

Multimodal Neuroelectric Interface Development: A Survey of Research at NASA Ames Research Center

Leonard J. Trejo, Kevin R. Wheeler, Charles C. Jorgensen, Roman Rosipal, Sam Clanton, Bryan Matthews, Andrew D. Hibbs, Robert Matthews, Michael Krupka

Abstract—We are developing electromyographic (EMG) and electroencephalographic (EEG) methods that bypass muscle activity and draw control signals for human-computer interfaces directly from the human nervous system. We have made progress in four areas: a) real-time pattern recognition algorithms for decoding sequences of forearm muscle activity associated with control gestures, b) signal-processing strategies for computer interfaces using EEG signals, c) a flexible computation framework for neuroelectric interface research, d) non-contact sensors, which measure EMG or EEG signals without resistive contact to the body.

Index Terms—Brain-computer interfaces, EEG, EMG, neuroelectric interfaces, electric field sensors.

I. INTRODUCTION

WE are exploring the potential for using neural signals from the human body to control computers or machines. We define a system that couples the human nervous system electrically to a computer as a neuroelectric interface: a sensing and processing system that can use signals from the brain or from other parts of the nervous system, such as peripheral nerves, to achieve device control. We regard brain-computer interfaces or BCIs [1] as a subset of neuroelectric interfaces. Our current focus is on using electroencephalograms (EEG) and electromyograms (EMG) as control signals for various tasks, such as aircraft or vehicle simulations and other graphic displays.

The broad objectives of our project are to: a) develop new methods 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. Our specific goals are also threefold: a) a signal acquisition and processing system for real-time control of data visualization and manipulation tasks, b) automatic EMG-based recognition and tracking of continuous human gestures, c) feasibility testing of EEG-based control methods suitable for use in parallel with other modes of communication and control.

In this paper we will survey selected results and demonstrations of EMG- and EEG-based neuroelectric

interfaces. We will describe an EMG-based flight stick, an EMG-based numeric keypad, an EEG-based interface for smooth, continuous control of a one dimension of motion in a graphic display, and comparison of algorithms for modeling the EEG patterns associated with real and imagined mouse motion or typing. Finally, we will present some new results on the development of non-contact electric field sensors for EMG and EEG recording. These sensors offer a less intrusive alternative to current sensing technology, which will make them more suitable for real-world applications.

Our approach is to describe a body of developmental research, mostly still in progress, and to indicate methods that have potential for engineering development. Given the BCI focus of this special issue, descriptions of purely EMG-based interfaces will be brief. We will describe the EEG results and the new sensor developments in more detail.

II. EMG INTERFACES

A. EMG-based Flight Stick

In our first demonstration, a computer transformed EMG signals recorded from four bipolar channels placed on the forearm of a person into control signals for an aircraft simulator. Thus, the processed EMG signals served as an imaginary flight stick [2]. EMG samples were processed in real time using a flexible signal-processing framework developed in our laboratory. Specifically, we use overlapping windows where the data within a window can be assumed close to stationary. Our feature extraction procedures included routines to filter out redundant and meaningless data with the use of information metrics such as mutual information [3]. Our model for mapping EMG signals to gestures uses mixtures of Gaussians within a Hidden Markov Model context.

This system was tested and validated with high-fidelity simulations of F-15 and Boeing 757 transport aircraft. Control of both aircraft was adequate for normal maneuvers. For the 757 simulator, a complete real-time landing sequence under neuroelectric control was demonstrated and recorded at NASA Ames Research Center [4-5]

B. EMG-based Numeric Keypad

We have also found that EMG signals from the arm can distinguish typing of one key from another on a "virtual

keyboard." In this demonstration, a computer was programmed to translate eight bipolar EMG channels recorded from the forearm into commands for typing the digits 0-9 on a virtual numeric keypad. The same flexible processing system and model architecture used for the EMG flight stick was used for the typing interface. However, the Hidden Markov model was retrained using EMG data recorded during typing. Tests were performed with random lists of data to be entered. Using such lists, we found that the digits 0-9 could be detected with 100% accuracy from the processed EMG signals. A demonstration of the system was recorded at NASA Ames Research Center [6].

III. EEG INTERFACES

A. One-dimensional Graphic Device Control

Previous research has shown that control signals for graphic devices, such as cursors can be drawn from EEG signals such as μ and β rhythms [7]. Our approach is to develop a flexible processing system that will adapt to different tasks and users. To do this we explored two tasks and an array of pattern recognition and machine learning algorithms. The tasks were virtual pointer motion and virtual typing. The algorithms included narrow-band filters for signals such as μ -rhythm, broadband filters developed with adaptive linear filters, on-line measures of complexity, and support vector machines [8-9].

In the each task, 64 channels of EEG were recorded with a QuickCap (Neuromedical Supplies, Inc.) using the extended International 10-20 System [10] with digitally linked mastoid references. We used singular value decomposition (SVD) to reduce the 64 channel recordings to a small number of orthogonal spatial filters. Then the spatial filters were approximated with a small number of electrodes (4 to 12), which were located near the extremes of the electric fields corresponding to the spatial filters. For these recordings we used either a commercially available EEG headset (Sensorphone, Allied Products, NY) or disposable self-adhesive Ag-Cl electrodes (Neuromedical Supplies, VA). Generally, from four to eight SVD components were sufficient to account for 95% or more of the variance in the 64-channel EEG recordings. For closed-loop tests using a needle-gauge task or a Mars Rover control task, EEG signals were sampled at 1000 Hz using a Neuroscan system and broadcast via a TCP/IP socket to our flexible processing system.

