement in real-time. The animals used visual feedback of the cursor position to make on-line error corrections to their center-out trajectories. This allowed them to improve their target hit rate over that of trajectories created off-line from cortical signals recorded during similar hand-controlled center out movements. The animals showed significant improvement within each day and across days in both a slow and a ballistic 3D movement task

In the experiment where both arms were restrained, a co-adaptive algorithm was used to translate cortical activity into cursor movements. This algorithm does not rely on any *a priori* knowledge of the brain's movement-related modulation patterns, and, therefore, could be implemented in immobile human patients. In the co-adaptation process, the movement prediction algorithm adapts to the brain activity while the subject attempts to make a sequence of brain-controlled calibration movements. The subject then uses visual feedback of these attempted brain-controlled movements to further modify its cortical activity and improve 3D cursor control.

In the arms-restrained animals, this co-adaptive process resulted in movement-related modulation patterns which were radically different from those seen during normal arm movements. Cortical tuning functions changed their preferred directions, became more cosine tuned, increased their modulation range, and decreased their movement-to-movement variability. This resulted in more accurate movements and a more uniform level of control throughout the workspace compared to the non-adaptive arms-free experiments. Off-line analysis using maximum likelihood estimation also showed these new cortical encoding patterns predicted the intended target better than the cortical activity recorded during regular center-out arm movements.

With regular practice, these beneficial changes significantly increased across days. Additionally, the subject's muscle activity during brain-control declined with regular practice. This daily increase in beneficial tuning function changes and the reduction in muscle activity were matched by a significant improvement in brain-controlled movement accuracy and reliability across days.

The co-adaptive algorithm used in the arms-restrained experiment allowed the subjects to encode movement with new preferred directions that were unrelated to those used during physical arm movements. However, in these novel movement encoding schemes, units that were located close to each other in the cortex usually maintained correlation patterns between units which were similar to those seen during hand-controlled movements. This suggests a local modular organization which may have implications for the design and spacing of electrodes for neural prosthetic use. Wider spacing between electrodes may yield more signals which can be *independently* controlled by the subject.

The animals were also tested for their ability to transfer the center-out brain-control skills to more practical applications. The movement prediction algorithm was held constant in a non-adaptive state, and subjects were able to make long continuous sequences of movements to novel as well as trained target positions. Additionally, one subject was trained to reliably move a brain-controlled robot to different 3D target positions to get rewards.

MULTIMODAL NEUROELECTRIC HUMAN-COMPUTER INTERFACE DEVELOPMENT

Leonard J. Trejo, Kevin R. Wheeler, Charles C. Jorgensen, Roman Rosipal
NASA Ames Research Center, Moffett Field, CA

This project aims to improve performance of NASA missions by developing multimodal neuroelectric technologies for augmented human-system interaction. Neuroelectric technologies will add new modes of interaction that operate in parallel with keyboards, speech, or other manual controls, thereby increasing the bandwidth of human-system interaction. The research builds on recent feasibility demonstrations of electromyographic (EMG) and electroencephalographic (EEG) methods, which bypass muscle activity and draw control signals directly from the human nervous system. The broad objectives of the project are to: a) develop new modes of interaction that operate in parallel with existing modes such as keyboards or voice, b) augment human-system interaction in wearable, virtual, and immersive systems by increasing bandwidth and quickening the interface, c) enhance situational awareness by providing immediate and intimate connections between the human nervous system and the systems to be controlled or monitored. Our specific goals are also threefold: a) a signal acquisition and processing system for reliable EMG-based neurocontrol methods for data visualization and manipulation tasks, b) EMG-based automatic recognition and tracking of continuous human gestures, c) evaluation and feasibility testing of EEG-based neurocontrol methods suitable for use in parallel with other modes of communication and control using μ-rhythm signals recorded from motor cortex and other, nonlinear measures of EEG dynamics.

We have made progress in four areas. First we have developed real-time pattern recognition algorithms for decoding sequences of forearm muscle activity associated with control gestures. A real-time system successfully used these algorithms to control a flight simulator and a virtual numeric keyboard. Second, we have developed and compared signal processing strategies for open- and closed loop tasks involving EEG-based tracking of real and imaginary motion. The tasks involved either real or imaginary arm motion without feedback (open loop) or controlling a visual display of a needle gauge or a surface vehicle (Mars rover). EEG was recorded from three subjects with arrays of 4 to 128 channels, and spatially decomposed into orthogonal components. Time series analysis or frequency analysis of the component signals were tested and compared for efficacy of tracking motion and EEG desynchronization effects. We replicated known effects of mu-rhythm based control and compared this to several other methods, including spectral entropy, wavelet entropy, and a nonlinear dynamic analysis known as coarse entropy rate. In some cases, we found that nonlinear analysis was more sensitive to motion as compared with mu-rhythm power and other methods. Third, we have also developed a flexible computation framework for neuroelectric interface research, using the Linux operating system. The frameworks allow for modular construction of real-time systems for data processing and control, and for rapid prototyping of new algorithms. Fourth, we have partnered with a private company to develop non-contact E-field sensors, which measure EMG or EEG signals without resistive contact to the body. Preliminary data show that these sensors can faithfully record signals that track the surface EMG or EEG changes measured by traditional resistive electrodes.

WADSWORTH BCI RESEARCH AND DEVELOPMENT PROGRAM

JR Wolpaw, DJ McFarland, TM Vaughan, G Schalk, I Goncharova, WA Sarnacki, HZ Sheikh
Wadsworth Center
New York State Department of Health and State University of New York
Albany, New York

The principal goal of the Wadsworth BCI Program is a new non-muscular communication and control technology for people with severe motor disabilities, particularly those who cannot use conventional assistive technologies, which require some voluntary muscle control.

The program focuses on an EEG-based BCI that uses mu and beta rhythms generated in sensorimotor cortex. People with and without motor disabilities learn to use these rhythms to control movement of a cursor on a video screen. Recent and current work is continuing and expanding this focus. The principal aims are:

1. The basic protocol is short- and long-term intra-subject comparison of promising alternative methods. Recent improvements in spatial filtering, signal feature selection, and online adjustment of translation parameters have yielded information transfer rates of 10-25 bits/min (e.g., a user can choose among 4 selections in 4 sec with 90% accuracy).
2. To further improve BCI performance by incorporating additional signal features into the algorithm that controls cursor movement and target selection. Possible additional features include slow cortical potentials and an error potential that occurs when well-trained users make a mistake. The protocol is to assess these time-domain features during the course of standard mu or beta rhythm-based cursor control, and, based on the results, to incorporate them into cursor control and assess the effect on performance.
3. To test the current BCI system in people with severe motor disabilities and demonstrate that it can provide them with reliable basic communication. The prototype application is a simple word-processing program, and the first target population are people with early- or middle-stage amyotrophic lateral sclerosis. We hope to show that they can learn to use the BCI and can continue to use it as their disease progresses.
4. To continue development of BCI2000, a general purpose BCI system that can use any brain signals (from single neurons to slow cortical potentials), signal processing methods, translation algorithms, output devices, and operating protocols. Each of the four BCI2000 components (i.e., signal acquisition, signal processing, output device, operating protocol) can be modified without affecting any other component. BCI2000 facilitates comparison, combination, and optimization of signals, methods, outputs, and protocols. We are giving it to other research labs with source code, documentation, and analysis tools.

In pursuit of these aims, the Wadsworth group collaborates with groups in Tübingen (Birbaumer et al.), Graz (Pfurtscheller et al.), Atlanta (Moore and Kennedy), and Philadelphia (Heiman-Patterson). The work is supported mainly by the National Center for Medical Rehabilitation Research at NIH, and also by the ALS Hope Foundation in Philadelphia and the Deutsche Forschungsgemeinschaft (DFG).

Recent review article: Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clinical Neurophysiology 113:767-791, 2002.

ABSTRACTS OF POSTERS AND DEMONSTRATIONS

EEG PATTERN CLASSIFICATION USING SUBSPACE METHODS AND SIMPLE CLASSIFIERS

Charles Anderson[1,3], Michael Kirby[2]
[1] Department of Computer Science
[2] Department of Mathematics
[3] Program in Molecular, Cellular, and Integrative Neuroscience
Colorado State University, Fort Collins, CO 80523

The manner in which EEG signals are represented for analysis and classification greatly affects the results obtained. To-date, most BCI research has relied on frequency-based representations, such as the energy within particular bands of frequency. Another common representation is based on autoregressive models, for which the coefficients have been shown to be very useful in classifying EEG as to which mental task a subject is performing[1]. A third class of representations are subspace methods that produce linear transformations designed to optimize various aspects of the transformed signals. In this poster, we describe a recent comparative study of several subspace methods for EEG classification.

One of the more common subspace methods is the Karhunen-Loève transform, also referred to as principal component analysis and singular value decomposition (SVD). The SVD transform maximizes the mean-square projection of the data on lower-dimensional subspaces, thus finding directions in the original data space along which the projected data has the highest variance. Less well-known transforms are maximum signal fraction analysis (SFA), that optimizes the amount of signal retained when signals are superposed, and canonical correlation analysis (CCA), that determines transformations of two data sets that produce the strongest correlation.

We compare each of these transformations on data that has been augmented by the method of delays, whereby values from consecutive samples are concatenated into one sample. As illustrated by our results, the size of the delay greatly impacts the efficacy of the data representation. We do not use the transformed signals for classification. Instead, we calculate the transformation matrix for overlapping half-second windows of data and use a subset of the columns of the transformation matrices as our representation.

Figure 1 shows classification accuracies of test data using the three subspace methods to represent the data and using either linear discriminant analysis (LDA) or a k-nearest-neighbor (kNN) classifier. As can be seen in the first column of Figure 1, the classification of the EEG data using the right singular vectors of the SVD depends significantly on the number of lags, or delays, used. No time lagging results in very poor classification rates for any number of modes; superior results are found empirically for lag two data. Five modes are required to obtain classification rates over 90%. Interestingly, lagging the data beyond two data points actually degrades classification performance. Fisher's LDA appears to consistently out-perform the kNN method. This suggests that only a subset of employed parameters are actually performing the discrimination, an hypothesis that warrants further study.

Classification results using CCA are shown in the second column of Figure 1. These results are similar to the SVD results, in that samples with zero lags do not contain enough information to discriminate the two tasks while adding one lag increases the classification accuracy significantly. The third column of Figure 1 shows the multi-mode discrimination capacity of SFA representation. Surprisingly, classification of the SFA modes with no lags works well. This is the only method examined that had this feature. It is also interesting to note that for zero to two lags there is no degradation in performance as more modes are included in the representation. Since it is the *noise* that is contained in the later modes, one may conclude that the correlated signal characterized by later modes is neither helpful nor problematic for the classification task. Performance of kNN does degrade with additional modes suggesting that this method is more sensitive to noise.

References

[1] Charles W. Anderson and David A. Peterson. Recent advances in EEG signal analysis and classification. In R. Dybowski and V. Gant, editors, *Clinical Applications of Artificial Neural Network*, chapter 8, pages 175–191. Cambridge University Press, UK, 2001.

Figure 1: Percent of test samples correctly classified by LDA and kNN classifiers for data with zero to four lags represented as SVD, CCA, and SFA transforms. Each row of graphs is for a different number of lags, starting with zero in the top row to four in the bottom row. The first column of graphs is for the SVD representation, the second column is for the CCA representation, and the third column is for the SFA representation. The horizontal axis in each graph is the number of modes used to perform the classification.

THE BF++ FRAMEWORK (THE BIOFEEDBACK SOFTWARE DEVELOPMENT KIT)

Luigi Bianchi[1,4], Fabio Babiloni[2], Marco Arrivas, Patrizio Bollero, Maria Grazia Marciani [1,3]
[1] Dip. Neuroscienze, University of Rome "Tor Vergata", ITALY
[2] Dip. Fisiologia Umana e Farmacologia, University of Rome "La Sapienza", ITALY
[3] IRCCS, Fondazione "S. Lucia", Rome, ITALY
[4] Brainware, Rome, ITALY

A problem that commonly arises while developing cognitive bio-feedback (CBF) systems for disabled people is that it is very difficult to reuse them in a wide range of pathological situations. Very often these systems are designed using a "bottom-up" approach that is that starting from the particular problem the whole system is developed. This kind of approach fails because optimal use of every subject residual capability could require modifying the whole system in a way that is incompatible with practical needs. Moreover, these systems are specific to a limited set of platforms so re-engineering them could be a huge task: what happens if one wants to port a Windows 95/98 CBF application that runs on a notebook to a smaller Pocket PC running Windows CE?

The aim of BF++ is to give support to the creation of CBF systems by implementing a cross-platform C++ framework. As it is implemented using only ANSI C++ features it is possible to recompile it on virtually any platform.

Such framework must:

- **minimize programming effort,** by providing a skeleton of a CBF application and other facilities such as DSP and matrix computation routines;
- be **independent** on the nature and number of the **biological signals** used;
- allow the **integration with existing devices** such as screen readers, tactile mice, text to speech engines, etc…;
- allow the **diffusion of the resources** (data, algorithms, etc.);
- maximize source and binary code reuse;
- be efficient, to guarantee good performances in a wide range of situations;
- allow the realization of **low-cost** systems;
- be **independent** on the hosting platform (software and hardware).

By grouping all the aspects that are common to all the CBF systems implementations it has been possible to use a "top-down" design approach which offers a much greater flexibility and that allows the creation of a framework that can dramatically speed up the realization of several systems. Four main different operating modalities were provided: Setup, Training, Testing and Run.

