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Brain-Computer Interface Research at the Wadsworth Center

J. R. Wolpaw, D. J. McFarland, and T. M. Vaughan

Abstract—Studies at the Wadsworth Center over the past 14 years have shown that people with or without motor disabilities can learn to control the amplitude of μ or β rhythms in electroencephalographic (EEG) activity recorded from the scalp over sensorimotor cortex and can use that control to move a cursor on a computer screen in one or two dimensions. This EEG-based brain–computer interface (BCI) could provide a new augmentative communication technology for those who are totally paralyzed or have other severe motor impairments. Present research focuses on improving the speed and accuracy of BCI communication.

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

I. ILIMITATIONS OF CONVENTIONAL AUGMENTATIVE COMMUNICATION AND CONTROL TECHNOLOGIES

People who are paralyzed or have other severe movement disorders need alternative methods for communication and control. Currently available augmentative communication methods require some muscle control. Whether they use one muscle group to supply the function normally provided by another (e.g., use extraocular muscles to drive a speech synthesizer) or detour around interruptions in normal pathways (e.g., use shoulder muscles to control activation of hand and forearm muscles [5]), they all require a measure of voluntary muscle function. Thus, they may not be useful for those who are totally paralyzed (e.g., by amyotrophic lateral sclerosis (ALS) or brainstem stroke) or have other severe motor disabilities. These individuals need an alternative communication channel that does not depend on muscle control. They need a method to express their wishes that does not rely on the brain's normal output pathways of peripheral nerves and muscles.

II. POSSIBLE DIRECT MODALITIES

A variety of noninvasive methods are now available to monitor brain function. These include electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI). PET, fMRI, and MEG are technically demanding and expensive. At present, only EEG,

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which is easily recorded and processed with inexpensive equipment, appears to offer the practical possibility of a new nonmuscular and noninvasive communication channel.

III. USING EEG FOR COMMUNICATION

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

A variety of studies over the past 60 years prompted an alternative approach [23]. These studies indicated that people can learn to control certain features of the EEG. They suggested that it might be possible to change the normal relationship between brain function and EEG. Normally, the scalp-recorded electrical fields that comprise EEG activity reflect brain function but are not thought to be necessary for that function. However, if people could learn rapid and accurate control of EEG features, the EEG could serve a new brain function, it could be converted into a new output signal, a signal that could communicate a person's wishes to an external device.

IV. POSSIBLE METHODS FOR EEG-BASED COMMUNICATION

EEG activity recorded at the scalp consists of voltage changes of tens of microvolts at frequencies ranging from below 1 Hz to about 50 Hz. It can be analyzed and quantified in the time domain, as voltage versus time, or in the frequency domain, as voltage or power versus frequency (or as the parameters derived by an autoregressive frequency analysis). Both forms of analysis can be used for EEG-based communication [19]. In the time domain, the form or magnitude of the voltage change evoked by a stereotyped stimulus, referred to as an evoked potential or evoked response, can serve as a command. For example, the evoked potential produced by the flash of a certain letter can indicate whether the user wants to select that letter [3], [16]. In the frequency domain, the amplitude of the EEG in a particular frequency band, referred to as a rhythm, can function as a command. For example, that amplitude can be used to control movement of a cursor on a computer screen [4], [9], [12], [20], [22]–[24].

V. μ and β Rhythms

The brain–computer interface (BCI) laboratory at the Wadsworth Center has focused on using 8–12 Hz μ and 13–28 Hz β rhythms in the scalp-recorded EEG for communication [9]–[11], [22]–[25]. These rhythms are produced in sensorimotor cortex and associated areas. We chose them because they are produced in those areas most directly related to movement, and because previous studies suggested that people could learn to control their amplitude [9], [23].

In our standard protocol, people with or without motor disabilities learn to control μ or β rhythm amplitude and use that control to move a cursor in one or two dimensions to targets on a computer screen. Ten

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

times per second, a linear equation translates μ (or β) rhythm amplitude into a cursor movement. Fig. 1 summarizes the protocol, which has been described in detail elsewhere [9]–[11], [13], [20], [23]–[25].

Users learn over a series of sessions to control cursor movement. Most develop substantial control within 5–10 half-hour practice sessions, and continue to improve with further practice. New users are advised

that various kinds of motor imagery are usually helpful in beginning to acquire control. As training continues, users often report that they use imagery less and less. Fig. 2 illustrates the control achieved by a well-trained user. While EEG from only one or two scalp locations is used to control cursor movement online, we gather data from 64 locations for later offline analysis (i.e., Fig. 3). This analysis defines the full topography of EEG changes associated with target position and helps develop improvements in online operation.