In Subject 1, a 45-year old male, open-loop recordings with real or imaginary hand motion (moving a mouse) showed that μ -rhythm bursts were visible in the raw EEG signals. A spectral analysis indicated that μ -rhythm power was centered at 8.7 Hz. We constructed a narrow-band digital FIR filter for this pass band in our processing system and used this as the control signal for a 1-D graphic display of a needle gauge. The subject's task was to move the needle right or left using increasing or decreasing μ -rhythm power. The subject was trained with a random sequence of targets.

In Subject 2, a 32 year old male, no clear μ -rhythm signals were present in raw EEG traces during the real or imagined arm motion task. Even with high-density recordings of up to

64 electrodes, a clear μ -rhythm source was not detected in this subject after various spatial and spectral analyses.

For the closed-loop control tests we used both the needle gauge task and a Mars Rover simulation. For the Mars Rover, EEG synchrony measures were mapped to left and right turns of the Mars Rover as it moved forward at constant velocity over a real-time rendition of a Mars terrain database.

For both subjects, we tested various on-line measures of EEG synchrony. The narrow band μ -rhythm filter was satisfactory for Subject 1 but not for Subject 2. So we also explored other, more general measures of EEG synchrony or complexity. The idea here is that regardless of the specific peaks at which sensorimotor EEG rhythms oscillate, their synchronization or lack thereof will contribute to signal complexity.

In our context we define complexity as a measure reflecting changes in regularity or predictability of EEG patterns. Signals corresponding to periods of increased EEG source synchronization will be more regular, predictable, and will have low values of complexity. Stages of higher desynchronization of EEG sources will possess high values of complexity. We examined coarse-grained entropy rates (CER), Gaussian process entropy rates (GPEn), spectral entropy (SE) and wavelet entropy (WE). CER represents an empirical complexity measure based on theoretical definition of entropy rates of stochastic processes and Kolmogorov-Sinai entropy of nonlinear dynamical systems [11-12]. CERs were successfully used in several applications when complexity or regularity of physiological signals were investigated [10, 13-14]. If we consider the EEG to be a zero-mean stationary Gaussian process we can estimate entropy rates directly from its spectrum [15-16]. Thus we define GPEn to be a linear measure, which can fully describe an underlying stationary Gaussian process but cannot describe data generated by a process involving nonlinearity. SE is a measure which computes Shannon entropy over the normalized power spectral density function; i.e., periodogram [17]. There is a clear connection between GPEn and SE as both measures reflect changes of the frequency spectra of the EEG over different brain states. For WE, we extend the concept of SE by replacing the Fourier transform with the wavelet transform [18-19]. So for WE, we computed Shannon entropy over the wavelets coefficients at individual resolution levels.

All of these methods detected periods of EEG synchrony or asynchrony correlated with real or imagined motion. Simulated real-time performance of the algorithms for Subject 1 performing real and imaginary mouse motions showed that spectral entropy measures and coarse-grained entropy rates appeared to be more sensitive to EEG desynchronizations correlated with real or imagined hand motions than a narrow-band μ -rhythm filter or wavelet entropy measures (Figure 1). Similar results were obtained for Subject 2. We completed several real-time tests and demonstrations of EEG-based control of the Mars Rover using complexity measures. For Subject 2, we recorded a demonstration of one of the sessions in which the CER served as the control signal [20].

Insert Figure 1 about here.

consisting of typing the keys *A* or *F* with the left pinkie and index fingers, or typing the keys *J* or; with the right index and pinkie fingers, or alternating use of the left and right hands within a single run. EEG data were sampled at 1000 Hz, digitally band-passed from 1 to 30 Hz, and re-sampled at 100 Hz. EMG data from the left and right forearms were recorded with four pairs of electrodes placed on the wrists and upper forearms. EMG signals were sampled at 1000 Hz, rectified and digitally band-passed from 30 to 150 Hz, then re-sampled at 300 Hz. To model typing behavior using EEG, we tested three different types of algorithms:

- *μ -Rhythm filter*: a linear FIR filter with a pass band centered on the peak of μ -rhythm signals observed near electrodes C3 or C4 in the subject's resting EEG.
- *Adaptive linear combiner (ALC)*: the Widrow-Hoff LMS algorithm [21] was used to train the combiner to model periods of the EMG signal corresponding to rest using the EEG time series.
- *Support vector classifier (SVC)*: we used the LIBSVM integrated software for support vector classification [22]. This implements a multi-class SVC based on 'one-against-one' scheme [23].

Insert Figure 2 about here.

Figure 1. Illustration of μ -rhythm filter performance as compared with various estimates of EEG complexity for the open-loop pointer control task in Subject 1. The red and blue traces are the time series corresponding to the filter output for a series of overlapping input windows through time. The vertical dashed lines indicate the times at which hand motions began or were imagined. a. Real left hand movement. b. Imaginary left hand movement.

B. EEG-based Typing

For the EEG-based typing tasks our goals were modest. We sought to detect the periods of physical keyboard typing activity from EMG-free EEG recordings and to use linear models or machine-learning algorithms to translate the EEG signals into interface commands. We did not seek to identify which keys were pressed. We sought to discriminate typing from rest and also to discriminate left- from right-hand typing.

Our approach was the same as for the pointer control tasks, in that multi-channel recordings of open-loop EEG were reduced to a few SVD components. These components were used as inputs to filters or algorithms that predicted typing behavior from the EEG signals. The same two subjects who performed the mouse motion task performed the typing tasks.

