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The Wadsworth Center Brain–Computer Interface (BCI) Research and Development Program

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***Abstract*—Brain–computer interface (BCI) research at the Wadsworth Center has focused primarily on using electroencephalogram (EEG) rhythms recorded from the scalp over sensorimotor cortex to control cursor movement in one or two dimensions. Recent and current studies seek to improve the speed and accuracy of this control by improving the selection of signal features and their translation into device commands, by incorporating additional signal features, and by optimizing the adaptive interaction between the user and system. In addition, to facilitate the evaluation, comparison, and combination of alternative BCI methods, we have developed a general-purpose BCI system called BCI-2000 and have made it available to other research groups. Finally, in collaboration with several other groups, we are developing simple BCI applications and are testing their practicality and long-term value for people with severe motor disabilities.**

***Index Terms*—Augmentative communication, brain–computer interface (BCI), conditioning, electroencephalography (EEG), mu rhythm, rehabilitation, sensorimotor cortex.**

I. INTRODUCTION

In awake people, primary sensorimotor cortical areas often display 8–12-Hz electroencephalographic (EEG) activity when not engaged in processing sensory input or producing motor output [1]–[3], (reviewed in [4]). This idling activity—called mu rhythm when focused over somatosensory or motor cortex, and visual-alpha rhythm when focused over visual cortex—is thought to be produced by thalamocortical circuits [4], [5]. Mu-rhythm activity comprises a variety of different 8–12-Hz rhythms and is usually associated with 18–26-Hz beta rhythms [6]–[9]. Mu and beta rhythms wax and wane in association with actual movement or imagination of movement [9]–[12].

In our brain–computer interface (BCI) studies, people with or without motor disabilities (e.g., amyotrophic lateral sclerosis, cerebral palsy, spinal cord injury) learn to control mu- and/or beta-rhythm amplitudes to move a cursor in one or two dimensions to choices on a computer screen [13]–[15]. Fig. 1(a) illustrates the basic phenomenon. In this example, the user controls vertical cursor movement by controlling the amplitude of a 12-Hz mu rhythm focused over left sensorimotor cortex. The frequency spectra indicate that control is focused in the mu-rhythm band and to a lesser extent in a beta-rhythm band.

In our standard protocol, a linear equation translates mu-rhythm or beta-rhythm amplitude from one or several scalp locations into cursor movement 10 times/s. Users learn over a series of 40-min sessions to control the cursor. They participate in 2–3 sessions per week, and most demonstrate significant control within 2–3 weeks. In initial sessions, users typically employ some form of motor imagery (e.g., imagination of hand movements, whole body activities, relaxation, etc.) to control the cursor. As training proceeds, imagery usually becomes less important, and users report that they move the cursor just as they perform normal movements, that is, without thinking about the details of performance.

While EEG from only one or two scalp locations control the cursor online, data from 64 locations over the entire scalp (recorded with an electrode cap) are stored for subsequent offline analysis. This analysis defines the full topography of EEG changes associated with target position, detects non-central nervous system (CNS) artifacts such as electromyographic (EMG) or electrooculographic (EOG) activity, and helps guide improvements in online operation. It relies largely on the measure r^2, the proportion of the total variance in mu- or beta-rhythm amplitude that is accounted for by target position and thereby reflects the user's level of EEG control. For example, the r^2 topographical analysis in Fig. 1(a) shows that control is sharply focused over left sensorimotor cortex and in the mu- and beta-rhythm frequency bands. This measure correlates well with the accuracy of target selection, and, thus, can be used in offline analysis to identify alternative signal features that are likely to improve performance [16].

With this control, users can move the cursor to answer spoken yes/no questions with accuracies $>95\%$ [17], [18]. They can also achieve independent control of two different mu- or beta-rhythm channels and use that control to move a cursor in two dimensions [19]. Recent work has concentrated on developing precise one-dimensional control, and on applying it to choosing among up to eight different selections. Users have achieved information transfer rates up to 20–25 b/min [20], [21].