A generic CBF system has been decomposed into 6 main functional blocks (plus the subject):

Acquisition, Kernel, Feedback Rule, Patient Feedback, Persistent Storage and Operator User Interface. Some of them are divided into sub-elements. For example the Kernel module is composed itself of more than 10 sub-objects. Assembling then it is possible to create a virtually infinite set of CBF systems that can be recompiled under any OS for which an ANSI C++ compiler is available. Special care was taken with respect to efficiency: in the PocketPC case this is obviously a key issue, while using Workstation it is possible to use many classifiers simultaneously in order to improve the overall system performance. This last feature was easily provided using well-known design patterns.

All the timing issues are also encapsulated into objects and no particular effort is required: special functions are automatically invoked whenever a trial starts (the OnTrailStart functions family), whenever a computation in performed (the OnTrialCompute family), whenever a trial ends (the OnTrailEnd family) and eventually whenever a classification occurs. By simply overriding them it is possible to provide a feedback to the user. An internal score is also provided to automatically evaluate the overall system performances: in the Testing modality, for example, the system ask to the patient to perform a task (e.g. one of many mental tasks) through a randomization engine and then it tries to recognize it. As it knows which task was required and which one was the classified one, it is able to update an internal score automatically. This and many other functionalities are already implemented in the framework as they do not depend on the nature of the biological signals used. Also file I/O is supported using XML as file format.

This approach was used to develop many different BCI systems for the Win32 platform. Some of them were already ported on a PocketPC device running Windows CE allowing the realization of wearable BCI systems. Also simulations using intracortical recordings were successfully done as well as using the Linux platform. Finally a simulation was also done on the SmartPhone 2002 platform: this suggests that it is also possible to realize PaceMaker like biofeedback and BCI systems using BF++.

BCI BIT RATES AND ERROR DETECTION FOR FAST-PACE MOTOR COMMANDS BASED ON SINGLE-TRIAL MULTI-CHANNEL EEG ANALYSIS

Benjamin Blankertz, Christin Schaefer, Guido Dornhege, Roman Krepki, Klaus-Robert Müller
Intelligent Data Analysis Group
Fraunhofer-FIRST, Berlin, Germany

Volker Kunzmann, Florian Losch, Gabriel Curio
Neurophysics Group, Dept. of Neurology
Klinikum Benjamin Franklin, Freie Universitäet, Berlin, Germany

The Leitmotiv of our BCI approach is 'let the machines learn', i.e., we aim to minimize the need for subject training while the major learning load imposed on two coupled adapting systems (human subject and computer) is to be accomplished by the machine. Here, we demonstrate detailed results from two different ERP types: 1) Our subjects take a decision that is coupled to an overlearned motor output, i.e., selfpaced typing on a computer keyboard. The spatial patterns of the slow cortical potentials preceding such voluntary movements show a negativity (Bereitschaftspotenzial) focussed over the corresponding primary motor cortex. Learning machines which are trained on spatiotemporal features of multi-channel EEG can predict the laterality of upcoming movements before EMG onset with accuracies of up to 97% in untrained subjects. One reason for choosing slow potentials as BCI-signal was that we expected this approach to work robustly also at a fast command pace. To test this hypothesis we conducted selfpaced typing experiments at different tap rates with 0.5, 1 and 2 taps per second (tps). For 8/9 subject who all were untrained for BCI the fastest tap performance (2 tps) worked efficiently, with bit rates about twice as high as in the 0.5 tps experiment. The theoretical peak bit rate, which could be attained in principle when using an optimal coding strategy, was between 6 and 10 bits per minute (bpm) for 4 subjects and even above 15 bpm for another 5 subjects. 2) One additive ('second-pass') strategy to enhance BCI classification accuracy, in particular for subjects who are facing a substantial fraction of 'first-pass' BCI classification errors, is a verification (of the first-pass classification) based on the detection of a cerebral 'error potential', as proposed by Schalk et al. In this context, we adopted the algorithmic strategy described above and introduced one small but psychologically crucial modification: because repeated false second-pass rejections of BCI trials, which had been correctly classified in the first-pass, would be detrimental, an important specification of our response verification algorithm is that the rate of false positive detections of first-pass errors should be strictly bounded. As our method detected 85% of errors in 7/8 subjects (working on a d2-test) at a predefined rate of false positives as low as 2%, this approach might provide a valuable add-on tool for improving BCI bit rates by an online EEG-based detection of first-pass classification errors.

SINGLE-TRIAL DENOISING OF EEG WITH A WAVELET DOMAIN HIDDEN MARKOV TREE

Adam Gerson, Paul Sajda
Laboratory for Intelligent Imaging and Neurocomputing
Department of Biomedical Engineering
Columbia University

We have investigated the application of a wavelet domain hidden Markov tree (wHMT) for denoising electroencephalgraphy (EEG), the aim being to improve single trial detection of mental motor imagery. A wHMT is a directed graphical model that captures statistical dependencies between wavelet coefficients across scale. In the wHMT, the probability density function of wavelet coefficients is approximated with a Gaussian mixture model. Observations of the distributions of wavelet coefficients of EEG evoked potentials reveal that the coefficients have near zero mean and long tails--i.e. they are supergaussian. Such a distribution may be approximated using a two state, zero mean, Gaussian mixture model in which the large number of small coefficients are modeled with a low variance Gaussian, and the small number of large coefficients are modeled with a high variance Gaussian.

The wavelet transform of evoked potentials, and indeed most types of natural signals, inherently exhibits the persistence of large or small coefficients across scale and the clustering of coefficients within scale. To efficiently describe the statistics of wavelet coefficients, each coefficient is associated with a hidden state variable that describes whether the coefficient is in either a high or low variance state as described by the Gaussian mixture model. In order to model the conditional relationships described by clustering and persistence properties of wavelet coefficients, hidden state variables are linked within and across scales. A model that contains links between state variables within scales captures the clustering properties of the wavelet transform and is referred to as a hidden Markov chain. Likewise, a model that contains links *across* scales captures the persistence properties of the wavelet transform and is referred to as a hidden Markov tree. Since modeling the local dependencies within scale becomes computationally expensive we consider the simplified case of a wHMT in which all coefficients within scale are assumed to have the same probability density function; an approximation referred to as tying within scale. A modified Baum-Welch upward-downward expectation maximization algorithm is used to determine the parameters of the hidden Markov tree.

Once the parameters of the wHMT have been determined, denoising is straightforward. Assuming that additive noise increases the variance of all wavelet coefficients, denoising is accomplished by removing the variance due to noise from the variance of each noisy coefficient, conditioned on the hidden state. An estimate of noise variance is derived from the variance of the finest scale wavelet coefficients. The denoised wavelet coefficients are estimated using a hidden state weighted Wiener filter. The inverse wavelet transform is then used to reconstruct the signal. The value of the wHMT over traditional wavelet denoising methods is that it captures the statistical dependencies between wavelet coefficients.

To evaluate the utility of the wHMT for denoising EEG signals and improving single-trial detection of mental activity we denoised single-trial EEG signals collected for a synchronized mental motor imagery task.[1] Data from 9 subjects was used in the evaluation. Separate wHMT's were trained for each subject and for each sensor using data from a time window centered over a period during which the subject was instructed to imagine pressing a button with their left or right index finger. Note that only one trial was used to train each wHMT. Subsequently, 90 left and 90 right trials were denoised for each subject. Logistic regression was used to classify trials as left or right imagined movement. Leave-one-out performance showed a statistically significant increase in the ROC area (A_z) and percent correct (PC) before and after denoising (before A_z=0.64; after A_z=0.66 $p<0.005$, before PC=62%; after PC=64% $p<0.005$). We conclude that denoising using a wHMT is able to improve single trial classification performance of our linear classifier for this set of mental motor imagery data. We are currently investigating the wHMT as a model for directly classifying single-trial EEG.

---

[1] Data were kindly provided by Allen Osman from the Psychology Department of the University of Pennsylvania. A description of the data can be found at http://newton.bme.columbia.edu/competition.htm

NEW METHODOLOGY FOR TRAINING HIDDEN MARKOV MODELS FOR BRAIN COMPUTER INTERFACES

M. Gibbs, S. Roberts, I. Rezek
Pattern Analysis and Machine Learning Group
Department of Engineering Science
University of Oxford, Oxford, U.K.

Abstract

We introduce a new method of training hidden Markov models (HMM) for use in a brain computer interface (BCI). Additional information is used in the train processes by generalising the HMM to a coupled hidden Markov Model (CHMM). The additional parts of the model are removed after training to leave the desired HMM. This method significantly improves the classification results.

In this poster we outline a new method for training a brain computer interface (BCI) for the classification of movement planning. The interface makes use of a hidden Markov model (HMM) for classification of the Electroencephalogram (EEG) Data. A HMM is a statistical model which utilises temporal information both in learning its parameters and in classification. In a HMM the probability of an observation, O_t, in this case the EEG data, is dependent on some hidden state, S_t, and the hidden states are related to each other by a first order Markov process, i.e. $P(S_t|S_t\text{-}1)$.

The training algorithm outlined here uses the more general Coupled Hidden Markov Model (CHMM) [RGRed]. These are two, or more, HMMs which are coupled via their hidden states, as can be seen in figure 1. This allows us to model the interaction of the two data sources in a probablistic manner.

HMM training has to be performed by an unsupervised method, which traditionally is performed by the Expectation Maximisation (EM) algorithm [PR98]. The drawback with the EM algorithm is the impossibility of ensuring that the algorithm picks up the relevant *state transitions* in the EEG data. A method that tackles this problem is Maximum a Posteriori (MAP) [RGRed], an extension to EM, which makes use of priors over the model parameters. These priors bias the learning algorithm towards a favoured area in the parameter space. In addition to priors we can introduce further information from data sources, which are related through their hidden states to the EEG (not necessarily a 1 to 1 mapping), to help with the learning process. In this case we use data recorded simultaneously from muscle movement.

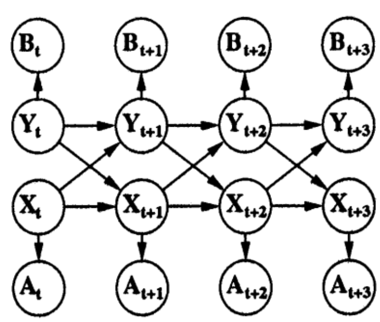


Figure 1: A Directed Acyclic Graph (DAG) of a Coupled Hidden Markov Model with two chains and a unitary lag. Where A_t and B_t are the observation models over the feature spaces and X_t and Y_t are the associated hidden states

In terms of the graphical model one of these chains is the EEG data and the other is the electromyogram (EMG) data from the muscles of interest. These additional sources of information are removed from the model, by marginalisation, after training to leave a model which is based purely on EEG data for classification. This trained model performs significantly better than one trained in the traditional manner.

References

[PR98] W.D Penny and S.J. Roberts. Hidden Markov Models with extended observation densities. Technical Report TR_98_15, Imperial College London, 1998.

[RGRed] Iead Rezek, Michael Gibbs, and Stephen J. Roberts. Maximum a posterior estimation of coupled hidden markov models. *Journal of VLSI Signal Processing_Systems for Signal, Image, and Video Technology*, to be published.

PRELIMINARY BRAIN COMPUTER INTERFACE DESIGN BASED ON MOVEMENT PLANNING

M. Gibbs, S. Roberts
Pattern Analysis and Machine Learning Group
University of Oxford, Oxford, U.K.

Abstract

The design of a Brain Computer Interface (BCI) has to be carefully considered. Experimental factors which might influence thought processes must be taken into consideration. This poster outlines our BCI design based on detecting movement planning. Our novel BCI design uses a gaming paradigm as its central concept.

Any BCI system designed to classify Electroencephalogram (EEG) data on-line must take into acount the effect of human brain plasticity, i.e. the ability to learn. One way to utilise this change in behaviour is to present the subject with information about how well the predictor in the system is performing. This is referred to as biofeedback.

Designing the BCI data collection system around a *game scenario* presents us with an intuitive method of channeling feedback to the subject. This change in paradigm will allow the study of the effects of biofeedback in its different forms, in a realistic environment, in a manner consistent with the eventual environments in which the BCI system is likely to be utilised.

This shift in paradigm gives several advantages over cued and selfpaced methodologies [GSN + 01]. It is intuitive to the user. Most people are now familiar with gaming enviroments and so require no additional training. The design of the game can make the system more engaging and help to focus the subject's mind on the task in hand.

We present an overview of the experimental protocol and setup under development. The aim is to, wherever possible, reduce experimental factors that can affect the thought processes of the subject from whom movement planning data is being collected [BB98, RER + 99]. We also give details of the prediction models under consideration [RGRed, GSN + 01].

References

[BB98] J.D. Bayliss and D.H. Ballard. The effects of eye tracking in a VR helmet on EEG recordings. Technical Report 685, The University of Rochester, Computer Science Department, Rochester, New York, 14627, December 1998.

[GSN + 01] C. Guger, A. Schlögl, C. Neuper, D. Walterspacher, Thomas Strein, and G. Pfurtscheller. Rapid prototyping of an EEG-Based Brain-Computer Interface (BCI). *IEEE Transactions on neural systems and rehabilitation engineering*, 9(1):49-58, March 2001.

[RER + 99] S.J. Roberts, R. Everson, I. Rezek, P. Anderer, and A. Schlöegel. Tracking ICA for EEG Eye Movement Artifact Removal. In *European Medical And Biological Engineering Conference*, pages 1646-1647, 1999.