For both subjects, we collected six five-minute runs

Figure 2. Transfer functions of the 50-tap (a) and 500-tap (b) ALCs trained to predict rest or right-hand typing periods for the first four SVD EEG components.

We found that the μ -rhythm filter was inadequate to model

the relationship between EEG time series and periods of typing or rest. We next explored modeling typing and rest segments with an ALC. Here we found that for Subject 1 an ALC using 50 taps was sufficient to track the motion and rest periods associated with typing. For Subject 2, who had no clear μ -rhythm, a 500-tap ALC converged to a filter that also tracked the rest and typing periods. The results, which are only qualitative at this time, show that EEG signals associated with typing behavior can serve as an index of the typing activity. A previous report using a different task drew a similar conclusion [24].

With the ALC, it is possible to freeze adaptation after training and plot the spectrum of the transfer function. Figure 2a shows the transfer functions for first four SVD components of the EEG for the 50-tap filter. Figure 2b shows the corresponding results for the 500-tap filter. For Subject 1, both the 50-tap and 500-tap filters converged to a set of simple, unimodal transfer functions that favored frequencies below 10 Hz.

For subject 2, the transfer functions appeared to be bimodal, with one broad peak in the 5 Hz to 10 Hz range and another broad peak in the 10 Hz to 15 Hz range. In the 500-tap filters for subject 2, a third broad peak is present in the 20 Hz to 25 Hz range. These results suggest that components of the EEG map differently to motion and rest periods across subjects.

The ALCs were trained to use EEG inputs to model EMG activity exclusively during rest periods. So the ALC output is high during the periods of rest and low during typing activity. Thus the filter output serves as a rest detector, or conversely, the filter error serves as a motion detector. For Subject 1, the 50-tap filter produced consistently higher output during rest periods in between periods of right-hand typing (Figure 3). For Subject 2 (not shown), the 500-tap filter performed in a similar fashion.

Insert Figure 3 about here.

for discriminating left- from right-hand typing. To solve this problem we attempted to model the EMG using the EEG signals as inputs to a SVC. A linear SVC was trained on three separate runs, which were the even-numbered runs for the session. Each run contained alternating periods of left- and right-hand key presses with periods of rest of about five seconds between the motion periods. The first eight SVD components of the EEG signals served as inputs to the SVC. The data were digitally low-pass filtered at 30 Hz and down sampled to 60 Hz. Successive 1000-point segments (1 second of data, with 75% overlap) were labeled as non-motion, left-hand motion, or right-hand motion. Periods of motion were classified as motion when the mean of the corresponding left- or right-hand EMG signal was greater than a predefined threshold. Data from the odd and even runs sets were processed by the SVC, first by training on the even trials and testing on the odd trials. Then the data sets were reversed, training on the odd and testing on the even. In each case, the SVCs successfully classify non-motion, left hand motion, and right hand motion with accuracies between 92% and 100%. For Subject 1 and training the SVC with even-numbered runs, the accuracies for classifying EEG segments as rest, left-hand typing, or right-hand typing were, 98%, 97%, and 97%, respectively. For training with odd-numbered runs, the corresponding values were 99%, 93%, and 97%. For Subject 2, the corresponding accuracies for these six tests were 100%, 92%, 98%, 99%, 98%, and 98%, respectively.

We also analyzed the weights derived using linear SVC as we did for the ALCs. Unlike the ALCs, the SVC-derived transfer functions had complex spectral structure, showing multiple peaks (Figure 4). A pattern of peaks with frequencies near 5, 9, 12-14, 16-18, 21, 25, and 291 Hz appeared in the transfer functions across the EEG components. The spectral peaks varied with the three one-against-one classifiers in the multi-SVC as well as with the EEG spatial components.

Insert Figure 4 about here.

Figure 3. Performance of the ALC on test data in Subject 1 over time, showing tracking of the motion and rest periods by the filter output.

For the conditions in which typing alternated between the left and right hands, the ALC filters, and some variants we explored using nonlinear transfer functions, did not serve well

Figure 4. Transfer functions of the SVC for the first four SVD components of EEG. The SVC was trained to predict rest, left-hand typing, and right-hand typing periods using the first eight SVD components of the EEG.

IV. NON-CONTACT SENSOR DEVELOPMENT

NASA Ames Research Center is collaborating with Quantum Applied Science and Research, Inc. (QUASAR), under a Space Act Agreement, for the development and testing of non-contact sensors for neuroelectric recordings. These sensors can measure the electric potential in free space and so do not require resistive, or even good capacitive coupling to the subject. The principal sensor innovation is providing a very high input impedance for the electrode that senses the free space potential, while accommodating the input bias current of the amplifier. The input capacitance of present electrometer grade amplifiers is of order 1 - 3 pF. This allows us to arrange the coupling capacitances of the electrometer to yield a near ideal measurement of the bioelectric potential.

Despite its small size, the new sensor is approximately 100 times better than prior state-of-the-art electric potential sensors [25]. At 10 Hz it has comparable sensitivity to conventional resistive contact (dry or paste) electrodes. In the off-body mode the sensor can make an accurate measurement through normal clothing. The sensor also has a broadband response from 0.01 Hz to 10 kHz, proving sufficient bandwidth to measure all EEG and EMG components, and essentially all other bioelectric signals of interest.

In our initial tests, we have made direct comparisons between surface recordings of EMG and EEG with non-contact recordings of the same signals.