II. CURRENT AIMS

Our research has concentrated on defining the topographical, spectral, and temporal features of mu- and beta-rhythm control and on optimizing the mutually adaptive interactions between the user and the BCI system. Our central goal is to improve the speed and accuracy of BCI communication and to show that it can serve the practical needs of people with severe motor disabilities. In accord with this goal, we are focusing on four major aims.

A. Optimizing Feature Selection, Extraction, and Translation

We are evaluating alternative methods for selecting and extracting the signal features, that is, the mu- and beta-rhythm amplitudes that control cursor movement. This evaluation includes assessments of additional signal processing methods, recording locations, and frequency bands. For example, we have found that the choice of spatial filtering method is critically important. For mu and beta rhythms, a common average reference or a large (6-cm interelectrode distance) Laplacian

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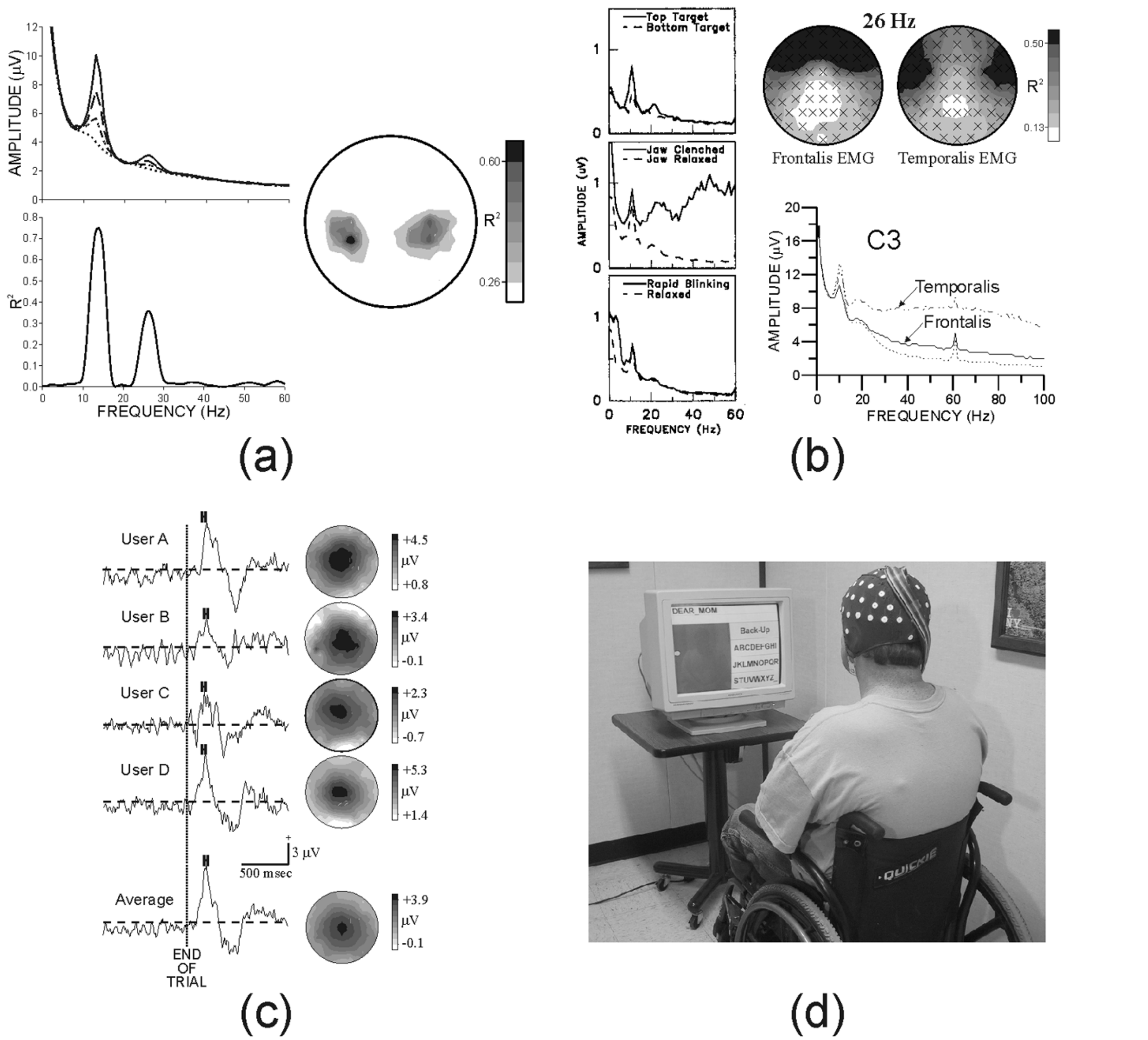