[RGRed] Iead Rezek, Michael Gibbs, and Stephen J. Roberts. Maximum a posterior estimation of coupled hidden markov models. *Journal of VLSI Signal Processing-Systems for Signal, Image, and Video Technology*, to be published.

FEASIBILITY OF INDEPENDENT COMPONENT ANALYSIS (ICA) FOR SEPARATION OF EMG ARTIFACTS FROM EEG FEATURES USED IN BCI OPERATION

I.I. Goncharova, D.J. McFarland, T.M. Vaughan, J.R. Wolpaw
Wadsworth Center
New York State Department of Health and State University of New York, Albany, NY 12201

EMG contamination is a well-recognized problem in EEG studies, particularly those relying on automated measurements. The goal of this study was to test the possibility of online artifact correction in BCI studies using ICA.

Spectral and topographical criteria for EMG identification were studied in 25 healthy adults intentionally producing EMG artifacts by weak (15±3% of maximal) contractions of the frontalis or temporalis muscles (raising eyebrows or jaw clenching). Identification and correction of unintentionally produced artifacts was performed on the data collected from two BCI users during 10 training sessions. ICA decomposition was performed using an information maximization neural network algorithm on 64 scalp-recorded signals having 25-min duration. The resultant 64 Independent Components (IC) were identified by their time courses (IC activations) and topographical distributions (IC projections). Offline artifact correction was performed by removing a subset of ICs reflecting artifactual sources and reconstructing the record from the residual non-artifactual components. Simulation of the online artifact correction was performed by applying an ICA-derived spatial filter obtained from one experimental session to new data.

Offline artifact correction based on ICA appeared to be highly effective for blinks and eye movements. Independent components reflecting muscle artifacts could be identified by their time courses and spectral and topographical distributions and removed from the data. However, a number of ICs from each data set were identified as a mixture of EEG and EMG activities. Online muscle artifact correction is possible by filtering out a set of ICs reflecting predominantly EMG sources. The ICA-derived spatial filter cannot be exported from one subject to another one due to individual differences in the sources generating artifacts. The results may aid development of new artifact detection procedures for BCI studies, particularly those focused on frontel EEG electrodes, which are most vulnerable to EMG contamination.

Supported by the National Center for Medical Rehabilitation Research, NIH.

CLASSIFICATION OF MOVEMENT-RELATED ERD/ERS PATTERNS IN ECOG

Graimann[1], B., Huggins[2], J., Levine[2], S., Neuper[1], C., Pfurtscheller[1], G.
[1]Dept. of Medical Informatics, Institute for Biomedical Engng.
University of Technology Graz, Austria
[2]Dept. of Physical Medicine and Rehabilitation, University of Michigan Medical Center,
Ann Arbor, MI

Event-related potentials (ERP) and event-related desynchronization (ERD) are responses of the brain to externally- or internally-paced events. It is important to note that ERP and ERD/ERS are different responses. The former can be read as a reactivity pattern of a stationary system to a stimulus, and the latter as a change in the ongoing ECoG resulting from alterations in the functional connectivity within a neural network (Pfurtscheller and Lopes da Silva, 1999).

It has already been demonstrated that the detection of movement-related potentials (MRP) in single ECoG channels is possible with high accuracy (Levine et al., 2000). The goal of this work is to demonstrate that the detection of ERD/ERS patterns is also possible with very good accuracy. In fact, classification results of more than 90% hit percentages and less than 10% false positive percentages were found.

Feature extraction was done by calculating adaptive autoregressive parameters (AAR). Linear discriminant analysis (LDA) together with a simple threshold detector was used as classifier. The training process of the classifier was extended by a genetic algorithm which divided the training data into action and resting periods.

The classification results obtained by the proposed ERD/ERS detection method were compared with the results of the ERP detection method suggested in Levine et al. (2000). It is of special interest that depending on the location of the ECoG electrodes, good classification results have been obtained either with both reactivity patterns (MRP and ERD/ERS) or with only one of the reactivity patterns (MRP or ERD/ERS).

References:

Pfurtscheller G, Lopes da Silva FH. Event-related EEG/MEG synchronization and desynchronization: basic principles. Clinical Neurophysiol 1999b; 110:1842-1857

Levine SP, Huggins JE, BeMent SL, Kushwaha RK, Schuh LA, Rohde MM, Passaro EA, Ross DA, Elisevich KN, Smith BJ. A direct brain interface based on event-related potentials. IEEE Trans Rehabil Eng 2000; 8(2):180-185

THE ROLE OF THE BEREITSCHAFT POTENTIAL AS AN INTERFACE FOR BRAIN-COMPUTER ACTIVATED PROTHESIS IN SPINAL CORD INJURY

Joseph B. Green, Leonid I. Rozhkov, Darren Strother, Nancy Garrott
Memphis Veterans Affairs Medical Center

To characterize the relative contributions to voluntary movements of a network which includes the Supplementary Motor Area (SMA), Primary Motor Area (M1), Primary and Secondary Sensory Areas, and Premotor Areas. We have compared the SMA activation with the Bereitschaft Potential (BP) and discovered interesting temporal and anatomic similarities between the two. The ultimate goal is to relate the BP (or the SMA) to external devices. This entails tapping the BP at various points with conversion of potentials to a "language" understood by the receiving devices. Prior to this it is necessary to have greater insight into the relationships between the BP and the SMA. Once accomplished, it may then be possible to convert activations of either or both to use neuroprosthetic devices (see Wessberg et al, 2000).

HOW MANY PEOPLE ARE ABLE TO OPERATE AN EEG-BASED BRAIN-COMPUTER INTERFACE (BCI)?

C. Guger[1], G. Edlinger[1], G. Pfurtscheller[2]
[1] g.tec – GUGER Technologies OEG, Plabutscherstr. 63 8051 Graz, Austria
[2] Department of Medical Informatics, University of Technology Graz, Inffeldgasse 16a, 8010 Graz, Austria

At this time, about 22 labs are working on communication channels between the brain and the computer (IEEE 2000). Published papers present results with a subject population of about 1-13. The data were used to develop systems with high information transfer rates. But subjects vary greatly in their ability to control a brain-computer interface (BCI). Some subjects were excluded from further investigations due to lack of BCI control in early training. Since the aim of a BCI is to help patients who suffer from severe motor impairments, development must focus on a broad population and not only on selected subjects. It is therefore of interest how many people are able to operate an EEG-based brain-computer interface after only 20-30 minutes of training with a minimum of 2 bipolar EEG derivations.

In a field study performed with visitors of an exposition 99 persons (all healthy) participated in a brain-computer interface experiment in Graz. The subjects spent 20-30 minutes for the BCI investigations. The experimental procedure was divided into two runs. The first run consisted of 40 trials without feedback. Then a subject-specific classifier was set up to give feedback to the subject. During the second run the subject had the task to control a horizontal bar on the computer screen (again 40 trials). All subjects were instructed to imagine a right hand movement and a foot movement after the cue stimulus depending on the direction of an arrow. Bipolar electrodes were mounted over the right hand representation area and over the foot representation area. Classification results achieved with (i) an adaptive autoregressive (AAR) model (39 subjects) and (ii) the bandpower estimation (60 subjects) are presented. In both cases linear discriminant analysis (LDA) is used for the classification of the parameters.

The experiments were carried out using a newly developed BCI system running in real-time under Windows with a 2 channel g.tec EEG amplifier. The installation of this system, based on a g.tec rapid prototyping environment, includes a software package that supports the real-time implementation and testing of different EEG parameter estimation and classification algorithms (Guger 2001). The tight coupling between the on-line experiments and off-line analysis of the acquired data is one of the major advantages of the new g.tec BCI system.

Classification Accuracy in %	**RLS Percentage of Runs (N=76)**	**BP Percentage of Runs (N=117)**	**RLS+BP Percentage of Runs (N=193)**
90-100	6.6	6.0	6.2
80-89	10.5	14.5	13.0
70-79	30.3	33.3	32.1
60-69	40.8	42.7	42.0
50-59	11.8	3.4	6.7
	100	100	100

Table 1: Percentage of runs which were classified with a certain accuracy for recursive least squares

(RLS) algorithm and bandpower (BP) estimation. N specifies the number of runs. RLS+BP shows the results for both algorithms.

It is of interest that in about 20 % of the runs (about 20 % of subjects) the 2 brain states were distinguishable with an accuracy of greater 80 % after only 20-30 minutes of training as shown in Table 1. Further 70 % of the runs were classified with an accuracy of 60-80 % and only in 6.7 % a marginal discrimination between brain states was possible. This results show that a BCI operation can be performed by a large population and that even a high accuracy of above 90 % can be achieved. We know from further investigations that even subjects which have no BCI control in the first few runs can learn the operation by biofeedback training.

References

[1] Guger, C., Schlögl, A., Neuper, C., Walterspacher, D., Strein, T., and Pfurtscheller, G., Rapid prototyping of an EEG-based brain-computer interface (BCI), IEEE Trans. Rehab. Engng., vol. 9, pp. 49-58, 2001.

[10] Special Section on brain-computer interfaces, IEEE Trans. Rehab. Engng., vol. 8, 2000.

THE THOUGHT TRANSLATION DEVICE (TTD) AS A MULTI-FUNCTIONAL BCI: COGNITION DETECTION, EEG-FEEDBACK IN FUNCTIONAL MRI AND COMMUNICATION

Thilo Hinterberger, Jürgen Mellinger, Barbara Wilhelm, Niels Birbaumer
Institute for Medical Psychology and Behavioral Neurobiology
University of Tübingen, Germany

The goal to achieve Brain-Computer-Communication (BCC) in severely paralyzed patients is not solely devoted to the question of how to design classification algorithms, feedback paradigms or spelling procedures. Two other important questions are focused in the current version of the Thought Translation Device (TTD) as a BCI for clinical and research purpose which utilizes physiological control of slow cortical potentials (SCP) to provide BCC:

1) Before successfully teaching a patient totally unable to communicate by muscular activity (locked-in syndrome) to self control his or her own brain signals, a knowledge about the state of consciousness and cognitive abilities needs to be obtained. For this purpose, a diagnostic Cognition Detection System (CDS) has been developed as a further extension of the TTD. The CDS consists of a freely expandable set of event related EEG experiments such as the well known oddball paradigm with “oddity” appearing on various levels of the brain’s information processing. The CDS investigates the ability of a patient to discriminate between, e.g., words, pseudo-words and her own name; between syntactically and semantically well-formed sentences on the one hand and sentences well-formed syntactically but ill-formed semantically on the other; or between “matching” and “non-matching” enumerations of ordinal numbers. This is done by recording auditory or visually evoked potentials and then carrying out a discriminant analysis of EEG patterns. Therefore, features for statistical analysis such as discriminant analysis and significance tests have been included in the TTD. A set of seven experiments with an event-related design and auditory stimuli have been developed to examine patients in a vegetative state or with locked-in syndrome for their cognitive abilities. From a technical point of view, implementing a stimulus-response paradigm within the framework of a multi-tasking oriented computer operating system introduces a latency problem, i.e. the problem of not being able to precisely determine the point in time where stimulus presentation will actually take place. Despite the TTD running on MS-Windows®, stimulus presentation latency is small compared to the accuracy required for analyzing evoked potentials. The TTD-CDS-system provides a powerful combination of diagnostic and brain-computer-communication applications in a single system. The first results are presented from one patient in a vegetative state who can be regarded as cognitively intact by analyzing the data of six event related experiments, which were carried out with the CDS-system. For a comparison, the data of the experiments from one healthy person are shown.

2) As not all human subjects learn to obtain SCP self control, functional MRI can be used as a method to investigate the mechanisms underlying SCP self control in the brain because it provides high spatial resolution. Therefore the TTD was modified with respect to the amplifier, the synchronization with the MRI scanner and the feedback paradigm to be applicable in an MRI environment. Several subjects, trained successfully and non-successfully outside the MRI, will be investigated with this combined EEG-feedback/fMRI method. Before the simultaneous EEG/fMRI recording is carried out subjects are trained to achieve self-control over SCPs in terms of evoking a positive or negative potential shift at the vertex on command. First results from one well trained subject show activation in the blood oxygen level during the task to produce cortical negativity primarily at the vertex (bilateral), the precuneus and the inferior temporal regions. During the positivity task, at the vertex (bilateral, mainly gyrus postcentralis), the precuneus, and additionally at the right temporal pole and inferior parietal left an activation occurred. Deactivation was only found during positivity and involved widespread visual areas, the medial orbital

frontal cortex and the superior parietal cortex. Comparisons between learners and non-learners help clarifying the basic mechanisms in physiological control of the EEG.

FEEDBACK TO IMPROVE DETECTION OF EVENT-RELATED POTENTIALS IN ELECTROCORTICOGRAM

J.E. Huggins, M.M. Rohde, S.P. Levine, R.K. Kushwaha,
S.L. BeMent, E.A. Passaro, K.J. Leneway
The University of Michigan, Ann Arbor, MI, USA

Introduction

Subjects given appropriate feedback have learned to modify the mu rhythm (Wolpaw, et al., 1991) or increase event-related desynchronization (ERD) and event-related synchronization (ERS) (Pfurtscheller, et al., 1998) in their electroencephalogram (EEG) for the purpose of operating a direct brain interface (DBI). Feedback for the improvement of DBI operation in electrocorticogram (ECoG) has not previously been demonstrated, however.