A. EMG Tests.

We recorded EMG from 2 surface Ag-AgCl electrodes spaced 2 cm apart on the forearm over the flexor carpi radialis. The subject was asked to make a fist and this signal was recorded for multiple trials. Then these wet electrodes were removed and replaced by a QUASAR non-contact E-field sensor and the subject repeated the fist clenching exercise. The non-contact sensor recordings tracked the conductive electrode recordings well in the desired range of EMG from 500 Hz. to 2000 Hz.

B. EEG Tests.

We recorded EEG from 8 surface Ag-AgCl electrodes spaced 4 cm apart and lying on lines 2 cm anterior or posterior to Cz, running from left to right, all referred to average mastoids with ground at Afz. A QUASAR non-contact E-field sensor was tested at the points A, B, and C, between the EEG electrodes. EEG was recorded with a Neuroscan Nuamp at gain of 19, band pass 0.1 to 300 Hz, and sampling rate of 1000. The Non-contact sensor tracked the main features of the EEG spectrum seen in the Ag-AgCL electrode recordings (Figure 5). For example both recordings show a clear peak in the spectrum near 10 Hz, which reflects endogenous alpha rhythm. The spectra also show a line at 60 Hz, which is mains noise resulting from imperfect shielding.

V. DISCUSSION

The EMG-based joystick and typing tasks were chosen to replicate something with which computer users are already familiar. These traditional types of interfaces are certainly not

suitable for gesture-based systems as they force unnatural and unintuitive movements. Signal processing and machine learning are maturing to a point whereby methods such as hidden Markov models are suitable for ordinary laptops without special hardware, however the user interfaces are still 2-D mouse based systems. The ultimate trial of this EMG methodology will be to have a system with a more natural gesture command interface. This could then be used to test the performance of EMG-based systems for everyday use by regular users. Once multiple users have been run on multiple tasks we will then be able to form a usability assessment.

Insert Figure 5 about here.

Figure 5. Power spectrum of recordings from QUASAR and Ag-Cl electrodes in a 21-y old male subject. The Quasar sensor tracks the main features of EEG spectrum seen in the Ag-AgCL electrode recordings. Including the peak near 10 Hz, which reflects endogenous alpha rhythm. The line at 60 Hz is noise from the main power lines resulting from imperfect shielding.

Our EEG-based developments show that 1-D control of a graphic device is feasible as a human computer interface. For different subjects different algorithms may be required, such as μ -rhythm filters or complexity measures. Our system is programmed to allow rapid switching among these algorithms or parallel use of the algorithms. We have demonstrated control of a needle gauge and a rendition of turning a Mars Rover simulator left and right in real time.

We found that the type of task and the qualities of EEG in a subject interact with the signal processing requirements of the interface. In the simplest case, virtual pointer motion could be tracked in one dimension with a band-pass filter. In other cases, more elaborate filters, such as an ALC or the SVC-derived filters were required. As the complexity of the task increased from one-dimensional motion to typing with different fingers on right and left hands, we found that increasing amounts of data and algorithmic complexity were required. For the two-hand typing task, as many as 8000 coefficients (eight components by 1000 samples) were required in a multi-class SVC to achieve good results. The complex set of spectral peaks in these SVC-derived filters call for increased analysis and physiological interpretation.

At least two serious limitations apply to our data. First, the number of subjects is small. This was necessary to allow us time to explore a wide range of algorithms. However, with more subjects, our sense of the feasibility of 1-D control could change. Second, our experiments are qualitative and lack quantitative metrics, such as bit rate, as used in other BCI studies. For the present, we must present these results as only indicative of promising approaches, which will be followed with quantitative metrics of performance.

Our initial findings with the QUASAR non-contact sensors show that it is possible to record both EMG and EEG signals of high fidelity without a conductive link to the body. The bandwidth and gain of these sensors are appropriate for practical applications.

Our approach allows for rapid inclusion and testing of a wide range of models and machine learning methods for mapping neuroelectric signals to control applications. Although our current system is research-oriented, and uses expensive hardware, there is no reason our system cannot function with low-cost dedicated hardware. In other words, it will be possible to replicate our system on a small portable computer suitable for field testing or space missions.

Our future directions include expanding our database to include more subjects, validating our tests with quantitative performance metrics, and considering the problem of multimodal control. Of these directions, the problem of multimodal and realistic application of neuroelectric interfaces will be the main focus of our future work. For example, when a subject is moving, will the EEG signals that we can currently use to control a graphic display lose their relationship to the task? If so, can user training allow for a true multimodal interface, in which physical gestures tracked with EMG signals and EEG-based control can link to separate aspects of a task at the same time? Although the answers to these questions are unknown, our initial results suggest that a flexible and powerful signal processing approach will allow us to isolate and apply neuroelectric signals to human-computer interfaces.

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Leonard J. Trejo was born in Mexico City, Mexico, February 24, 1955. He received a B.S. (1977) degree in psychology from the University of Oregon, and M.S. (1980) and PH. D. (1982) degrees in physiological psychology from the University of California, San Diego. He did postdoctoral studies in visual neuroscience at the University of Washington from 1982 to 1984 and postgraduate studies in neural networks and adaptive signal processing at UCLA in 1987.

He served as a research psychologist for the Navy Personnel R & D Center in San Diego from 1984 to 1994, and as assistant professor of psychology at the University of Illinois at Urbana-Champaign from 1994 to 1997. Since 1998 he has served as Chief of the Human Information Processing Research Branch and as a scientist in the Computational Sciences Division at NASA Ames Research Center.

