BRAIN–COMPUTER INTERFACE RESEARCH AT THE WADSWORTH CENTER: DEVELOPMENTS IN NONINVASIVE COMMUNICATION AND CONTROL

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Brain–computer interface (BCI) research at the Wadsworth Center focuses on noninvasive, electroencephalography (EEG)-based BCI methods for helping severely disabled individuals communicate and interact with their environment. We have demonstrated that these individuals, as well as able-bodied individuals, can learn to use sensorimotor rhythms (SMRs) to move a cursor rapidly and accurately in one and two dimensions. We have also developed a practical P300-based BCI that enables users to access and control the full functionality of their personal computer. We are currently translating this laboratory-proved BCI technology into a system that can be used by severely disabled individuals in their homes with minimal ongoing technical oversight. Our comprehensive approach to BCI design has led to several innovations that are applicable in other BCI contexts, such as space missions.

I. Introduction

The potential utility of BCI for space applications will be to provide alternative and supplemental control to astronauts for purposes of multitasking during critical mission tasks or when normal physical movement is not possible or restricted, such as during shuttle ascent. Additionally, it would be possible to monitor indicators of alertness and fatigue via brain waves during these critical activities and incorporate these indicators into BCI control. In the foreseeable

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future, any application of BCI technology in space will be noninvasive in nature due to the relative infancy of and obvious risks associated with invasive technology. Currently, noninvasive BCI has evolved to the point where it is accurate and reliable enough to be evaluated for suitable space mission tasks.

Since 1986, much of the foundational noninvasive BCI research has been conducted at the Wadsworth Center in Albany, New York. This research continues to focus on the development of practical BCI-based communication and control devices for severely disabled individuals. Nevertheless, many of the findings and developments of this research are directly applicable in other contexts where alternative communication channels are desired, including space missions.

All relevant aspects of BCIs are systematically investigated at the Wadsworth Center including signal acquisition and characterization; development and evaluation of hardware, software, algorithms, and applications; user training; system dissemination; and evaluation of efficacy. We have developed the BCI2000 software platform, a general purpose system that supports and facilitates all reasonable combinations of brain signals, recording methods, processing methods, and output devices (Schalk *et al.*, 2004). To date, BCI2000 has been adopted by more than 350 laboratories worldwide and applied to BCI investigations using sensorimotor rhythms (SMRs) (Krusienski *et al.*, 2007; Wolpaw and McFarland, 2004), slow cortical potentials, P300-evoked potentials (Krusienski *et al.*, 2008; Sellers *et al.*, 2006), steady-state visual-evoked potentials (Allison *et al.*, 2008), and signals recorded from the surface of the cortex (electrocorticographic activity, ECoG) (Leuthardt *et al.*, 2004) in conjunction with a variety of user applications (Moore, 2003). Although we have investigated all of the aforementioned BCI paradigms to various extents, our research continues to focus on the development of select noninvasive paradigms that rely on two of the most promising brain signals for practical BCI control: SMRs and P300-evoked potentials.

A personal computer can be considered the ultimate communication device, in the sense that they are ubiquitous, the vast majority are connected to the Internet and/or a local communication network, and they are driven by operating systems that are designed to interact with limitless software applications and external devices. In addition, personal computing devices continue to become more portable and functional. Nearly all computing or electronic devices rely on two basic user interface modalities: continuous or actuated inputs such as a mouse or stylus pad, and discrete selections such as a keyboard or keypad. By developing reliable BCI control schemes that emulate the action of these standard user interface modalities, a BCI user would be able to access the full functionality of a personal computer, including unlimited communication and device control possibilities.

To achieve this objective, we are continuing to develop SMR-based paradigms for continuous control (e.g., mouse) and P300-evoked potential-based paradigms for discrete control (e.g., keyboard). Recent progress in these two paradigms has led to the current development of a BCI home system for disabled users. The evolution and future direction of these two paradigms at Wadsworth, as well as relevant aspects of the BCI home system, are described herein.