The University of Michigan DBI is based on the detection of event-related potentials (ERPs) in human ECoG. Research subjects are patients in epilepsy surgery programs who have subdural electrodes implanted for clinical purposes unrelated to the research objectives. Previously reported off-line detection experiments (Levine, et al., 2000) have relied on off-line processing. As a consequence, no feedback has been provided and movement-related ERPs (instead of preferred motor imagery ERPs) have been required for determination of movement onset and detection accuracy. .

Methods

The UM-DBI first generation ERP acquisition, analysis and training system allowed selection of a feedback template and then provided the subject with feedback on the quality of subsequent ERPs (Rohde, et al., 1999). The feedback experiment session involved a template collection block of 50 repetitions of an action and 6 feedback blocks each containing 25 repetitions of the same action. Sessions lasted no more than 2 hours. Feedback was based on a comparison between the incremental change in the signal-to-noise ratio (SNR) of the ERP template caused by the addition of the current ERP (Rohde, et al., 2002) and the average change in the SNR of the ERP template during the previous template collection or feedback block. The feedback was in the form of a deflection of a vertical green bar on a computer screen approximately 2.2 seconds after movement onset (Rohde, 2000). The subject was instructed to try to get the bar to go all the way to the top of the computer screen. The maximum possible height of the feedback bar was the average change in the SNR from the previous block scaled by 0.2 to 2.

Results

Data is reported from six subjects who participated in 11feedback experiment sessions. ERP templates with SNR's above 3.0 were found for all subjects. Dramatic improvements in the template SNR between the baseline template collection block and subsequent feedback blocks were found for 3 subjects. For these subjects the SNRs improved from 3.5 to a maximum of 7.8, from 4.8 to a maximum of 10.5 and from 5.1 to a maximum of 8.0 over the six feedback blocks. Of the three subjects who were able to improve the SNR of their ERPs, only one had a corresponding improvement in the accuracy with which the ERP could be detected using cross-correlation based template matching. This subject was able to improve the detection from 79% hits and 22% false positives in the template collection session to 100% hits and 0% false positives in the 6^{th} feedback session. In two subsequent sessions with this subject, template SNR improved in the first feedback blocks, but then rapidly decreased.

Discussion

These results indicate that improvements in the SNR of ERPs related to actual movement and in the resultant detection accuracy are possible over a relatively short period of time given only simple feedback, however, performance variability needs to be further explored. The next generation system, which is under development, will provide online feedback based on the cross-correlation value used for detection, rather than an indirect measure of "quality." Also, feedback will be provided continuously (instead of only at the time of the actions) to promote the reduction of false positives as part of improved detection accuracy. Online feedback will also permit experiments using imagined movements.

References

S.P. Levine, J.E. Huggins, S.L. BeMent, R. K. Kushwaha, L.A. Schuh, M.M. Rohde, E.A. Passaro, D.A. Ross K.V. Elisevich, B.J. Smith: "A Direct Brain Interface Based on Event-Related Potentials." *IEEE Transactions on Rehab. Eng.,* Vol. 8:2 p. 180-185, 2000.

Pfurtscheller G. Neuper C. Schlogl A. Lugger K. Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. [Journal Article] *IEEE Transactions on Rehabilitation Engineering*. 6(3):316-25, Sep 1998.

M. M. Rohde, "Voluntary Control of Cortical Event Related Potentials", *Doctoral Dissertation,* University of Michigan, 2000.

M.M. Rohde, S.L. BeMent, J.E. Huggins, S.P. Levine, R.K. Kushwaha, E. A. Passaro, "Event Related Potential Acquisition, Analysis, and Training System" *Conf. Proc.: IEEE Conf. Eng. Med. & Bio.,* paper 0376, 1999.

M. M. Rohde, S. L. BeMent, J. E. Huggins, S. P. Levine, R. K. Kushwaha, L. A. Schuh, "Quality Estimation of Subdurally Recorded, Event Related Potentials Based on Signal to Noise Ratio." *IEEE Transactions Biomed. Eng*., Vol 49:1 p. 31-40, 2002.

Wolpaw JR. McFarland DJ. Neat GW. Forneris CA. An EEG-based brain-computer interface for cursor control. *Electroencephalography & Clinical Neurophysiology.* 78(3):252-9, Mar 1991.

UCLA NEUROENGINEERING PROGRAM

Jack Judy
Department of NeuroEngineering
UCLA
Los Angeles, CA

The goal of the UCLA NeuroEngineering Training Program is to prepare graduate students to be leaders in the revolutionary technology developments that will affect neuroscience in the 21st Century. Unfortunately, graduate programs in the life sciences prepare trainees to be academic scientists within traditional disciplines, almost always using the standard tools of that discipline. By expanding the synergies between the UCLA Brain Research Institute (BRI) and the Henry Samueli School of Engineering and Applied Science (HSSEAS), the UCLA NET Program will promote the application of new engineering technologies to neuroscience, including micromachining, microelectromechanical systems (MEMS), nanotechnology, and tissue engineering. The UCLA NET Program has the following objectives: (1) to enable students with a background in biological science to develop and execute projects that make use of state-of-the-art technology; (2) to enable students with a background in engineering to develop and execute projects that address problems that have a neuroscientific base; and (3) to enable all trainees to develop the capacity for the multidisciplinary teamwork that will be necessary for new scientific insights and dramatic technological progress. Many of the details and highlights of the program will be presented and descriptions of several NE projects will be described.

EFFECTS OF TRANSCRANIAL MAGNETIC STIMULATION (TMS) ON SLOW CORTICAL POTENTIALS OF THE BRAIN

A.A. Karim[1,2], N. Neumann[1], A. Kübler[1], N. Birbaumer[1,3]
[1] Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Gartenstrasse 29, 72072 Tübingen, Germany
[2] International Max Planck Research School of Neural & Behavioral Sciences, Tübingen, Germany
[3] Institute of Biophysics, University of Trento, Italy

Several studies show that humans can acquire control over EEG parameters like slow cortical potentials (SCP) by means of neurofeedback (Birbaumer, 1984; Kübler et al., 2001).

These results were used to develop a brain-computer interface (the Thought Translation Device, Birbaumer et al., 1999), which enables patients with locked-in syndrome to communicate via computer by self-regulating their SCP.

Unfortunately several patients as well as healthy subjects were not able to control SCP even after extended training. Is there a possibility to support those non-learners in learning to control their SCP?

The main goal of our study is to explore whether it is possible to shift the SCP by means of transcranial magnetic stimulation (TMS) and hence to develop further methods in order to facilitate the learning process. Results from current studies will be presented.

References

Birbaumer, N. (1984). Operant control of slow brain potentials: A tool in the investigation of the potential's meaning and its relation to attentional dysfunction. In T. Elbert, B. Rockstroh, W. Lutzenberger, & N. Birbaumer (Eds.), Self-regulation of the brain and behaviour (pp. 227-239). Berlin, Germany: Springer.

Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kübler, A., Perelmouter J., Taub, E., & Flor, H. (1999). A spelling device for the paralysed. *Nature*, 398, 297-98.

Kübler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J. R., & Birbaumer, N. (2001). Brain-computer communication: Unlocking the locked-in. *Psychological Bulletin*, 127 (3), 358-375.

DECISION-SPEED AND INFORMATION TRANSFER IN PARAPLEGIC PATIENTS USING THE 'GRAZ BRAIN-COMPUTER-INTERFACE'

Krausz, G., Neuper, C., Müller, G., Pfurtscheller, G.
Dept. of Medical Informatics, Institute for Biomedical Engineering
University of Technology Graz, Austria

The "Graz Brain-Computer-Interface (BCI)" transforms changes in oscillatory EEG activity into control signals for external devices or feedback. These changes are induced by various motor imageries performed by the user. For this study two different imageries (movement imagination of the right vs. left hand or right hand vs. both feet) were classified by processing two bipolar EEG-channels (positions C3 and C4). Within a few training sessions, four young paraplegic patients learned to control the BCI. The goal was to find values for the trial length enabling a maximum information transfer rate.

In accordance to the participant's performance, the decision speed (i.e. trial length) was varied (shortened) step-by-step during training. The information transfer rate was calculated for each run with respect to the number of classes, number of hits and failings and the error probabilities. After one offline-classification run at the beginning of each session, all others were feedback-runs employing a simple computer game-like paradigm: The patient saw a black screen divided into two halfs by a dotted line with a red and a green "basket" at the bottom. After a pause with a fixed length of 1 second a little red ball appeared at the top of the screen and started to fall downward with constant speed. The subjects task was to hit the red basket (which changed sides randomly from trial to trial) as often as possible. Each run consisted of 40 trials always assuring 20 right- and 20 left- sided goals in a random order. The horizontal position was controlled by the BCI-output signal and the falling speed (i.e. trial length) was varied by the investigator across experimental runs. For both EEG channels two features were extracted taking the natural logarithm of band-power values for the 10-12 Hz alpha band and the 16-24 Hz beta band. Band-power estimation employed a 5^{th}-order Butterworth-filter and simple squaring. The feature values were calculated by averaging across a 1-second time window which was shifted sample-by-sample along data. Classification of data was performed by linear discriminant analysis (LDA). The BCI- output signal was weighted by offline-calculated gain factors to lead the mean deflection for each direction to the middle of the basket.

Three out of four participants had good results after a few runs. The analysis of their last two experimental sessions, consisting of 10 – 16 runs each, showed that the trial length can be reduced to values around 2 seconds to obtain the highest possible information transfer rate. Attainable transfer rates were between 5 and 17 bit/min depending on the participant's performance and condition. It has to be noted that these results were obtained with an average of only 20-30 training runs for each participant. Further improvement could be expected for a prolonged training. Of course, the used 'basket-paradigm' represents a task with low level of cognitive effort. The more complex the decision task is, the more time might be necessary for the BCI-decision.

A BRAIN-COMPUTER INTERFACE AS A TOOL FOR PSYCHOLOGICAL INTERVENTION IN DEPRESSED PATIENTS DIAGNOSED WITH AMYOTROPHIC LATERAL SCLEROSIS?

Andrea Kübler
Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Germany
Trinity College, Dublin, Ireland

A group of 76 patients diagnosed with amyotrophic lateral sclerosis were interviewed to assess depressive symptoms and quality of life. In contrast to many reports in the literature (e.g., Rabkin et al., 2000) a remarkable portion of the patients showed mild to moderate (58%) or clinically relevant (43%) depressive symptoms. Depression was assessed with the ALS-Depressions-Fragebogen (ALS-depression-questionnaire, Kübler et al., submitted), a questionnaire developed to assess depression in ALS patients taking into account the specific situation of increasing physical impairment culminating in total motor paralysis. Correlation between the severity of depression and physical impairment was moderately positive indicating that variables other than the stage of the disease play a role in how patients cope with an intractable illness. No differences in depression and quality of life was found between patients on artificial ventilation and other ALS patients. A strong negative correlation between depression and quality of life was found. Losing the ability to communicate was a major worry in many patients. By providing patients with a brain-computer interface, quality of life may be maintained or improved when communication is already restricted or impossible. Although a correlation between decreased quality of life and depression does not imply a causal relationship it may well be speculated that by improving quality of life, depressive symptoms may be reduced. Thus, a brain-computer interface may become a tool in psychological treatment of depression in ALS patients.

Rabkin, J. G., Wagner, G. J., & Bene, M. D. (2000). Resilence and distress among amyotrophic lateral sclerosis patients and caregivers. *Psychosomatic Medicine, 62,* 271-279.

Kübler, A, Kaiser, J & Winter, S (submitted). ADF-12: Ein 12 Item Fragebogen zur Messung von Depressivität bei Patienten mit amyotropher Lateralsklerose (A 12 items questionnaire to assess depression in patients diagnosed with amyotrophic lateral sclerosis). *Diagnostica*.

GRAZ BCI: FIRST RESULTS OF DIFFERENT TYPES OF VIRTUAL KEYBOARDS

G. Müller, B. Obermaier, C. Neuper, G. Pfurtscheller
Dept. of Medical Informatics, Institute for Biomedical Engineering
University of Technology Graz, Austria

It is possible that completely paralyzed patients get the possibility to communicate with their environment by the use of a 'Virtual Keyboard' (VK). A 'Virtual Keyboard' is a letter spelling device operated by the Graz-BCI, based on the spontaneous EEG. The EEG is modulated by imaginations of hand or foot movements. Two types of VKs are presented, which have been tested in 3 able-bodied subjects.

To select a certain letter, using the standard VK, 5 steps of selection and two further levels of confirmation ('ok') and correction ('back/del') are provided. In a dichotomous structure with 5 levels 32 characters can be selected. Six steps are necessary to select a single letter. With this type of a VK and the standard BCI timing [Pfurtscheller 2000] a spelling rate _ of 1.25 letters per minute can be achieved (classification accuracy of 100 % assumed). The VK can be operated in two modes: a 'free spelling' mode and a 'copy spelling' mode for training. There is also a switch for 'error-ignoring' training.

A study on 3 able-bodied subjects was performed. The results (Table 1) show the number of written letters, performed trials and resulting _ [Obermaier 2002].

Table 1: Results of 3 subjects writing with the Virtual keyboard

Subject	Letters	Trials	_
i6	44	388	0.85
k3	46	340	1.02
m6	44	494	0.67

The newly developed VK is based on T9 technology of a cell phone including a dictionary. There are 8 keys, whereby each contains 4 letters (first one: 'A','B','C','D', last but one: 'Y','Z' and the last one: only a '.'). Each key is represented by a number, thus each word in a wordlist is coded, e.g. the word KAUFEN (buy) would be represented by 316224. In the wordlist 145 words, commonly used for a basic communication, are saved. Using the VK-T8 4 steps are necessary to select a letter.