Dr. Trejo has published over 50 articles in physiology, neuroscience, and biomedical signal processing. In 1992, he pioneered the use of the discrete wavelet transform to analyze complex spatiotemporal data from brain electromagnetic fields. More recently, he has published original research in the area of automatic feature extraction and classification of time-series data corrupted by noise.

BIOGRAPHIES for Kevin R. Wheeler, Charles C. Jorgensen, Roman Rosipal, Sam Clanton, Bryan Matthews, Andrew D. Hibbs, Rob Matthews, and Michael Krupka will be supplied upon acceptance of the paper.

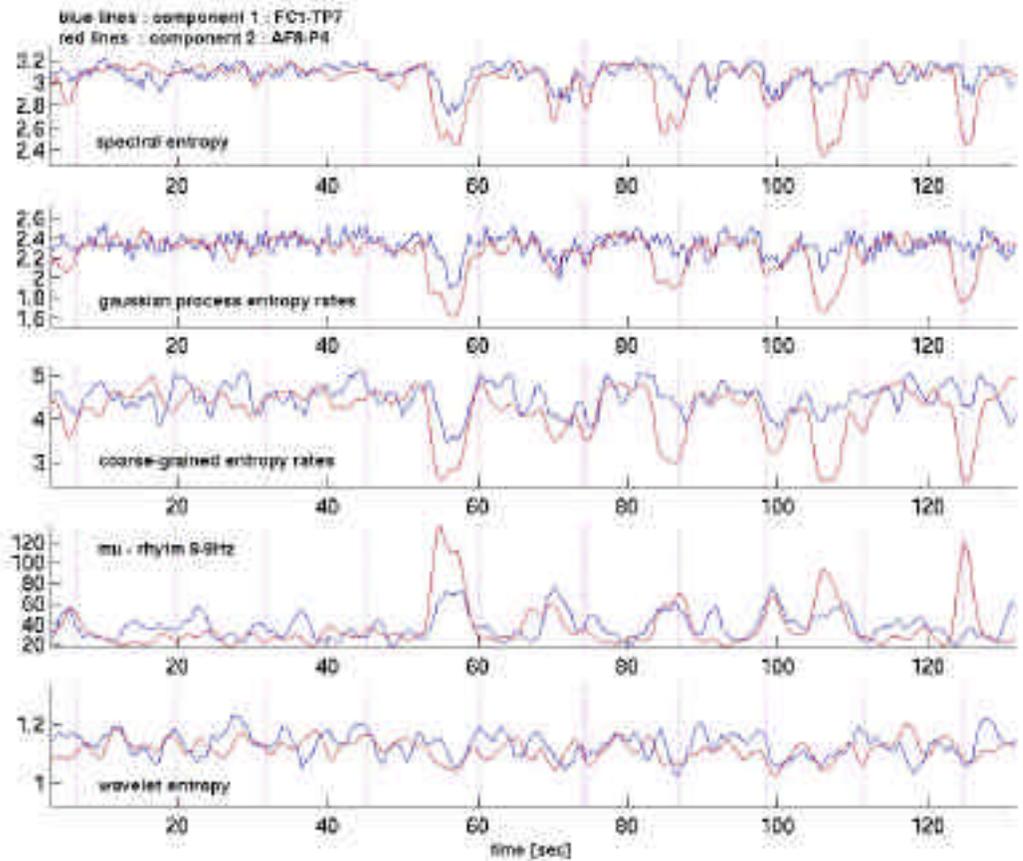


Figure 1a.

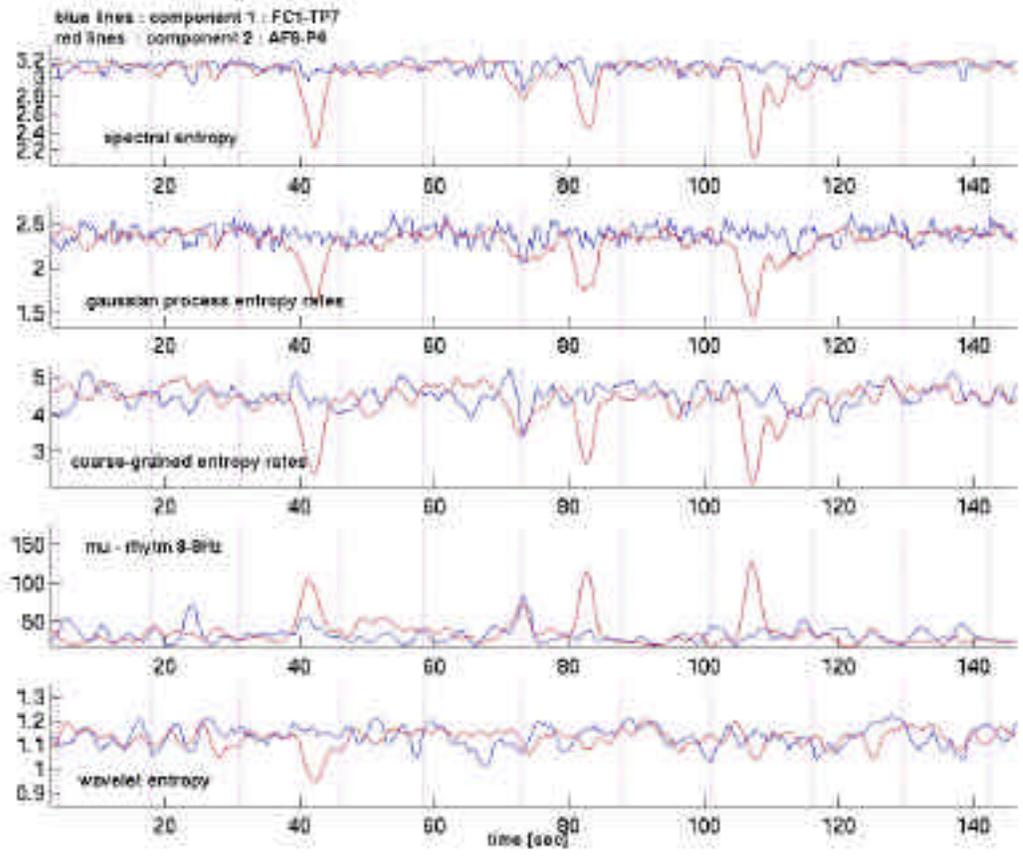


Figure 1 b.

