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CHAPTER 26

Brain–computer interface signal processing at the Wadsworth Center: mu and sensorimotor beta rhythms

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Abstract: The Wadsworth brain–computer interface (BCI), based on mu and beta sensorimotor rhythms, uses one- and two-dimensional cursor movement tasks and relies on user training. This is a real-time closed-loop system. Signal processing consists of channel selection, spatial filtering, and spectral analysis. Feature translation uses a regression approach and normalization. Adaptation occurs at several points in this process on the basis of different criteria and methods. It can use either feedforward (e.g., estimating the signal mean for normalization) or feedback control (e.g., estimating feature weights for the prediction equation). We view this process as the interaction between a dynamic user and a dynamic system that coadapt over time. Understanding the dynamics of this interaction and optimizing its performance represent a major challenge for BCI research.

Keywords: BCI; adaptation; signal processing

Introduction

Many people with severe motor disabilities require alternative methods for communication and control. Over the past decade, a number of studies have evaluated the possibility that scalp-recorded EEG activity might be the basis for a brain–computer interface (BCI), which is a new augmentative communication interface that does not depend on muscle control (e.g., Farwell and Donchin 1988; Wolpaw et al., 1991; Sutter, 1992; Pfurtscheller et al., 1993; Birbaumer et al., 1999; Kubler et al., 1999; Kostov and Polak, 2000; reviewed in Kubler et al., 2001; Wolpaw et al., 2002). EEG-based communication systems measure specific features of EEG activity and use the results as control signals. In some systems, these features are potentials evoked by stereotyped stimuli (Farwell and Donchin, 1988; Sutter, 1992). Other systems use EEG features that are spontaneous in the sense that they are not dependent on specific sensory events (Wolpaw et al., 1986; McFarland et al., 1993; Pfurtscheller et al., 1993; Birbaumer et al., 1999).

Developing a BCI as a real-time closed-loop system

Many studies that involve investigations of neurophysiological or psychophysiological phenomena, such as the basic cellular mechanisms of motor control (e.g., Sergio et al., 2005) or scalp potentials associated with target detection (e.g., Allison and Pineda, 2003), could be construed as being related to BCI development. However, BCI research is concerned with the development of complete systems that can provide alternative means of

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communication and control by directly accessing information from the brain and using it to perform functions directed by the user (Wolpaw et al., 2002). Human communication and movement control occur in real time and involve feedback to the user. This requires closing the loop, in real time, between brain sensors, signal processing, and the user's perceptual apparatus as shown in Fig. 1.

The real-time requirements of a BCI system introduce certain design considerations. For example, there have been several data sets used in BCI competitions (e.g., Blankertz et al., 2004; Schlogl et al., 2005) that provide a convenient means of evaluating alternative prediction algorithms. However, real-time prediction algorithms need to estimate parameters in a causal manner (i.e., only the data collected up to the present time are available, rather than the entire session, as is the case with offline analysis). Offline prediction algorithms may estimate the statistics of the data from observations across an entire session and can do these computations over a protracted period of time. This is not possible for a system operating in real time. In addition, users of BCI systems change over time as a result of learning, fatigue, changes in motivation, etc. As a result, an adaptive BCI system coevolves with an adaptive user (Taylor et al., 2002; Wolpaw et al., 2002). To further complicate the issue, it is extremely difficult to evaluate or fine tune new signal-processing algorithms offline, using data collected from an adaptive or closed-loop system. This is because the user in no longer in the control loop and it is impossible to exactly model how the user would react to the feedback produced by a new algorithm. Thus, sufficient online experiments as well as intelligently designed offline simulations are necessary for effective algorithm development in an adaptive or closed-loop system.

Effective BCI operation

With our current sensorimotor rhythm-based communication system, users learn over a series of training sessions to use EEG to move a cursor on a video screen (see McFarland et al., 1997a; Schalk et al., 2004, for full system description). In the one-dimensional mode, the user is presented with a target along the right edge of the screen and a

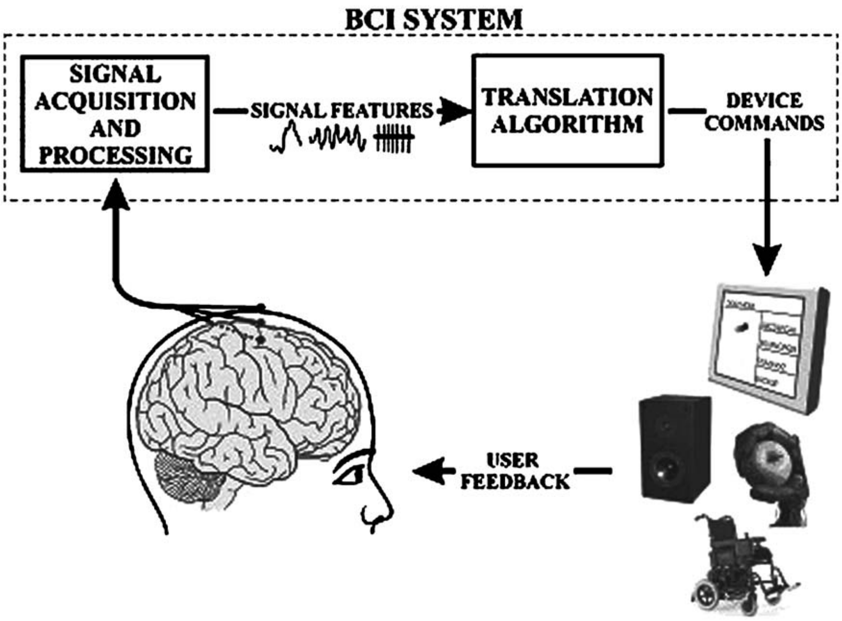

Fig. 1. Basic BCI system. Signals are acquired from the user's brain; features are extracted and translated into device commands.