In order to find the theoretical average spelling rate, which can be achieved by the BCI-VK8, 40 randomly selected words were simulated, assuming 100% correct decisions. The theoretical average spelling rate for the BCI-VK8 is 2.73 characters/min +/- 0.94, based on a trial length of 7.5 seconds.

In a first study 3 subjects wrote with the VK-T8. Two of them (S1, S2) were trained using the standard VK before. S3 never did so. Results are shown in Table 2.

Table 2: Required number of decisions and corresponding spelling rate _ in characters per minute. Trial length was 7.5 seconds. Values for the standard VK are given for comparison. The best (theoretical) values for 100% correct decisions are given as well as the results achieved by subjects S1, S2, and S3, respectively.

	old VK dec	best dec/_	S1dec/_	S2dec/_	S3 dec/_
BRAUCHEN (to need)	48	16/4.00	16/4.00	31/2.06	49/1.31
SCHMERZEN (pain)	54	17/4.24	22/3.27	17/4.24	29/2.48
BITTE (please)	30	14/2.86	14/2.86	14/2.86	14/2.86
HUNGRIG (hungry)	42	16/3.50	21/2.67	16/3.50	30/1.87
HELFEN (to help)	36	16/3.00	16/3.00	45/1.06	19/2.53

Fewer decisions had to be made with the help of a wordlist behind the VK-T8. The spelling rate varied from 1.06 to 4.24 letters/min. It should be taken into account that the spelling rates from the VK-T8 depend on the wordlist. The present results are based on a list with 145 entries.

A problem using the VK, controlled by BCI, is the contiguity of decisions per letter and the classification accuracy reached by the BCI. Some examples are given in Table 3.

Table 3: Probability for correct letter selection with different classification accuracies.

	accuracy				
dec./letter	**0.80**	**0.90**	**0.95**	**0.99**	
6	0.26	0.53	0.74	0.94	standard VK
5	0.33	0.59	0.77	0.95	
4	0.41	0.66	0.81	0.96	VK-T8
3	0.51	0.73	0.86	0.97	
	Probability for a correct letter				

Using the standard VK (6 decisions/letter) with an accuracy of 90 % the probability to type a correct character is 53%, whereas using the VK-T8 it is 66%. The probability increases by decreasing the number of decisions per letter or by increasing the BCI's accuracy. Thus, further investigations on developing intelligent Virtual Keyboards and improving the classification accuracy of the BCI system to reach optimal performance have to be done.

References:

[Pfurtscheller 2000] Pfurtscheller G, Neuper C, Guger C, Harkam W, Ramoser H, Schlogl A, Obermaier B, Pregenzer M.: Current trends in Graz Brain-Computer Interface (BCI) research. IEEE Trans Rehabil Eng. 2000 Jun;8(2):216-9.

[Obermaier 2002] Obermaier B, Müller GR, Pfurtscheller G: ‘Virtual Keyboard’ controlled by spontaneous EEG activity. IEEE Trans Rehabil Eng., in review, 2002.

DOES THE SELF-REGULATION OF SLOW CORTICAL POTENTIALS AUTOMATE?

Nicola Neumann, Thilo Hinterberger, Jochen Kaiser, Ulrike Leins,
Niels Birbaumer, Andrea Kübler
Institute of Medical Psychology and Behavioral Neurobiology
University of Tuebingen, Germany

The Thought Translation Device is based on the self-regulation of slow cortical potentials (SCP), i.e. changes in cortical polarization that last from 300 ms to several seconds. Patients are required to produce voluntary SCP shifts of either positive or negative amplitude, thereby moving a cursor on a notebook screen to select letters, words or symbols from a computer menu. For communication, it is very important that patients obtain a high percentage of correct potential shifts, because errors decelerate communication exponentially. Until now, it has been unclear if SCP self-regulation represents a skill that can automate. It was demonstrated, however, that SCP self-regulation improves over time and remains stable even without feedback training. In this study, we investigated whether SCP self-regulation automates with training and could thus be considered as a skill. In accordance with the neurophysiological literature it was hypothesized that at the beginning of SCP-training widespread cortical areas are activated. If SCP self-regulation automates with increasing practice, cortical activation was expected to become more focal under the feedback electrode at Cz (neurophysiological indicator of automaticity). At the same time performance was assumed to become more stable (less variability across training sessions) and less erroneous (increasing percentage of correct responses) (behavioral indicators of automaticity). The participant was a male patient first diagnosed with amyotrophic lateral sclerosis at the age of 38. EEG was recorded from Fz, Cz and Pz referenced to both mastoids. Data are reported from a total of 179 runs (a run comprising 70 single trials) at the beginning of feedback training. Successful cursor control was revealed in the voltage difference between positive and negative SCP shifts measured in µV. The magnitude of the voltage difference was considered as an indicator for the learning of SCP self-regulation. Our hypothesis implied that with increasing automaticity the voltage difference would increase at Cz and decrease at both Fz and Pz. At the same time, the performance measured as percent correct responses should improve, and the variability measured as standard deviation in 10 consecutive runs should decrease. Results indicated that the voltage difference increased at Cz as a function of runs. Thus the patient learned to move the cursor up and down according to the task requirements. The voltage difference at Fz and Pz, decreased, i.e. with increasing practice the patient's cortical activity became topographically more focal underneath the recording electrode. This is confirmed by the fact that the correlation between cortical activation at Fz and Cz was negative and no correlation was found between the activation at Cz and Pz. At the same time, the percentage of correct responses correlated with the increase of the voltage difference at Cz and with the decrease at Fz. The patient's performance became more and more stable with increasing practice. For him the criteria for automaticity were met. He learnt SCP self-regulation very well and reached 100% correct responses. SCP self-regulation may not be performed without any attentional resources, because it must comply with the trial rhythm. However, as demonstrated in this study, SCP self-regulation automates with increasing practice and requires less attentional resources that can be employed for aspects of communication.

TRAINING PATIENTS: A CHALLENGE FOR THE USE OF BRAIN-COMPUTER INTERFACES

Nicola Neumann & Andrea Kübler
Institute of Medical Psychology and Behavioral Neurobiology
University of Tübingen, Germany

Brain-computer interfaces are highly developed technical systems. However, the feasibility of BCIs for the target group, for example, severely disabled or brain damaged patients, have to be considered. Training patients who are diagnosed with intractable neurological diseases to self-regulate their brain potentials poses several difficulties. The following questions will be discussed:

1) Which patients should be selected if there is a choice? Are there any predictors for good performance?

2) How to communicate with locked-in patients? How do they perceive their environment?

3) How to take the patient's social environment into account? Who wants that the patient can communicate? Who is going to conduct the training?

4) How to motivate patients for weeks and months of training during which patients have to maintain their effort?

5) Are patients with intractable neurological diseases always depressive?

6) In case of a failure: When to stop training?

7) What about burn-out of research associates?

FUNCTIONAL AND BEHAVIORAL ROLES OF NEURAL PROCESSES UNDERLYING BCI

Julie Ann Onton, Arnaud Delorme, Scott Makeig
Swartz Center for Computational Neuroscience
Institute for Neural Computation
University of California San Diego 0961

We are working on dissect the neural dynamcis of EEG feedback. This follows our previous work of using ICA to identify and localize alpha and mu rhythms that we presented at the previous BCI meeting (Makeig, Enghoff, Jung, and Sejnowski, 2000, IEEE transactions on Rehabilitation Engineering, 8(2)), and our previous work on alertness monitoring (Makeig and Inlow, 1993; Jung et al, 1997). We also developed new techniques to visualize event-related brain dynamics (Delorme, Makeig and Sejnowski, in press, available on line at www.cnl.salk.edu/~arno/mypapers/DelormeCNS2001.PDF). As a first step, we used these techniques to identify brain areas that elicit specific oscillatory processes of interest for brain-computer interface work (e.g., specific classes of alpha or mu rhythms). The goal of our study is to understand the interactions and functional roles of the underlying neural processes.

EARLY FINGER MOVEMENT PREDICTION FROM A GENETIC SEARCH OF EEG SPECTRA

David A. Peterson[1,2,3,4], Charles W. Anderson[1,2], Michael H. Thaut[2,4]
[1] Department of Computer Science
[2] Program in Molecular, Cellular, and Integrative Neuroscience
[3] Department of Psychology
[4] Center for Biomedical Research in Music
Colorado State University
Fort Collins, CO 80523

We used EEG spectra to predict laterality of finger movement in a self-paced key typing experiment (Blankertz et al 2002). Our goal was to determine how well key types could be predicted from temporal windows well before the keystroke. We hypothesized that a custom spectral representation consisting of a composition of multi-resolution frequency bands would provide better classification than the standard EEG frequency bands.

We used the EEG recorded from each of 6 bilateral frontal, central, and centroparietal electrodes. We used a support vector machine (SVM) with a Gaussian kernel for classifying a test set of 10% of 413 trials. We searched the high-dimensional feature space using a genetic algorithm (GA) as a wrapper around the SVM classifier.

Both standard and custom features could be classified at a greater than chance level. The custom spectral features performed significantly better than the standard EEG spectra. The genetic search of feature spaces illuminates unconventional frequency band compositions that provide better classification accuracy.

The results suggest that EEG frequency information can be used for distinguishing between different motor intentions well before the actual movement. The results also suggest that compositions of multiresolution EEG spectra may be more informative than standard EEG frequency bands. Given the complex, noisy, and relatively unknown relationship between EEG and mental processes like motor intentions, global stochastic search methods like GAs may be a preferred method of selecting features from a high-dimensional EEG feature space.

References:

Benjamin Blankertz and Gabriel Curio and Klaus-Robert Muller, “Classifying Single Trial EEG: Towards Brain Computer Interfacing”, Advances in Neural Information Processing Systems, Vol. 14, ed. by T. G. Diettrich and S. Becker and Z. Ghahramani, MIT Press, 2002.

BCI DATA ANALYSIS COMPETITION: RESULTS, LESSONS LEARNED AND THE FUTURE

Paul Sajda[1], Lucas Parra[2], Klaus-Robert Müller[3]
[1] Department of Biomedical Engineering, Columbia University
[2] Adaptive Image and Signal Processing, Sarnoff Corporation
[3] Intelligent Data Analysis Group Fraunhofer FIRST

In an effort to foster development of machine learning techniques and evaluate different algorithms for BCI systems, we announced a data analysis competition during the NIPS*2001 Brain Computer Interface Workshop (December 2001). Three EEG data sets involving separate BCI tasks were provided. Participants were asked to follow a few simple rules:

1. All data sets should be evaluated single-trial--do not average across multiple trials.
2. Report the statistics/metrics outlined in the description of each dataset.
3. Use of these datasets implies that the participant agrees to cite the origin of the data in any publication (see each dataset description for bibTeX entry).
4. Please do not cheat! In some cases we have given labels for both training and test data, or because of limited data size a leave-one-out validation is required. You are on your honor to do the evaluation properly and unbiased (minimum bias at least).

The three datasets in the competition included:

EEG self-paced key typing (courtesy of Benjamin Blankertz and Klaus-Robert Mueller, Fraunhofer FIRST, and Gabriel Curio, FU-Berlin). This dastset consists of 513 trials of 27 electrode EEG recordings from a single subject. While sitting in a normal chair, relaxed arms resting on the table, fingers in the standard typing position at the computer keyboard (index fingers at 'f','j' and little fingers at 'a',';') the subject was instructed to press the aforementioned keys with the corresponding fingers in a self-chosen order and timing. The task was to classify EEG potentials as being associated with left or right finger movement.

EEG synchronized imagined movement task (courtesy of Allen Osman, University of Pennsylvania). The task of each of 9 subjects during the EEG Synchronized Imagined Movement data set was to imagine moving his or her left or right index finger in response to a highly predictable timed visual cue. The goal of competition participants was to classify EEG recordings as belonging to left or right imagined movement. EEG was collected using 59 sensors and there were 90 trials for each subject (45 left and 45 right)

Wadsworth BCI Dataset (courtesy of Gerwin Schalk, Wadsworth Center) The data set consists of 64 electrode EEG recordings from 3 subjects. The task of each subject was to move a cursor on a video screen to 1 of 4 predetermined positions. Each target position differed only in vertical location. Horizontal coordinates were identical for each target position. The objective of this contest was to classify EEG recordings as belonging to the correct target position.

We will describe the datasets in further detail, present results from the competition and discuss lessons learned. We will also have an open discussion on the general utility of such competitions for promoting algorithm development in BCI and identify opportunities for a future competitions. More details can be found at http://newton.bme.columbia.edu/competition.htm.

BCI2000 IMPLEMENTATION OF A FOUR-CHOICE APPLICATION

G. Schalk[1] D.J. McFarland[1] T. Hinterberger[2] N. Birbaumer[2] J.R. Wolpaw[1]
[1] Wadsworth Center, New York State Dept Health & SUNY, Albany, NY, USA
[2] Institute Medical Psychology Behavioral Neurology, Univ Tübingen, Tübingen, Germany

Many labs are developing and testing BCI systems that are intended to provide new communication channels to those with severe motor disabilities. These systems focus on different brain signals, use different signal processing methods, and control different output devices. Many factors (e.g., the chosen brain signals, feature extraction methods, translation algorithms, output devices) determine the performance of each BCI system. To optimize BCI performance, the alternatives for each factor need to be compared, combined, and tested systematically. In response to this requirement, we have developed a documented general-purpose BCI research and development platform, called BCI2000, that is based on a general model of the BCI process and can incorporate alone or in combination any of the different possible BCI input signals (from neuronal spikes to slow cortical potentials), processing methods, and outputs.