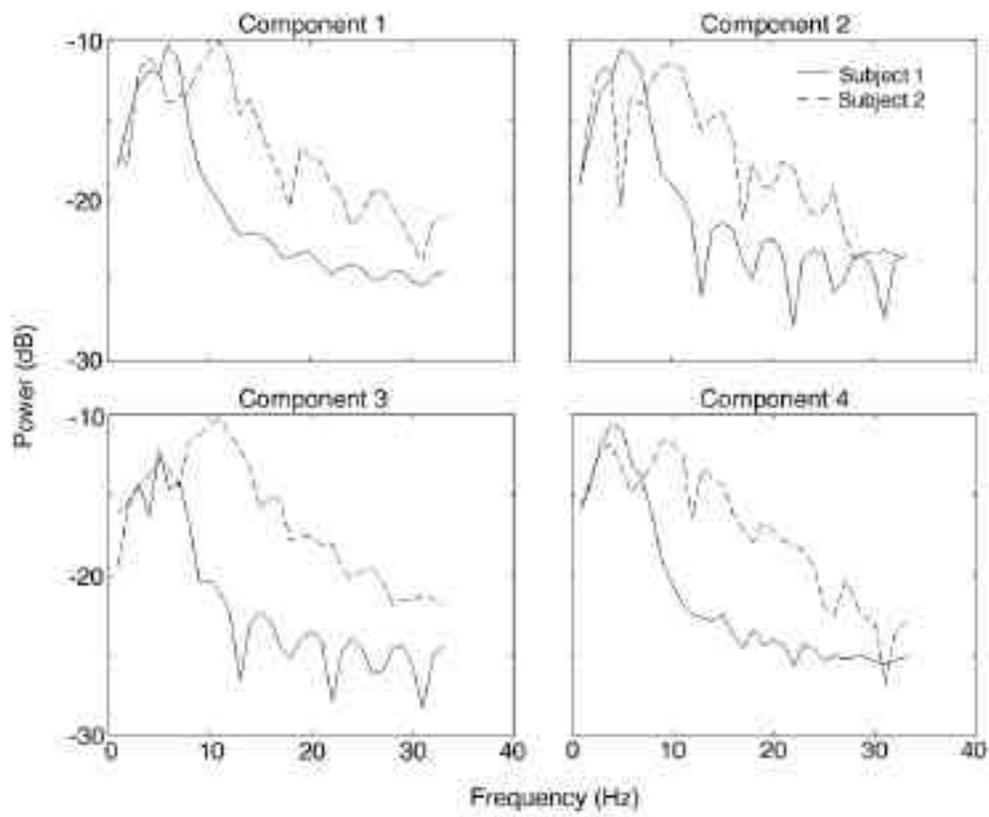


Figure 2 a.