Fig. 1. (a) Sensorimotor-rhythm control. A trained BCI user controls vertical cursor movement to targets located at four possible vertical positions. Mu-rhythm (12-Hz) amplitude from the scalp over left sensorimotor cortex controls the cursor. Left top: Voltage spectra over left sensorimotor cortex for the top target (solid line), the next-highest target (long-dashed line), the third-highest target (short-dashed line), and the lowest target (dotted line). Left bottom: Corresponding R^2 spectrum showing the proportion of variation in voltage accounted for by target height. The user has developed control that is sharply focused in the mu-rhythm and beta-rhythm frequency bands. Right: Scalp topography (with nose at top) of the user's mu-rhythm control (again expressed as R^2). The user's control is sharply focused over sensorimotor cortex (modified from [16]). (b) Distinguishing sensorimotor-rhythm control from non-EEG artifacts. Left: Spectra of activity recorded over sensorimotor cortex from a well-trained BCI user. In the top graph, she is using a 10-Hz mu rhythm to control cursor movement to top (solid) or bottom (dashed) targets. In the middle graph, she is gritting her teeth (solid) or simply sitting quietly (dashed). In the bottom graph, she is blinking her eyes rapidly (solid) or simply sitting quietly (dashed). The sharply focused EEG control evident in the top graph is easily distinguished from the non-EEG artifacts in the middle and bottom graphs [15]. Right top: Average R^2 scalp topographies (with nose at top) for 25 adults at 26 Hz for 15% frontalis muscle contraction versus relaxation and 15% temporalis contraction versus relaxation. (The R^2 scale shows significant effects: the lowest (i.e., white) values are significant at $p < 0.01$ and the highest (i.e., black) are significant at $p < 0.00001$.) These topographies of EMG artifact are focused on the periphery near the contracting muscle group, and are, thus, clearly distinguishable from the topographies of actual sensorimotor-rhythm control [e.g., Fig. 1(a) right]. Right bottom: Average voltage spectra over left sensorimotor cortex during relaxation (dotted line) and during weak (15% maximum) contraction of frontalis or temporalis muscles. The effect of EMG is broadly distributed over the spectra, and is, thus, readily distinguished from the sharply focused effect of actual sensorimotor-rhythm control [e.g., Fig. 1(a) left, 1(b) left top] [30]. (c) Error potential associated with BCI operation. Average miss-minus-hit EEG traces at the vertex (electrode Cz) from 0.92 s before the end of a cursor-movement trial to 1.08 s afterward (left), and scalp topographies for 40-ms periods (indicated by bars in the traces) near the positive peak of the error potentials (right), for four users (A–D) and for all users together. The horizontal dashed lines indicate zero voltage. Each user shows a positive error potential focused at the vertex that might be used online to help detect and cancel errors [27]. (d) BCI-2000 spelling program and user. The cursor moves steadily across the screen from left to right with its vertical movements controlled by the amplitudes of mu and/or beta rhythms recorded from the scalp over sensorimotor cortex. With this vertical control, the user selects among the four choices arrayed along the right edge. Each letter is chosen by a sequence of three selections [36].

filter is clearly superior to a monopolar or small (3-cm interelectrode distance) Laplacian filter [22]. Other improvements include autoregressive frequency analysis that gives higher resolution for short time segments and, thus, permits more rapid device control [15].

We are also assessing the value of combining amplitudes from different frequency bands and/or different locations. A model that includes an interaction between the components can be better than one that includes only simple linear effects [23]. We are exploring the value of continual online adaptation of the weights accorded to amplitudes in specific frequency bands at specific locations in the linear equations that control cursor movements. Such adaptation can respond to changes in the user's EEG control, and hopefully both accommodate and encourage improvements in that control [21].