BCI2000 consists of four modules (signal acquisition, signal processing, output control, and operating protocol) that communicate through a network-capable protocol. Each of the four modules can be executed on any machine on a network (e.g., the interface to the investigator may run on a different machine), and each module can be changed without affecting any other module.

As an example of the utility and practical applicability of BCI2000, we will demonstrate its implementation of a spelling paradigm. In this paradigm, the system calculates mu and/or beta rhythm amplitude at one or several scalp locations and uses the result to control cursor movement. In each trial, the cursor moves from left to right at a constant rate with its vertical movement controlled by the user's EEG. The user's goal is to hit the correct one of four possible targets on the right edge of the screen. After an initial screening protocol and training, users can achieve accuracies of 70%-95% (note that accuracy in the absence of any user control would be 25%).

Supported by the National Center for Medical Rehabilitation Research, NIH.

MU/BETA RHYTHM-BASED BRAIN-COMPUTER INTERFACE (BCI): IMPROVING PERFORMANCE WITH TIME-DOMAIN SIGNAL FEATURES

H. Sheikh, D.J. McFarland, T.M. Vaughan, J.R. Wolpaw
Wadsworth Center, New York State Department of Health and State
Uiversity of New York, Albany, NY 12201

People can learn to control the amplitude of the 8-12 Hz mu or 18-25 Hz beta rhythm of EEG recorded over sensorimotor cortex and use it to move a cursor to selections on a computer screen (e.g., Electroenceph Clin Neurophysiol 78:252-259, 1991 & 90:444-449, 1994). To define additional EEG features that could improve performance speed and accuracy (measured as bit rate), we are examining in the time-domain EEG activity recorded from 64 scalp locations during BCI operation. A trial begins with the appearance of a target occupying one of the four quarters of the right screen edge. A cursor appears in the middle of the left screen edge 1 sec later and moves steadily across the screen in 2 sec. The user's mu or beta rhythm amplitude at one or several locations over sensorimotor cortex controls vertical cursor movement and thus determines whether the target is hit. We examined in the time-domain the EEG activity associated with topmost and bottommost targets. Time-domain EEG at specific times during the trial and at specific electrodes is significantly correlated with target location. These times and electrodes vary among users. The results imply that time-domain EEG analysis properly tailored to each user could supplement current frequency-based analyses and improve BCI performance.

Supported by the National Center for Medical Rehabilitation Research, NIH.

DETECTION OF EVENT-RELATED SIGNALS IN ELECTROCORTICOGRAM

W.M. Sowers, J.A. Fessler, S.P.Levine, J.E. Huggins
The University of Michigan—Ann Arbor

Introduction

A direct brain interface (DBI) is defined as a human-computer interface that accepts voluntary commands directly from the brain. The University of Michigan DBI is based on the detection of event related activity in electrocorticogram (ECoG). The movements used here are not prompted by a cue, thus the DBI must detect the execution of a particular movement without the knowledge of when that movement might occur.

Two distinct forms of neural activity have been observed in ECoG during the preparation and execution of a movement. Event-related potentials (ERPs) are time-locked and phase-locked to an externally or internally paced event and can be understood in terms of the response of a stationary system with a specific neuronal circuitry. Event-related desynchronization and synchronization (ERD/ERS) are also time-locked, but not phase-locked, and can be understood as an alteration in the ongoing neural activity resulting from changes in the functional connectivity within the cortex or from changes in various feedback loops [1]. These phenomena may occur individually or linked together spatially and temporally [2].

Methods

The current method for the DBI is based on the single channel detection of ERPs in ECoG [3]. Averaged ECoG templates are developed using triggered averaging, where the trigger is directly derived from some aspect of the external movement. For detection, normalized cross-correlation is performed between the template formed from a training set and the continuous ECoG from the test set, and the result is compared to a set threshold.

This correlation detector is optimal for the model assuming a known signal in additive white Gaussian noise. Experimental observations, however, show that the noise is not white as it is neither uncorrelated nor stationary (see Results). For this model assuming "colored" noise, it can be shown that the optimal detector depends on the covariance of the time samples. The problem with this model is that, because the ERP may last several seconds, we can never expect to have enough event observations from a given subject to estimate the full covariance matrix. Thus, there is no way to implement the optimal detector.

An alternative would be to improve the performance of the detection scheme by using other information present in the ECoG. Neural activity such as ERD/ERS is not phase-locked and, therefore, is absent from the averaged template used in the Gaussian model described above. By using additional features, we can exploit information in the signal that is ignored by the correlation detector. Two feature sets that have been investigated for this purpose are the Hjorth parameters [4] and the adaptive autoregressive parameters [5].

Results

We have identified that both increases and decreases occur in the intertrial variance of the ECoG data that are correlated with the event. This confirms that the noise in the additive Gaussian noise model is not white, and thus the correlation detector is not optimal.

Preliminary results using the additional parameter sets indicate that detection performance may increase on average when certain features are combined with the ERP information. This indicates that additional signal information exists in the ECoG that is not present in the ERP.

Discussion

If we can determine a simplified model for the data by assuming some underlying structure for the covariance of the additive Gaussian noise, then it may be possible to estimate a covariance matrix from the observations that is more descriptive than that assuming white noise. Using this information, an improved detector based on the ERP could then be developed. Future improvements are also expected to result from the identification of the particular features in the data that are most predictive of an event.

References

[1] F. Lopes da Silva, and G. Pfurtscheller. Basic concepts on EEG synchronization and desynchronization, *Handbook of Electroenceph. and Clin. Neurophysiol.* Revised Series, Vol. 6. G. Pfurtscheller and F. H. Lopes da Silva (Eds.). Elsevier Science, 1999.

[2] G. Pfurtscheller, A. Aranibar, and H. Maresch. Amplitude of evoked potentials and degree of event-related desynchronization during photic stimulation. *Electroenceph. and Clin. Neurophysiol.*, 47:21-30, 1979.

[3] S.P. Levine, J.E. Huggins, S.L. BeMent, R.K. Kushwaha, L.A. Schuh, M.M. Rohde, E.A. Passaro, D.A. Ross, K.V. Elisevich, and B.J. Smith. A direct brain interface based on event-related potentials. *IEEE Trans. Rehab. Eng*, 8(2):180-185, June 2000.

[4] B. Hjorth. EEG analysis based on time domain properties. *Electroenceph. and Clin. Neurophysiol.*, 29:306-310, 1970.

[5] A. Schlögl. *The electroencephalogram and the adaptive autoregressive model: theory and applications*. PhD thesis, Medizinische Informatik and Bioinformatik, Graz, 2000.

BRAIN-COMPUTER WIRELESS DATA COMMUNICATION THROUGH VOLUME CONDUCTION

Mingui Sun, Marlin Mickle, Chung-Ching Li, Donnald J. Crammond, Brian L. Wessel, Paul A. Roche, Qiang Liu, Wei Liang, Robert J. Sclabassi

Laboratory for Computational Neuroscience

Departments of Neurosurgery, Electrical Engineering, and Bioengineering

University of Pittsburgh, Pittsburgh, PA 15260

Current research on implantable brain-computer interface has been focused on recording and interpreting signals from the human cortex. Sophisticated electrodes and implantable chips have been developed to interface with the brain. However, one extremely important problem has not yet been addressed: How do we wirelessly pass this information to the computer outside the human body? Radio transmission is unsuitable due to the shielding effect of brain tissues and power restrictions. We have been investigating an alternative approach based on the mechanism of volume conduction of biological tissues.

We have performed theoretical investigation on the volume conduction properties of the human head and computed scalp potential distribution in response to both implanted current dipoles and transmitters (antennas) of different shapes within the brain. A spherical model was physically constructed to verify theoretical results. A number of experiments have been performed on animals to wirelessly transmit data from an implanted volume conduction antenna.

Our study and experiments have produced encouraging results. We found that: 1) data can be transmitted wirelessly with a good signal to noise ratio by emitting a small amount of current from the antenna; 2) the volume conduction based data transmission channel obeys the reciprocity theorem which constitutes the same sensitivity regardless of the direction of information flow (from brain to computer or from computer to brain; 3) using a new antenna design the far-field potential distribution, which effectively passes signal from the transmitter to the receiver, can be greatly enhanced; and, 4) the data communication module on the implantable device within the brain is very energy-efficient, potentially providing a mechanism to support continuous operation lasting for a life time. The details of these results will be demonstrated on a poster at the conference.

This work was supported in part by National Institutes of Health grant No. NS43791 and Computional Diagnostics, Inc.

ADAPTIVE BCI BASED ON VARIATIONAL INFERENCE

P. Sykacek[1], S. Roberts[1], M. Stokes[2]

[1] Department of Engineering Science, University of Oxford, Oxford, UK

[2] Research Department, Royal Hospital for Neurodisability, Putney, London, UK

Abstract

The objective of our work is to improve the bit rate of existing BCI systems. We propose for that purpose a fully adaptive classifier which adapts to modified user behaviour. When applied to binary and 1-of-3 classification of single trial EEG, the proposed system significantly outperforms the corresponding offline method.

An adaptive variational classifier

Adaptive classification refers here to an algorithm that constantly adapts to user behaviour. We assume that the joint density $p_n(y_n, \boldsymbol{x}_n)$ over cognitive states y_n and some pattern $\boldsymbol{x}_n$ extracted from the EEG signal is time dependent. Assuming that the cognitive states can occur only exclusively, y_n is coded as a 1 of c target coding for which we predict posterior probabilities $P(y_n|\boldsymbol{x}_n)$. We model the classifier as a generalized linear model with a nonlinear feature space spanned by a set of basis functions and use a logistic output transformation.

$$\begin{array}{l} p(\boldsymbol{w}_{n-1}) \\ p(\boldsymbol{w}_n|\boldsymbol{w}_{n-1}, \boldsymbol{\Lambda}) \text{ for times } n \geq 1 \\ p(y_n|\boldsymbol{x}_n, \boldsymbol{w}_n) \text{ for times } n \geq 1 \end{array} \quad (1)$$

Adaptive inference is mathematically best described as state space formulation of a first order Markov process.

Assuming a linear model and Gaussian noise, this leads to the well known Kalman filter equations. In our case $\boldsymbol{w}_n$ are the coefficients of the classifier, which is nonlinear and non Gaussian. Past discussions of analytic solutions for such models have used the ideas of the extended Kalman filter (e.g. [dFNG98]) to find a Laplace approximation of the posterior.

We propose here a method for adaptive nonlinear classification which is based on variational Kalman filtering. Variational methods are attractive for BCI systems because compared with Laplace approximations they allow for more flexibility and, contrary to particle filters, they still provide a parametric form of the posterior. For the adaptive model discussed in this paper, using a variational method affects primarily how we estimate the precision of the process noise λ. Variational methods have recently been quite popular tools for inference in probabilistic models (see e.g. [JGJS99]). The key idea of variational inference as applied for our work is to find a lower bound of the log evidence (2), which is then maximized with respect to all variational parameters introduced in

$$\log(p(\mathcal{D}_n)) = \log\Big(\int_\lambda \int_{\boldsymbol{w}_{n-1}} \int_{\boldsymbol{w}_n} p(\boldsymbol{w}_{n-1}|\mathcal{D}_{n-1}) p(\boldsymbol{w}_n|\boldsymbol{w}_{n-1}, \lambda \boldsymbol{I}) P(y_n|\boldsymbol{w}_n, \phi_n) p(\lambda|\alpha, \beta) d\boldsymbol{w}_n d\boldsymbol{w}_{n-1} d\lambda\Big) \quad (2)$$

setting up this bound.

Cognitive task	Generalization results		
	νkf	νsi	P_{null}
navigation/auditory,	0.86	0.85	0.02
navigation/movement	0.8	0.8	0.31
auditory/movement	0.78	0.76	0
navig./audit./move, 3 class	0.75	0.73	0

Table 1: This table shows a summary of a series of BCI experiments that were carried out by 10 untrained subjects. Column *νkf* and *νsi* show the generalization accuracies obtained with the variational Kalman fillter and with variational sequential inference. The last column shows the probability of the null hypothesis that the two classifications are equal. We obtain in 3 of 4 experiments a significant improvement over the offline method. The quoted results are obtained *without* reject option, i.e., we classify every segment in the data.

Single trial results

The data used in these experiments is EEG recorded from 10 young, healthy and *untrained* subjects while they perform different cognitive tasks. The experiments are based on 3 cognitive tasks: an auditory imagination, an imagined spatial navigation task and an imagined right motor task. Each task was performed for 7 seconds. Each experiment consisting of alternating these tasks was repeated for 10 times. The recordings were taken from 2 electrode sites: T4, P4 (right tempero-parietal for spatial and auditory tasks), C3' , C3" (left motor area for right motor imagination). The ground electrode was placed just lateral to the left mastoid process. The data were recorded using an ISO-DAM system (gain of 10^4 and fourth order band pass filter with pass band between 0.1 Hz and 100 Hz). These signals were sampled with 384 Hz and 12 bit resolution.

The computer experiment reported in table 1 is based on extracting reflection coefficients from the recorded EEG signals (2 seconds windows, 1 second offset, further details can be found in [SRR + 01]). The classification experiment compares variational Kalman filtering (column *νkf*) with non adaptive variational sequential inference (column *νsi*). All predictions are done on a 1 seconds basis, without smoothing or reject options. In order to allow the method to converge, predictions are obtained from the second half of the data.