II. Sensorimotor Rhythm-Based BCI Control

We have shown that people can learn to use motor imagery (McFarland *et al.*, 2000) to actively modulate scalp-recorded EEG signals to move a cursor on a video screen in a continuous fashion in one (McFarland and Wolpaw, 2003; McFarland *et al.*, 2004) or two dimensions (Wolpaw and McFarland, 1994, 2004). Specifically, the users are trained to modulate SMR amplitudes in the mu (8–12 Hz) and/or beta (18–26 Hz) frequency bands over left and/or right sensorimotor cortex. This is not a normal function of this brain signal, but rather the result of training (McFarland *et al.*, 2004). In our early reports of SMR-BCI control, a single mu- or beta-band spectral feature from a single electrode over the sensorimotor cortex was used to control cursor movement in one dimension to hit a target randomly positioned along the edge of a video monitor (McFarland *et al.*, 1993, 2003; Wolpaw *et al.*, 1991). We have progressed to using two hemispherical channels to control cursor movement independently in two dimensions to hit targets along the periphery of the monitor (Wolpaw and McFarland, 1994, 2004). Examples of the 2D SMR control task, along with representative control signal topographies, are illustrated and described in Fig. 1.

We have found that Laplacian spatial filters are well suited for localizing SMR signals and reduce the impact of non-EEG artifacts such as the electromyographic (EMG) and electrooculographic (EOG) activity (McFarland *et al.*, 1997; Goncharova *et al.*, 2003). Our current SMR control protocol employs a regression model to produce the control signals. In contrast to our early studies, this model incorporates a linear combination of spectral features (i.e., amplitudes from 3 Hz autoregressive frequency bins) from multiple Laplacian-filtered channels. We found that this regression approach is well suited for SMR cursor control since, in contrast to a discriminant function, it provides continuous output and generalizes well to novel target configurations (McFarland and Wolpaw, 2005; Wolpaw and McFarland, 2004). The basic linear equation used for control is provided in Equation (1), where A are the EEG features (amplitudes) over the left (L) and right (R) hemispheres at frequencies f, w are the associated feature weights, b is the intercept, and K is the gain.

$$\Delta_{xy} = K\left(\sum_{f_{\mathrm{L}}} w_{\mathrm{L}}^{f} A_{\mathrm{L}}^{f} + \sum_{f_{\mathrm{R}}} w_{\mathrm{R}}^{f} A_{\mathrm{R}}^{f} + b\right). \tag{1}$$