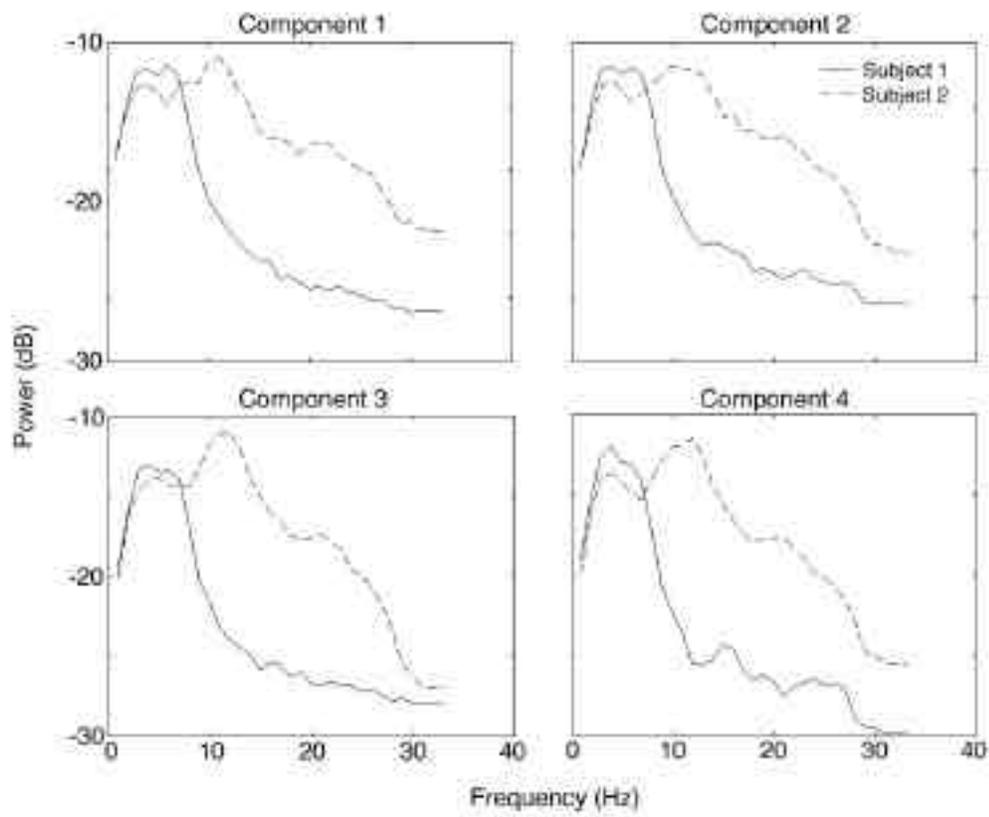


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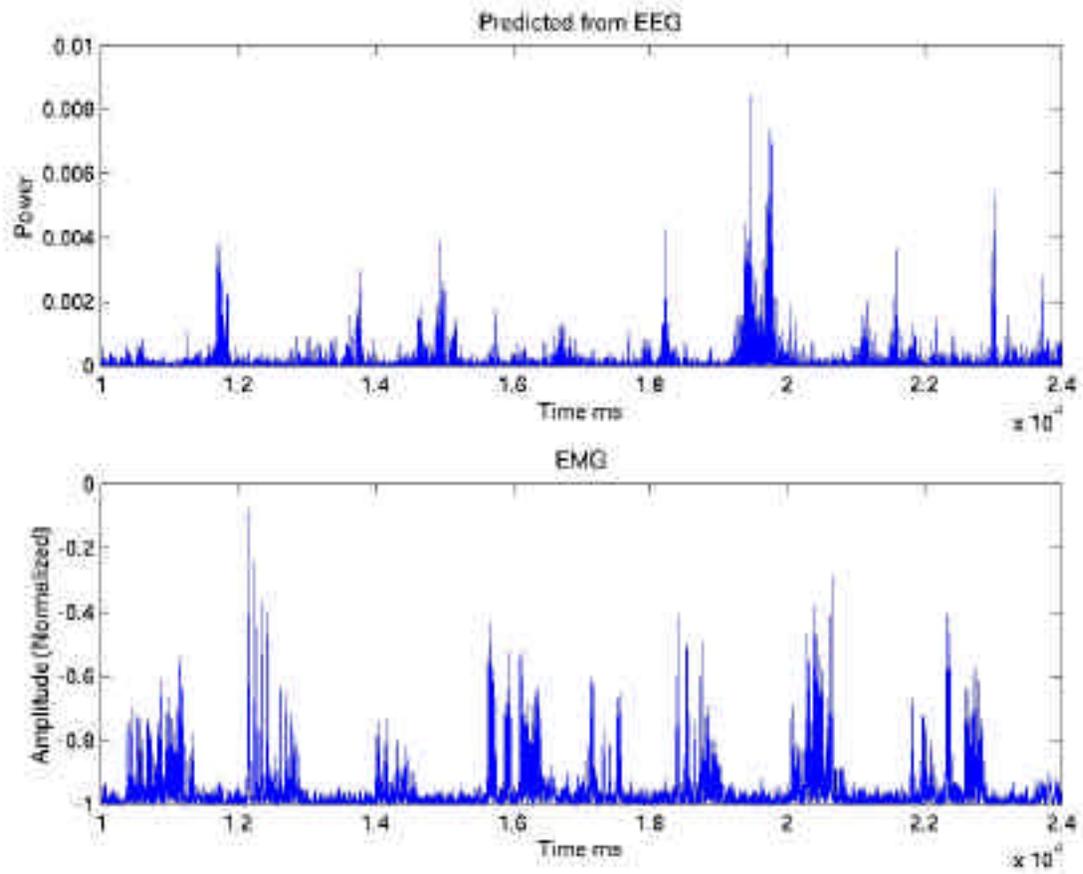


Figure 3.