The probability of observing these results under the null hypothesis that the classifiers are equal is shown in the third column. In 3 cases we can reject this null hypothesis at a p-value of 0.05. Hence we may conclude that the adaptive method leads to a significant improvement of BCI bit rates.

References

[dFNG98] J.F.G. de Freitas, M. Niranjan, and A.H. Gee. Regularisation in Sequential Learning Algorithms. In M. Jordan, M. Kearns, and S. Solla, editors, Advances in *Neural Information Processing Systems (NIPS 10)*, pages 458-464, 1998.

[JGJS99] M. I. Jordan, Z. Ghahramani, T. S. Jaakkola, and L. K. Saul. An introduction to variational methods for graphical models. In M. I. Jordan, editor, *Learning in Graphical Models*. MIT Press, Cambridge, MA, 1999.

[SRR + 01] P. Sykacek, S. Roberts, I. Rezek, A. Flexer, and G. Dorffner. A probabilistic approach to high resolution sleep analysis. In G. Dorffner, editor, *Proceedings of the International Conference on Neural Networks (ICANN)*, pages 617-624, Wien, 2001. Springer.

ANNIEM8: A BRIEF SUMMARY OF MASTERS RESEARCH

David J. Weston

Warwick University, Coventry, England

ANNIEM8 utilizes a significant proportion of practical EEG analysis and pattern classification. Raw EEG data were obtained from sources in the UK and US that contained free running off-line EEG, collected during movement imagery tasks involving left and right side motor cortices. The data was originally sampled at 125Hz.

To simplify data analysis, I first segregated data obtained from electrodes C3 and C4 from the whole 25-electrode montage. Following this I band-pass filtered the extracted data between 8-12Hz to isolate mu-activity. The filtered data was segmented into discrete subsets that represented 1 second of EEG (125 values).

This subset formed a window on the entire EEG dataset. The waveform displayed in each window was manually classified as exhibiting either an event-related desynchronization (ERD) or some other activity e.g. event-related synchronization (ERS). The window was gradually moved over the data with each iteration until the whole dataset was classified. This process was repeated for both left and right cortices independently. A value of one was recorded for an ERD feature whilst a zero represented any other activity.

The manually classified data was further divided into a training set and a testing set for classification by an artificial neural network (ANN). The ANN comprised of 125 input nodes, 50 hidden nodes and 1 output node. The ANN assumed a multi-layer perceptron topology and implemented the back-propagation algorithm. The network was trained with 1000 iterations of the training data with cessation occurring when the network error reached 0.03.

To improve the network classification accuracy I normalized the data before training commenced. Normalization is similar to finding a mean, as a different set of data will generate a unique normalization score. The third and final data pre-processing technique involved performing Independent Components Analysis on the raw EEG data. The algorithm was permitted to calculate all independent components with a covariance eigenvalue greater than zero.

The relative results of the three data pre-processing techniques are shown as averages in the table below:

	ORDINARY (%)	NORMALIZED (%)	ICA (%)
NETWORK	92.3	98.2	99.9

LEFT SIDE (C3)	73.5	89.9	99.1
RIGHT SIDE (C4)	66.9	88.1	98.7

The public domain software named NETLAB implemented as a MatLab toolkit was used for all ANN functionality. Having classified all datasets I joined the left and right side network outputs together to give a sequence of commands. Each command was a member of the set {0,1,2,3}.

This coding scheme is summarized in the table below:

LEFT SIDE (C3)	RIGHT SIDE (C4)	C3/C4 ACTIVITY	ROBOT COMMAND
0	0	ERS/ERD	0
1	0	ERD/ERS	1
0	1	ERS/ERD	2
1	1	ERD/ERD	3

A wheelchair simulation and navigation system was developed in Java 1.1.6. A robot image to navigate a pre-determined static environment according to the command sequence described earlier. To allow rather complex robot behaviour, given the limited command set, a state transition model or deterministic finite automaton was proposed that afforded command reuse. To ensure that the robot successfully completes the given environment, the ANN-generated command sequence is re-ordered according to a template of desired movement and behaviour. I also added collision detection and avoidance facilities to the robot to override potentially dangerous action by the user.

PARTICIPANTS

Brendan Z. Allison
Cognitive Neuroscience Laboratory
University of California, San Diego
9500 Gilman Drive
La Jolla, CA 92093-0515
phone: 858-534-9754
ballison@ucsd.edu

Prof. Dr. Florin Amzica
Department of Physiology
School of Medicine
Laval University
Quebec, Canada, G1K 7P4
phone: 418-656-2131 ext. 4631
fax: 418-656-3236
florin.amzica@phs.ulaval.ca

Charles W. Anderson, Ph.D.
Associate Professor
Department of Computer Science
Colorado State University
Fort Collins, CO 80523-1873
phone: 970-491-7491
fax: 970-491-2466
anderson@cs.colostate.edu

Philip S. Anton, Ph.D.
RAND Senior Information Scientist
1700 Main Street, P.O. Box 2138
Santa Monica, CA 90407-2138
phone:310-393-0411 x7798
fax: 310-393-4818
anton@rand.org

Jessica D. Bayliss
Assistant Professor
Department of Computer Science
Rochester Institute of Technology
102 Lomb Memorial Drive, Ross Rm A186
Rochester, NY 14623-5608
phone: 716-475-2507
fax: 716-475-7100
bayliss@cs.rochester.edu

Luigi Bianchi, Ph.D.
Department of Neurosciences
University of Rome “Tor Vergata”
Rome, Italy
fax: xx39-06233211623
Luigi.Bianchi@uniroma2.it

Prof. Dr. Niels Birbaumer
Institute of Medical Psychology and
Behavioral Neurobiology
University of Tuebingen
Gartenstrasse. 29
D-72074 Tübingen, Germany
phone: 07071 29 74219
fax: 07071 29 5956
niels.birbaumer@uni-tuebingen.de

Gary Birch, Ph.D.
Executive Director
Neil Squire Foundation
Suite 220, 2250 Boundary Rd.
Burnaby, BC
V5M 3Z3 Canadah
phone: 604.473.9363
fax: 604.473.9364
garyb@neilsquire.ca

Benjamin Blankertz, Ph.D.
Intelligent Data Analysis Group
Fraunhofer-FIRST
Kekule Str. 7
Berlin, 12489, Germany
phone: +49 (0) 30 / 63 92 - 18 00
fax: +49 (0) 30 / 63 92 - 18 05
benjamin.blankertz@first.fraunhofer.de

Jaimie Borisoff
Neil Squire Foundation
Suite 220, 2250 Boundary Rd.
Burnaby, BC V5M 3Z

phone: (604) 473-9363
fax: (604) 473-9364

John K. Chapin, Ph.D.
Dept of Physiology and Pharmacology
SUNY Health Science Center
450 Clarkson Ave
Brooklyn, NY 11203
phone: 718-270-2767
john_chapin@netmail.hscbklyn.edu

Dr. Febo Cincotti
Neurophysiopathology Laboratories
Fondazione Santa Lucia, IRCCS
Via Ardeatina, 306
I-00174 Rome, Italy
phone: +39 06 5150 1466
tel/fax: +39 06 4991 0917
febo.cincotti@uniroma1.it

Tammy Coleman
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-474-5610
fax: 518-486-4910
tlc04@health.state.ny.us

Adriane Davis
Computer Information Systems
Georgia State University
35 Broad Street
Atlanta, Georgia 30302
phone: 404 651-3880

Arnaud Delorme, Ph.D.
Computational Neurobiology Lab,Salk Institute
10010 North Torrey Pines Road
La Jolla, CA 92037 USA
arno@salk.edu
phone: 858-453-4100 ext 1124

borisoff@cord.ubc.ca

fax: 858-587-0417

Bruce H. Dobkin, M.D.
Professor, Department of Neurology
University of California Los Angeles
Reed Neurologic Research Center
Neurologic Rehabilitation and Research Program
710 Westwood Plaza Rm 1-129
Los Angeles, CA 90095-1769
phone: 310-2066500
fax: 310-7949486

Emanuel Donchin, Ph.D.
Professor and Chair
Department of Psychology
PCD 4118G
University of South Florida
4202 Fowler
Tampa, FL. 33620
phone: 813-974-0466
fax: 813-974-8617
donchin@chuma.cas.usf.edu

John P. Donoghue, Ph.D.
Henry Merritt Wriston Professor and Chair
Department of Neuroscience
Executive Director, Brain Science Program
Box 1953
Brown University
Providence RI 02912
phone: 401 863 2701
fax: 401 863 1074

John_Donoghue@Brown.edu

Eberhard E. Fetz, Ph.D.
Department of Physiology & Biophysics
University of Washington
Seattle, Washington 98195-7290
phone: 206-543-4839
fax:206- 685-8606
fetz@u.washington.edu
Herta Flor, Ph.D.
Professor and Director of the Department of
Clinical and Cognitive Neuroscience
University of Heidelberg,
Central Institute of Mental Health
Mannheim, Germany.
phone: ++49-(0)621-1703-918
fax: (++49 6 21) 1703-932
flor@as200.zi-mannheim.de

Gyongyi Gaal, Ph.D.
Neuroprosthesis Research Organization
GPO Station PO Box 20350
Brooklyn NY 11202-0350
G_Gaal@email.msn.com

Professor Shangkai Gao
Institute of Biomedical Engineering
Dept. of Electrical Engineering
Tsinghua University
Beijing 100084, China
phone: 8610-62785472
fax: 8610-62783057

Xiaorong Gao, M.D.
Institute of Biomedical Engineering
Dept. of Electrical Engineering
Tsinghua University
Beijing 100084, China
phone: 8610-62785472
fax: 8610-62783057

Adam Gerson
Department of Biomedical Engineering
Columbia University
1013 CEPSR-Schapiro Center, mc8904
530 W. 120th Street
New York, NY 10027
phone: 212-854-5279
adg71@columbia.edu

Alan Gevins, D.Sc.
President
SAM Technology Inc.
425 Bush Street, 5th Floor
San Francisco CA 94108
phone: 415- 837-1600
fax: 415-274-9574
sam@eeg.com

Michael Gibbs
Robotics Research Group
Dept. Engineering Science
University of Oxford
Parks Road, Oxford OX1 3PJ
phone: +44-1865/274740
fax: +44-1865/274752
mgibbs@robots.ox.ac.uk

Irina Goncharova, Ph.D.
Laboratory of Nervous System Disorders

Wadsworth Center, NYS Dept. of Health
Albany NY 12201
phone: 518 486-2677
gonchar@wadsworth.org
and
ALS Hope Foundation
219 North Broad Street, Seventh Floor
P.O. Box 40777
Philadelphia, PA 19107
phone: 215-762-7684
irina@alshopefoundation.org

Joseph B. Green, M.D.
Professor of Neurology
The University of Tennessee Health Sciences Center
415 Link Building
855 Monroe Avenue
Memphis, TN 38163
phone: 901 448 6198
JosephGreen@med.va.gov

Christoph Guger, Ph.D.
Chief Executive Officer
Guger Technologies OEG
Plabutscherstrasse 63
8051 Graz, Austria
phone/fax ++43-316-675106
mobile ++43-676-9330673
office@gtec.at

William Heetderks, M.D., Ph.D.
Program Director, Neural Prosthesis Program
NINDS, NIH
Neuroscience Center, Room 2207
6001 Executive Boulevard
Bethesda, MD 20892-9525
phone: 301 496-1447
Heet@nih.gov

Stephen Helms Tillery, Ph.D.
Dept. of Bioengineering (MS 9709)
Arizona State University
Tempe, AZ 85287-9709
phone: 480-965-0753
Steve.HelmsTillery@asu.edu

Thilo Hinterberger, Ph.D.
Institute of Medical Psychology and
Behavioral Neurobiology
University of Tuebingen
Gartenstrasse 29
D-72074 Tuebingen, Germany
phone: ++49 7071 29 74 222
fax: ++49 (0)7071 29 59 56

Stacie E. Hitchcock
Dept. of Biology
Georgia State University
Atlanta, GA
phone:404-651-2259
staciehitchcock@hotmail.com

Clemens Hoffman
Corporate Technology
Mch-P 63-418

CT IC 4, Siemens AG
D-81730 Muenchen, Germany
phone: +49 89 636 55734
fax: +49 89 636 49767
clemens.hoffmann@mchp.siemens.de

Jane E.Huggins, Ph.D.
Asst. Research Scientist, Biomedical Engineering
Department of Biomedical Engineering
1C335 University Hospital
University of Michigan
Ann Arbor, MI 48109-0032
phone: 734- 936-7170
janeh@umich.edu

Jack W. Judy, PhD.
Assistant Professor in Electrical Engineering
Co-Director of the NeuroEngineering Program
University of California Los Angeles
6731E Boelter Hall
UCLA Box 159410
420 Westwood Plaza
Los Angeles, CA 90095-1594
phone: 3109 206-1371
fax: 310 861-5055
jjudy@ee.ucla.edu

Dipl.-Psych. Ahmed A. Karim
Institute of Medical Psychology
and Behavioural Neurobiology
University of Tuebingen
Gartenstr. 29, D-72074
Tuebingen, Germany
phone: ++40 7071 297438
fax: ++49 7071 295956
elkarim@gmx.net

Philip R. Kennedy, MD, PhD
CEO/Chief Scientist
Neural Signals Inc.
430 10th Ave Suite N009
Atlanta, GA 30318
phone: 404-872-5757
fax: 404-872-5422
pkennedy@neuralsignals.com