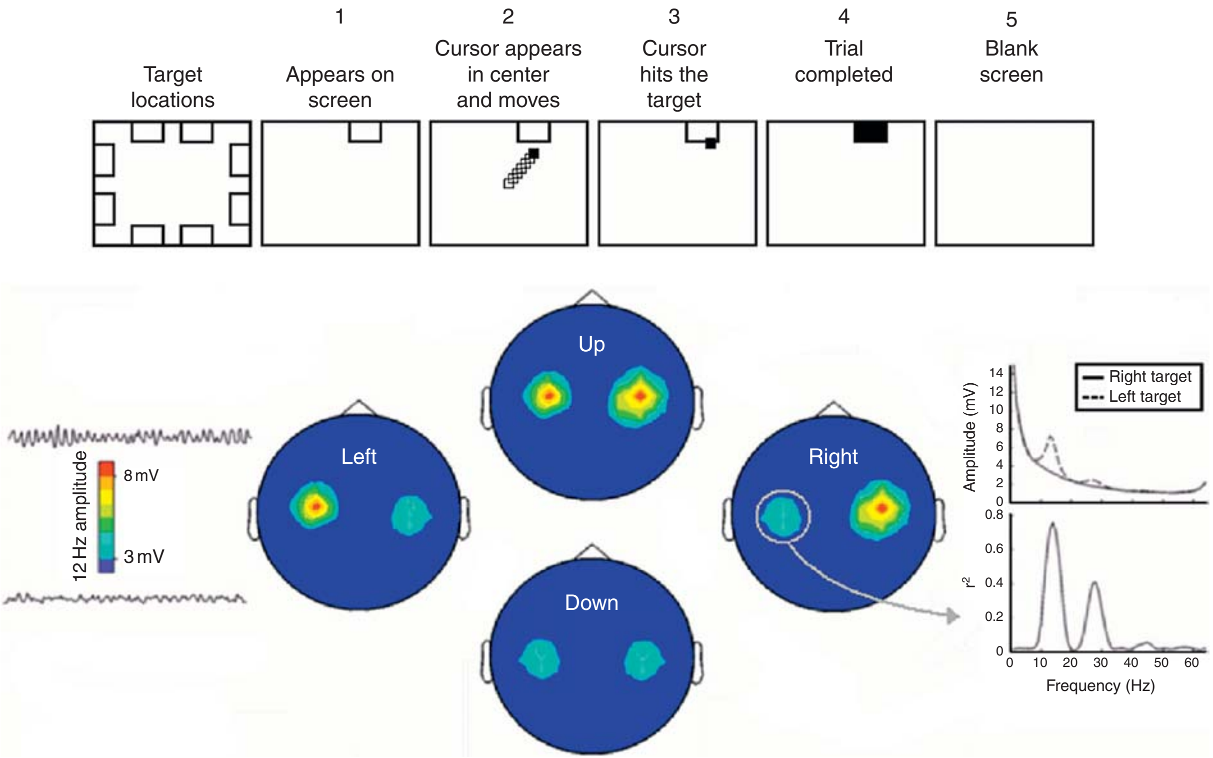

FIG. 1. The 2D sensorimotor rhythm (SMR) paradigm. *Top*: The screen at left shows the eight possible target locations. The other screens show the sequence of events in one trial. 1, a target appears; 2, 1 s later the cursor appears and moves in two dimensions controlled by the user's EEG activity; 3, the cursor reaches the target; 4, the target flashes for 1 s; 5, the screen is blank for 1 s and then the next trial begins. *Bottom*: Representative topographical and spectral properties of 2D EEG control. The four topographies indicate the average amplitudes of the 12-Hz mu-rhythm for the labeled control directions. The correlation of these amplitudes with target direction is highest at locations C3 and C4 over sensorimotor cortex, which are associated with right and left hand imagery. The amplitude spectrum and associated r^2 correlation plot for the horizontal dimension are shown to the right. The highest correlations with target direction are observed in the mu- and beta-frequency bands, which can be combined for control. The spectra and correlations for the vertical dimension exhibit similar characteristics.

For our online protocol, this equation translates the EEG features into cursor movement 20 times/s. Recent changes in automatic online adaptations of the gain (K), intercept (b), and feature weights (w) have resulted in a significant improvement in user performance (McFarland and Wolpaw, 2003, 2005).

To attain 2D control, users initially learn cursor control in one dimension (i.e., horizontal) based on a regression function. After achieving reliable 1D control, they are trained on a second dimension (i.e., vertical) using an independent regression function. The two functions are then used simultaneously to produce full 2D control. We have demonstrated that this approach results in simultaneous independent control of horizontal and vertical movement, which is comparable in accuracy and speed to that reported in studies using implanted intracortical electrodes in monkeys (Wolpaw *et al.*, 2002).

We perform comprehensive spectral and topographical analyses of 64-channel EEG during BCI operation to guide improvements in online operation. In Fabiani *et al.* (2004), we determined that 2D linear and nonlinear Bayesian classifiers offer improved performance over 1D linear classifiers. In Schalk *et al.* (2000), we showed that time-domain features could be combined with SMR amplitudes to increase accuracy of the cursor control task by detecting errors. In another recent study, we developed an empirically derived matched filter for improved tracking of the mu rhythm based on its amplitude- and phase-coupled harmonic components (Krusienski *et al.*, 2007).

To further develop SMR control to emulate the function of a computer mouse, we have recently added an additional transient EEG feature that allows users to select an individual icon if desired after intercepting it with the cursor (McFarland *et al.*, 2008). In this scheme, the user first moves the cursor to hit one of multiple possible targets by controlling two independent EEG features (as described previously) and then selects or rejects the target by performing or withholding hand-grasp imagery. This imagery evokes a transient response that can be detected and used to improve the overall accuracy by reducing unintended target selections.

Most recently, because autoregressive (AR) spectrum estimation has gained such wide acceptance in BCI, we have investigated the impact of AR model order on performance (Krusienski *et al.*, 2006b; McFarland and Wolpaw, 2008). These studies show that a properly selected model order can produce superior performance, including reducing the correlation between signals for 2D control. Additionally, these studies demonstrate that a performance-based model order selection criterion should be applied rather than traditional criteria that rely on residual error and do not adequately account for the signal dynamics for BCI purposes.

We have also conducted preliminary studies that suggest users are also able to accurately control a robotic arm in two dimensions by applying the same techniques used for cursor control. This demonstrates the potential of the SMR protocol to be extended to a variety of applications, with the level of control obtained for one task directly transferring to another task.