VI. RECENT STUDIES

Our recent work has focused on realization of a general purpose EEG-based BCI system suited for developing and studying EEG control and for determining the best methods for translating it into device control [9], [21]. The key feature of this system is recognition and use of the principle that EEG-based communication depends on successful interaction of two adaptive controllers: the system user who produces EEG control and the BCI system which translates that control into device control.

With this laboratory system, we have also sought to delineate the topographical, spectral, and temporal characteristics of the 8–12 Hz μ rhythms used in our initial BCI studies. These rhythms are usually focused near the midpoint of the central sulcus bilaterally. In trained users, they respond to command within 0.5 s [20], and are associated with 18–25 Hz β rhythms which in some users may be better control signals [e.g., Fig. 4(a)]. The locations and frequencies that provide optimal control may vary within days and between days, particularly early in training.

Another objective has been improvement in the algorithm that translates EEG control into device control. These improvements include: spatial filters that match the spatial frequencies of the user's μ or β rhythms, autoregressive frequency analysis which gives higher resolution than fast Fourier transform (FFT) analysis for short time segments and thus permits more rapid device control, and better selection of the intercepts and gains in the equations that translate EEG control into device control [9], [10], [13].

In ongoing studies, we are seeking additional frequency-domain EEG rhythms that users can learn to control. Topographically distinct rhythms may be controlled simultaneously, so that one increases when the other decreases [18]. Of particular interest is a rhythm recorded over parietooccipital cortex [8]. This rhythm might be combined with μ or β rhythms to provide several independent control channels.

We have also conducted studies indicating that EEG-based communication is not associated with and does not depend on peripheral muscle activity [17]. This demonstration is an important step in establishing EEG-based communication as a new communication channel for those who lack voluntary muscle control.

Most recently, we have begun to evaluate the possible contributions to control of time-domain EEG features. μ and β rhythm control may be associated with slow cortical potential activity comparable to that which Birbaumer and his colleagues have shown to be useful for communication [1], [2], [6]. A collaborative effort with these investigators is focused on determining whether frequency-domain control based on μ and β rhythms can be combined with time-domain control based on slow potentials to yield better EEG-based communication. Another time-domain feature might provide a method for detecting errors in communication.

Finally, we are exploring several practical applications for EEGbased communication and control. The Wadsworth BCI system can be used to answer simple questions and to select items from a screen menu, and may be able to operate the "Freehand" neuroprosthesis which provides hand-grasp control to people with cervical spinal cord injuries [5], [7], [11], [25].



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



Fig. 3. The standard 64 scalp electrodes (from [15]) used by the laboratory BCI system. The subject's nose is at the top. While only a few electrodes control cursor movement online, activity from all 64 is stored for later analysis. All electrodes are recorded versus an ear reference so that spatial filters can be applied after digitization.

VII. PRESENT GOALS

Over the next several years, we will evaluate three hypotheses: 1) that increasing the adaptibility of the online algorithm will increase the accuracy and speed of communication; 2) that time-domain EEG



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

features can supplement and improve the control now provided by frequency-domain features; and 3) that the EEG-based BCI can provide cursor-based menu selection and operate a neuroprosthesis. In accord with these hypotheses, we plan three sets of studies.

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

Second, we will try to supplement the control provided by μ and β rhythms with that provided by other frequency-domain features and by time-domain features such as slow cortical potentials and error-related potentials. This aim combines the two prevailing methods of EEG-based communication, use of frequency-domain features and use of time-domain features (e.g., [14]). We expect that this combination will improve the system's detection of the user's commands.

Third, we will try to demonstrate the practicality and usefulness of EEG-based communication. We will evaluate several different methods by which the BCI can support cursor-based letter or icon selection. One method uses simultaneous control of horizontal and vertical cursor movements; the other uses sequential control (i.e., vertical movement

to select a row followed by horizontal movement to select a column). We will also continue to contribute to application of the interface to operation of the "Freehand" neuroprosthesis that provides hand grasp function to people with cervical spinal cord injuries [7]. We expect that this commercially available prosthesis, which is presently controlled by shoulder muscles, can also be controlled by EEG. This demonstration would expand the population of potential users.

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

VIII. CONCLUSION

The continued development of EEG-based communication depends on progress in three crucial areas. First, the EEG features, whether time-domain or frequency-domain, that people are best able to control must be fully characterized and improved methods for detecting and measuring them must be developed (e.g., [10]). Second, the methods used to translate (i.e., interface) these measurements to device control (e.g., movement of a cursor, prosthesis activation, or letter selection) must be optimized. Third, the fact that EEG-based communication inevitably involves the interaction of two adaptive controllers—the system and the user—must be recognized and accomodated. Improvements in training methods and delineation of reliable techniques for maintaining stable interaction beyond initial training are essential.

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