Daryl R. Kipke, PhD.
Associate Professor
Department of Biomedical Engineering
3304 G.G. Brown, 2350 Hayward Ave.
University of Michigan
Ann Arbor, MI 48109-2125
phone: 734-764-3716
fax: 734-936-2116
dkipke@umich.edu

Todd Kirby, Ph.D.
Neural Signals Inc.
430 10th Ave Suite N009
Atlanta, GA 30318
phone: 404-872-5757
fax: 404-872-5422
tkirby@neuralsignals.com

Michael Kositsky, Ph.D.
Robotics Laboratory
Sensory Motor Performance Program
Room 1385, Rehabilitation Institute of Chicago
345 East Superior Street

Chicago, IL 60611
phone: 312-503-5173 at NU Physiology
kositsky@northwestern.edu

Andrea Kübler, Ph.D.
Institute of Medical Psychology and Behavioral Neurobiology
University of Tuebingen
Gartenstrasse 29
D-72074, Tuebingen, Germany
and
Trinity College
Dublin, Ireland
phone: +353 1 671 2006
kueblera@tcd.ie
Volker Kunzmann, Ph.D.
Neurophysics Group
Dept. of Neurology
Freie Universitaet Berlin
Berlin, Germany
phone:+49 (030) 8445
volcris@zedat.fu-berlin.de

Simon P. Levine, Ph.D.
Professor
Director, Rehabilitation Engineering Program
Dept. of Physical Medicine and Rehabilitation
and Biomedical Engineering
University of Michigan
Ann Arbor MI
phone: 734 936-7170
fax: 734 936-7515
silevine@med.umich.edu

F. H. Lopes da Silva, Ph.D.
Professor Emeritus, General Physiology
Faculty of Sciences
University of Amsterdam
Kruislaan 320
1098 SM Amsterdam
phone: +31 20 525 7637 or 7638
silva@science.uva.nl

Florian Losch, Ph.D.
Neurophysics Group, Dept. of Neurology
Freie Universitaet Berlin
Berlin, Germany
phone:+49 (030) 8445

Steven Mason, Ph.D.
The Neil Squire Foundation Brain-Computer
Interface Laboratory
GF Strong Rehabilitation Center
Vancouver, B.C. Canada
smason@telus.net
phone:604-714-4123

Dennis J. McFarland, Ph.D.
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-473-4680
fax: 518-486-4910
mcfarlan@wadsworth.org

Jürgen Mellinger
Institute of Medical Psychology & Behavioral Neurobiology
University of Tuebingen
Gartenstrasse 29

Tuebingen, Germany
phone: +49-7071-2974219
fax: +49-7071-295956

Brett Mensh, Ph.D.
Dept. of Brain and Cognitive Sciences
MIT, E25-425
Cambridge, MA 02139
phone: 617-452-2694
fax: 617-452-2913
brett@mensh.com

José del R. Millán, Ph.D.
Swiss Federal Institute of Technology
Visiting Professor
EPFL-LCN
CH-1015 Lausanne
phone: +41 21 693 5593
fax: +41 21 693 5263
jose.millan@jrc.it
jose.millan@pfl.ch

Mohammad M. Mojarradi, Ph.D
Power and Precision Conversion Systems and Technology
Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Drive, Mail Stop 303-300
Pasadena California 91109-8099
phone 818-354-0997
fax: 818-393-4272
Mohammad. M. Mojarradi@JPL.NASA.GOV
Melody M. Moore, Ph.D
Computer Information Systems
Georgia State University
35 Broad Street
Atlanta, Georgia 30302
phone: 404 651 3880 x087
melody@gsu.edu

Daniel W. Moran, Ph.D.
Assistant Professor
Departments of Biomedical
Engineering and Neurobiology
Washington University
Campus Box 1097
One Brookings Drive
St. Louis, MO 63130-4899
phone 314-935-8836
fax: 314-935-7448
dmoran@biomed.wustl.edu

Prof. Dr. Klaus-Robert Müller
Fraunhofer-FIRST
Intelligent Data Analysis Group
Fraunhofer-FIRST
Kekule Str. 7
Berlin, D-12489, Germany
phone: +49 (0) 30 / 63 92 - 18 00
fax: +49 (0) 30 / 63 92 - 18 05
klaus-robert.mueller@first.fraunhofer.de

Gernot Müller
Institute for Biomedical Engineering
Inffeldgasse 16a
8010 Graz
Austria
phone: ++43-316-873-5313
fax: ++43-316-873-5349
gernot.mueller@tugraz.at

Nicola Neumann, Ph.D.
Institute of Medical Psychology and
Behavioral Neurobiology
University of Tuebingen
Gartenstr. 29
D-72074 Tuebingen, Germany
phone: 49-7071-2975997
fax: 49-7071-295956
nicola.neumann@uni-tuebingen.de

Christa Neuper, Ph.D.
Dept. of Medical Informatics, Institute for Biomedical Engineering
University of Technology
Graz, Austria
phone: ++43 316 873 5317
neuper@dpmi.tu-graz.ac.at

Boura Noureddin
Neil Squire Foundation
Suite 220, 2250 Boundary Rd.
Burnaby, BC V5M 3Z
phone:604-714-4123
bornan@ece.ubc.ca

Paul L. Nunez, Ph.D.
Brain Physics Group
Department of Biomedical Engineering
Lindy Boggs Center 530
Tulane University
New Orleans, LA 70118
phone: 504-865-5857
fax: 504-862-8779

Julie Ann Onton
Swartz Center for Computational Neuroscience
Institute for Neural Computation
University of California San Diego 0961
La Jolla CA 92093-0961
phone: 858- 458-1927
fax: 858-458-1847 fax
julie@sccn.ucsd.edu

Kevin J. Otto
Department of Biomedical Engineering
2350 Hayward Ave.
University of Michigan
Ann Arbor, MI 48109-2125
phone: 734-764-9588
fax: 734- 936-1905
kjotto@umich.edu

Lucas Parra, Ph.D.
Technology Leader
Adaptive Image and Signal Processing
Sarnoff Corporation
201 Washington Road
Princeton, NJ 08540
phone: 609-734-3068
fax: 609-720-4875
lparra@sarnoff.com

David A. Peterson
Department of Computer Science
Colorado State University
Fort Collins, CO 80525
phone: 970-491-5291
petersod@cs.colostate.edu

Lyndsey Pickup
Robotics Research Group,
Dept. Engineering Science

University of Oxford
Parks Road, Oxford OX1 3PJ
phone: +44-1865/274745
fax: +44-1865/274752
u981cp@robots.ox.ac.uk

Jaime A.Pineda, Ph.D.
Associate Professor
Department of Cognitive Science
José C. Principe, Ph.D.
Distinguished Professor,
BellSouth Professor and Director
Computational NeuroEngineering Laboratory
EB 451, Bldg #33
University of Florida
Gainesville, FL 32611
phone: 352-392-2662
fax: 352-392-0044
principe@cnel.ufl.edu

Louis Quatrano, Ph.D.
NICHD
6100 Executive Blvd. 2A03
Rockville, MD 20852
phone: 301-402-2242
quatranl@hd01.nichd.nih.gov

Charles Robinson, D.Sc., P.E.
Max T. Watson Chair & Professor of BmE. & Micromanufacturing
Director for Center for Biomedical Engineering and Rehab Science
Louisiana Tech University
202 Biomedical Engineering Building
phone: 318 257 4562
fax: 318-255-4175
robinson@coes.latech.edu or c.robinson@ieee.org
Roman Rosipal, Ph.D.
NASA Ames Research Center
Mail Stop 269-3

Cognitive Science Bldg, Room 146
University of California, San Diego
9500 Gilman Drive
La Jolla, CA 92093-0515
phone: 619-534-7087
fax: 619-534-1128
pineda@cogsci.ucsd.edu

Moffett Field CA 94035
phone: 650-604-0971
fax: 650-604-3594
rrosipal@mail.arc.nasa.gov

Michael Rudko, Ph.D.
Computer Engineering
Union College
Steinmetz Hall, Room 206
Schenectady NY 12308-3107
phone: 518-388-6316
rudkom@union.edu

Professor William Z Rymer MD Ph.D.
John G Searle Professor & Director of Research
Rehabilitation Institute of Chicago
Professor of Physical Medicine and Rehabilitation
Physiology and Biomedical Engineering
Northwestern University Room 1406
345 East Superior
Chicago, Illinois, 60611
phone: 312-238-3919
fax: 312-238-2208
w-rymer@nwu.edu

Paul Sajda, Ph.D.
Associate Professor

Department of Biomedical Engineering
Columbia University
1013 CEPSR-Schapiro Center, mc8904
530 W. 120th Street
New York, NY 10027
phone: 212-854-5279
fax: 212-854-8725
ps629@columbia.edu

William A. Sarnacki
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-486-2677
fax: 518-486-4910
sarnacki@wadsworth.org

Gerwin Schalk
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-486-2559
fax: 518-486-4910
schalk@wadsworth.org

Robert N. Schmidt, P.E.
President, Cleveland Medical Devices Inc.
11000 Cedar Ave.
Cleveland, OH 44106
phone: 216-619-5925
rschmidt@CleveMed.com

Mijail Serruya
Department of Neuroscience
Brain Science Program
Box 1953
Brown University
Providence RI 02912
phone: 401-863-2701
mijail_serruya@brown.edu

William Shain, Ph.D.
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518 473-3630
shain@wadsworth.org

Hesham Sheikh
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-474-7958
fax: 518-486-4910
sheikh@wadsworth.org

Wesley Sowers
Dept. of Physical Medicine and Rehabilitation
University of Michigan Medical Center
Ann Arbor, MI
phone: 734-764-9588
fax: 734-936-1905
wsowers@med.umich.edu

Arizona State University
phone: 480-727-6010
DAWN.TAYLOR@asu.edu

Mingui Sun, Ph.D.
Associate Professor of Neurosurgery
Electrical Engineering and BioEngineering
Suite B-400, PUH
Department of Neurosurgery
University of Pittsburgh
Pittsburgh, PA 15213
phone: 412-648-9234
mrsun@neuronet.pitt.edu

Peter Sykacek
Robotics Research Group
Dept. Engineering Science
University of Oxford
Parks Road, Oxford OX1 3PJ
phone: +44-1865/274745
fax: +44-1865/274752
psyk@robots.ox.ac.uk

Dawn M. Taylor
Neuromechanical Control Lab
Bioengineering

Ann Tennissen, Ph.D.
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-473-4887
fax: 518-486-4910
tenniss@wadsworth.org

Leonard J. Trejo. Ph.D.
NASA Ames Research Center, MS 269-3
Moffett Field, CA 94035-1000
phone: 650-604-2187
fax: 520-832-9732
ltrejo@mail.arc.nasa.gov

Theresa M. Vaughan
Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health
P.O. Box 509
Albany, New York 12201-0509
phone: 518-486-4920
fax: 518-486-4910
vaughan@wadsworth.org

Meel Velliste
Biomedical Engineering
Carnegie Mellon University.
4400 Fifth Avenue
Box 16
Pittsburgh, PA 15213
phone: 412.268.3478 (Lab)
fax: 412.268.6571
velliste@andrew.cmu.edu

Jacques J. Vidal
Prof Emeritus
University of California Los Angeles
Computer Science

Box 951596 3531D BH
Los Angeles, CA90095-1596
phone: 310-825-2858, 310-825-1322
vidal@cs.ucla.edu

Michael Weinrich, M.D., Director
National Center for Medical Rehabilitation Research
National Institute of Child Health and
Human Development
National Institutes of Health
6100 Executive Blvd.
Room 2A03, MSC 7510
Bethesda, MD 20892-7510
phone: 301-402-4201
fax: 301-402-0832

Justin K. Werfel
Dept. of Electrical Engineering and
Computer Sciences
MIT, E25-425
Cambridge, MA 02139
phone: 617-452-1739
fax: 617-452-2913
jkwerfel@MIT.EDU

David Weston
Warwick University
Coventry, England
David.Weston@yahoo.co.uk

Barbara Wilhelm
Institute of Medical Psychology and
Behavioral Neurobiology
University of Tuebingen
Tuebingen, Germany
phone: +49-7071-2974219
fax: +49-7071-295956

Justin C. Williams, Ph.D.
Department of Biomedical Engineering
University of Michigan
Ann Arbor, MI 48109-2125
phone: 734-647-2123
fax: 734-936-2116
Department of Neurosurgery
University of Wisconsin
Madison, WI 53705
phone: 608-265-9544

Jonathan R. Wolpaw, M.D.
Chief, Laboratory of Nervous System Disorders
Wadsworth Center
New York State Department of Health and State University of New York
P.O. Box 509
Albany, New York 12201-0509
phone: 518-473-3631 or 518-474-7958
fax: 518-486-4910
wolpaw@wadsworth.org

LOCAL RESOURCES

Conference Center, The Rensselaerville Institute, Rensselaerville, NY
Telephone: 518-797-5100
Fax: 518-797-3692

Medical and Dental
Emergency: 911
Emergency Room, Albany Medical Center Hospital: 262-3131
Helderberg Medical Associates, Berne: 872-9262
Greenville Family Dental Center: 966-5323

Religious Institutions in Rensselaerville
Trinity Episcopalian Church, Rensselaerville: 797-5295
Catholic Service at Trinity Episcopalian Church at 9:00 am

Restaurants
The Palmer House, Rensselaerville: 797-3449
Thompson's Lake Enterprises, East Berne: 872-2353

Airline Reservations and Flight Information

American	1-800-433-7300
Continental	1-800-523-3273
Delta	1-800-221-1212
United	1-800-241-6522
US Airways	1-800-428-4322