Our current research efforts toward improving the SMR paradigm are refining control procedures with the intention of improving accuracy and progressing to higher dimensional control. This includes the identification and transformation of EEG features so that the resulting control signals are as independent, trainable, stable, and predictable as possible.

III. P300-Based BCI Control

We are also continuing to develop the potential of the P300 matrix class of BCI systems originally introduced by Farwell and Donchin (1988). In the original paradigm, the user views a monitor displaying a 6 × 6 matrix of 36 symbols (refer to Fig. 2). The user focuses attention on a desired symbol in the matrix while the rows and columns of the matrix are highlighted in a random sequence of flashes. Because flashes of the attended symbol are random and rare in the context of the other flash stimuli, a P300 response occurs when the desired symbol is highlighted. By training a classifier using specific spatiotemporal features of the time-locked EEG responses to the stimuli, the classifier can be used to identify the row and column that contain the desired symbol in an online scenario. By assigning a particular command or function to each symbol in the matrix, a user is able to discreetly select from a variety of commands, similar to using a computer keyboard.

Our recent studies have aimed to examine and refine the P300 matrix presentation and classification techniques to improve the speed, accuracy, reliability, and generalizability of the paradigm. We examined the effects of matrix size and interstimulus interval on classification accuracy (Sellers *et al.*, 2006). The results suggest that these matrix presentation parameters can have a considerable impact on performance and should therefore be carefully designed.

We also investigated the impact of various combinations of channel selection, channel referencing, data decimation, and the number of regression model features on classification accuracy using stepwise linear discriminant analysis (SWLDA) (Krusienski *et al.*, 2008). We found that, by adding three occipital electrodes (PO7, PO8, and Oz) to the traditional electrodes used for capturing the P300 (Fz, Cz, and Pz), the classification accuracy increased substantially. Furthermore, these six electrodes provided equivalent classification accuracy to an expanded set of 19 electrodes, indicating that the signals from these six electrodes comprise the majority of unique information for classification purposes. We also found that, in general, the parameters evaluated for channel referencing, data decimation, and number of model features did not have a significant effect on accuracy. Nevertheless, in addition to the six electrode montage (P3 and P4 were

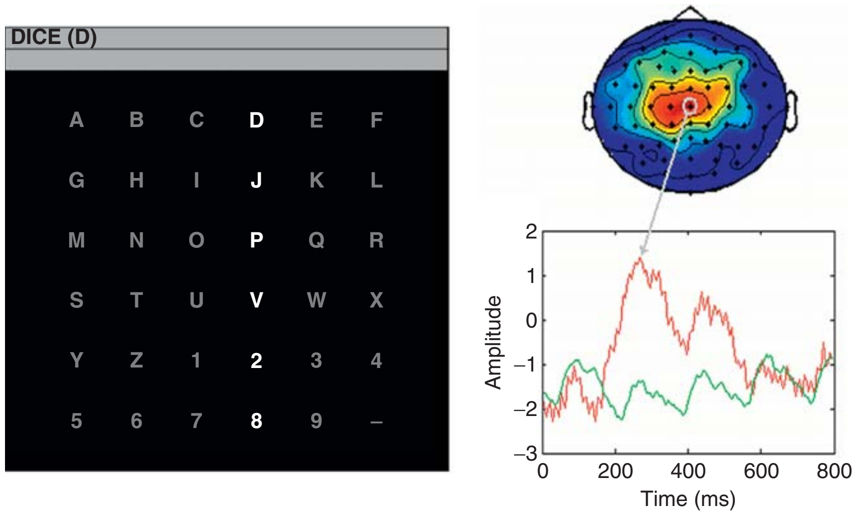

FIG. 2. The P300 matrix speller paradigm. *Left side*: The standard 6 × 6 matrix. The letter in parentheses at the top of the window is the current target letter "D". A P300 should be elicited when the fourth column or first row is intensified. After the intensification sequence for a character epoch, the result is classified and online feedback is provided. *Right side*: (Top) A representative topography indicating a strong correlation over the central electrodes between the target letter intensifications and the EEG amplitude at 300 ms after the intensifications. (Bottom) The associated averaged P300 temporal response for the targets (red) and the non-targets (green) at electrode Cz.

also added after the study, resulting in a more universal eight electrode montage), we established the following preprocessing and model parameters that produce very consistent and effective results across users: ear referencing, low-pass filtering followed by data decimation at 20 Hz, and a maximum of 60 features in the regression model. These parameters, in addition to the long-term stability of the P300 response, were validated using online experiments in this and subsequent studies. Due to the data smoothing and statistically derived SWLDA classifier, this methodology is generally resilient to modest artifacts and response latency issues. This protocol forms the processing basis for our current P300 system.