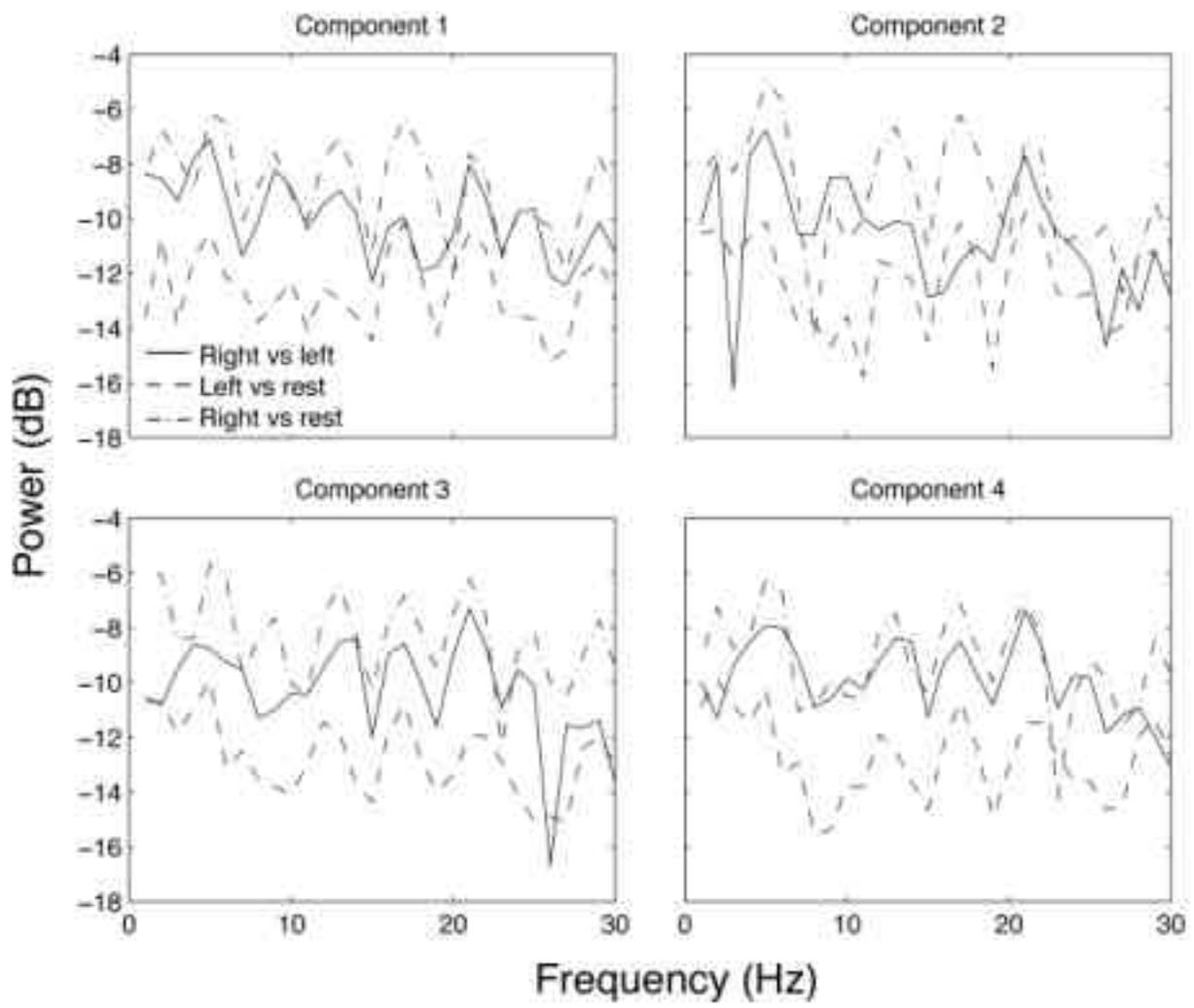


Figure 4.

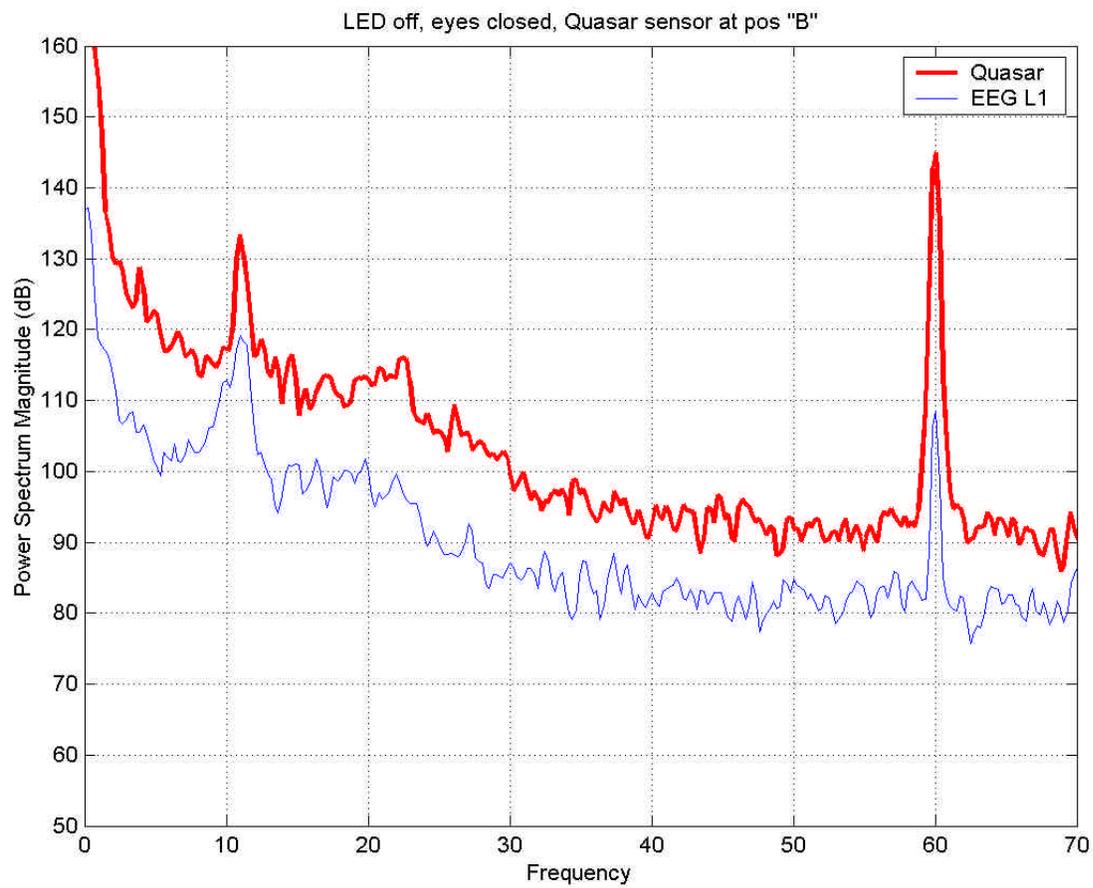


Figure 5.