In addition, we are also exploring other options for the translation algorithm that converts these features into cursor movements. Up to the present, we have used linear equations for two reasons. First, we have as yet encountered no clear evidence that more complex methods produce better BCI performance. Second, the continual automatic online adjustments in the translation algorithm that are essential for consistent performance are much simpler for linear equations and generally require fewer data [24]. In these evaluations (e.g., [25]), we use as the primary measure of performance information transfer rate, or bit rate, a standard measure of communication capacity that combines speed and accuracy.

B. Incorporating Additional Signal Features and Avoiding Non-EEG Artifacts

We are also exploring the benefits of using other EEG signal features, in combination with or instead of mu and beta rhythms, e.g., evoked potentials or other time-domain signals. Offline analyses indicate that mu- and/or beta-rhythm cursor control is associated with time-domain signals that are correlated with the position of the target and might, therefore, be used to improve performance [26]. As illustrated in Fig. 1(c), in well-trained users, incorrect selections are associated with an error potential, a positive potential centered at the vertex, that might be used to identify and cancel mistakes [27]. Other error-related signals may be useful in initial user training [28]. Additional efforts are evaluating the possibilities for combining slow cortical potentials with mu/beta rhythms to improve performance. We are also investigating the use of P300 potentials [29].

With any of these features, it is important to ensure that the features are not contaminated by EMG, EOG, or other non-CNS artifacts. As shown in Fig. 1(b), we continue to address the issues of the identification and elimination of EMG artifact in EEG signals. A recent study defined in detail the topographical and spectral characteristics of EEG contamination by EMG from frontalis and temporalis muscles [30].

C. A General-Purpose BCI Research and Development System

Up to now, BCI research has demonstrated that a variety of different methods using different brain signals, signal analyses, and operating formats can convey a person's commands to a computer [31]. Future progress that moves from this demonstration stage to systematic evaluation of a variety of BCI methods and ultimately to practical applications of long-term value to those with motor disabilities requires a flexible general-purpose BCI system that can incorporate, compare, and (if indicated) combine these different methods, and can support generation of standard protocols for the clinical application of this new communication and control technology. In response to this need, we are developing, using, and providing to other labs a general-purpose BCI system, called BCI-2000 [29], [32], [33].

BCI-2000 can implement alone or in combination any of the different possible BCI methods. It is based on a four-module framework [i.e., Source (signal acquisition and storage), Signal Processing, User Application, and Operator (control protocol)] that describes any BCI system. It stores all data (e.g., raw brain signals and all events associated with online operation) in a standard format. The four modules communicate via a documented protocol and are independently modifiable. The system has export capabilities to ASCII and Matlab. While its main goal is to facilitate laboratory research studies, BCI-2000 also supports actual practical applications of BCI technology. BCI-2000 can currently use mu and beta rhythms, slow cortical potentials, P300 potentials, and single-neuron activity in conjunction with a variety of user applications. It is available with appropriate documentation to other research groups free of charge [29], [32], [33].

D. Clinical Applications

The ultimate importance of BCI technology hinges on its clinical applications, that is, to what degree it can provide to people with motor disabilities useful communication and control capacities. The first important applications are likely to be very simple communication tools for those with the most severe motor disabilities, such as those locked in by amyotrophic lateral sclerosis, brainstem stroke, or cerebral palsy. In collaboration with investigators at Drexel University, Philadelphia,PA, and at the University of Tuebingen, Tuebingen, Germany, we are developing and studying BCI operation in such potential users and plan to evaluate the long-term value of simple communication applications [34], [35]. We are focusing initially on simple letter/icon selection devices that use mu/beta rhythms, slow cortical potentials, or P300 potentials as the signal features that communicate the user's intent [e.g., Fig. 1(d)].

III. Conclusion

The Wadsworth Center BCI Research and Development Program now focuses on: 1) increasing BCI performance by broadening and improving the selection and extraction of signal features and their translation into device commands; 2) developing and distributing a general-purpose BCI system that supports comparison and combinations of alternative methods; and 3) validating the long-term value of BCI applications for improving the communication and control capacities and quality of life of those with severe motor disabilities.

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