To evaluate whether the performance of the channel selection and data preprocessing method established in the aforementioned study could be further improved by using an alternative classifier, we compared SWLDA to a linear support vector machine, a nonlinear support vector machine with a Gaussian kernel, Pearson's correlation method, and Fisher's linear discriminant in an offline analysis (Krusienski *et al.*, 2006a). The results revealed marginal differences between the classification algorithms, with the exception of the overly simplistic Pearson's correlation method, which was clearly inferior to all other methods tested. Interestingly, the comparatively simple Fisher's discriminant and SWLDA linear methods provided superior performance to the support vector machines.

We are currently investigating the impact of alternate matrix presentations including various matrix sizes, configurations, flashing schemes, and flash intensities. We are also developing new methods of evaluating the relationship between the number of flashes and classification accuracy to further improve the information transfer rate of the system in practical settings.

IV. Current and Future Directions

Based on our recent progress with the SMR and P300 paradigms, extensive tests in the laboratory and the homes of disabled individuals (Kübler *et al.*, 2005; Nijboer *et al.*, 2008; Sellers and Donchin, 2006), and ultimate goal of developing a practical system for disabled individuals to use in their daily lives, we are currently designing and testing a clinical or "home" BCI system based on these paradigms (Vaughan *et al.*, 2006). The current home system includes a laptop computer, a flat panel display, a custom designed eight-channel electrode cap, and a custom designed digital biosignal amplifier. The amplifier has been reduced to $15 \times 4 \times 9$ cm, and we anticipate a smaller amplifier with wireless capabilities in the future. While the current electrode cap with gel application is sufficient for the key goals of this project, we are seeking improved sensor and cap solutions that provide reliable, long-term recordings, even in electrically noisy environments, in addition to maximizing comfort and cosmesis. This includes exploring the possibilities of active and dry electrodes.

We have also modified the BCI2000 software to include a configurable, menu-driven item selection structure that allows the user to navigate various hierarchical menus to perform specific tasks (e.g., basic communication, environmental controls, etc.). Furthermore, we have configured the P300 matrix to emulate a standard computer keyboard such that users can access the full functionality of a personal computer and associated applications. To further enhance the flexibility and communication rate, we have incorporated a predictive speller, a speech synthesis output option, a function that allows the user to suspend and recommence operation using EEG signals for prolonged or continuous operation, and an auditory mode for users who lack sufficient vision. Our preliminary studies have shown that an auditory mode provides stimuli adequate for eliciting a P300 response that is effective for BCI operation (Sellers *et al.*, 2006).

We are currently testing and evaluating the BCI home system in the homes of several disabled individuals, including a 50-year-old man with amyotrophic lateral sclerosis (ALS) who is totally paralyzed except for limited eye movement. He has successfully used the system for daily work and communication tasks over the past 3 years at least five times per week for up to 8 h per day (Vaughan *et al.*, 2006). He is currently using the P300 matrix paradigm with a 9×8 matrix representing a computer keyboard with arrows for scrolling and additional customized function calls. This configuration, in addition to the predictive speller, allows him to access and effectively utilize all of his familiar Microsoft Windows-based applications (e.g., Eudora, Word, Excel, PowerPoint, Acrobat) completely via EEG control.

V. Conclusion

The primary objective of BCI research at the Wadsworth Center is to produce a practical and effective BCI for disabled individuals who are unable to use existing technology to communicate or perform everyday tasks. By focusing on emulating standard computer interfaces such as the keyboard and mouse, the knowledge gained from our studies and endeavors can be directly transferred to other BCI contexts where continuous and discrete control/communication are desired, such as space missions. In addition to the enhanced accuracy and reliability, recent work on the BCI home system has resulted in several other practical improvements well suited for any BCI application. These improvements include the system's minimized sensors and hardware; portability; improved comfort; extensive external device interface capabilities; and generalized, configurable software and applications. We will continue to reduce the complexity of our BCI systems and increase their flexibility, capacity, and convenience through systematic testing and evaluation on representative user groups.

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