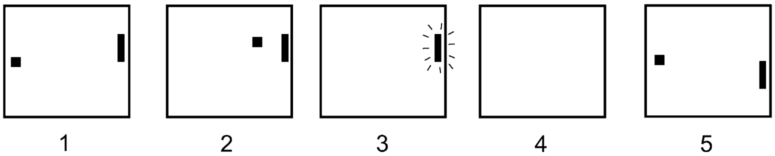

Fig. 2. One-dimensional trial structure. (1) The target and cursor are present on the screen for 1 s. (2) The cursor moves steadily across the screen for 2 s with its vertical movement controlled by the user. (3) The target flashes for 1.5 s when it is hit by the cursor. If the cursor misses the target, the screen is blank for 1.5 s. (4) The screen is blank for a 1-s interval. (5) The next trial begins.

cursor on the left edge (Fig. 2). The cursor moves across the screen at a steady rate, with its vertical movement controlled by EEG amplitude in a specific frequency band at one or several scalp locations. The user's task is to move the cursor to the height of the target so that it hits the target when it reaches the right edge of the screen. At present, cursor movement is typically controlled either by the amplitude of mu-rhythm activity — which is 8–12-Hz activity focused over sensorimotor cortex — or by the amplitude of higher frequency (e.g., 18–25 Hz) beta-rhythm activity, also focused over sensorimotor cortex.

Effective BCI operation has several requirements. First, the user must learn to control the EEG feature, such as mu-rhythm amplitude, that determines cursor movement. Second, signal processing must extract the EEG feature from background noise. For example, we use spatial filtering operations that improve the signal-to-noise ratio (McFarland et al., 1997b). Third, the system must translate these features into appropriate cursor movement that the user can freely and accurately control, with equal accessibility to all targets. In our system, each dimension of cursor movement is a linear function of mu-rhythm amplitude. This linear function has two parameters: an intercept and a slope. We use an adaptive algorithm to select values for these parameters that make all the targets equally accessible to the user (McFarland et al., 1997a; Ramoser et al., 1997; Wolpaw and McFarland, 2004).

Signal processing

BCI signal processing must occur in real time. This means that signal processing should occur with a minimal deterministic delay. Since our system uses cursor movement in one or several dimensions, feedback to the user becomes an important requirement for optimal performance. With two-target applications, a "ballistic" response is possible. However, with more targets in one dimension (McFarland et al., 2003) or with two-dimensional cursor movement (Wolpaw and McFarland, 2004), corrective movements based on feedback are possible. As a result, feedback should be provided without undue delay. The real-time requirements for signal processing result from the fact that feedback in the form of cursor movement depends upon signal processing.

BCI signal processing can be divided into two parts: feature extraction and feature translation (Wolpaw et al., 2002). The purpose of feature extraction is to obtain EEG signals that are relatively free of noise and that can be controlled by the user. We use spatial filtering and spectral analysis to extract features that characterize the mu or beta rhythm. The purpose of feature translation is to provide optimal control given the available features. We use regression to optimize prediction weights and a form of normalization of the resulting control signals to make targets equally accessible. These four processes (i.e., spatial filtering, spectral analysis, regression, and normalization) are arranged as a series of cascaded operations. Overall, this process is linear with the exception of the step that computes power in the spectral analysis. As such, it might be possible to combine these operations into a single step. However, this would greatly complicate the process of adaptation, since the criteria for each step differ. This is illustrated below.

Feature extraction

Our approach to mu rhythm-based cursor control training involves updating specific channels and spectral bins used in the computation of cursor movement as training progresses. Currently this feature selection process is conducted between sessions based on off-line analysis of data from prior sessions. This process of feature selection could be done online in real time; but we have yet to attempt the implementation of such a process. There are two concerns that make automation of this process difficult. First of all, it is important to ensure that the features used reflect EEG activity and are not the result of artifacts. Second, it is desirable that changes in the features that control cursor movement are not so extreme over a short time period that user performance is disrupted.

Use of spatial filtering follows from the observation that an appropriate spatial filter improves the signal-to-noise ratio (McFarland et al., 1997b). To date, we have used Laplacian and common average spatial filters. Both use fixed weights and do not involve adaptation. Alternative data-driven spatial filters are possible, such as those produced by principal components analysis, independent components analysis, and common spatial patterns. Use of data-driven spatial filters would introduce the possibility of adaptation in this step. To date, we have not done this in real-time experiments.

Use of spectral analysis is based upon the fact that the mu rhythm is a rhythmic signal. Much of our work has involved the use of spectral estimates derived from an autoregressive model. The actual weights for the model terms are estimated from blocks of EEG data, but other parameters such as the model order and data window length remain fixed.

Figure 3 illustrates an empirical analysis of the AR model order and data window length for users in the early stages of training in the one-dimensional cursor control task described previously. This figure shows that the mu rhythm is best modeled with a fairly high model order (i.e., 30 coefficients or more). This empirical result differs considerably from what is typically used in the literature (e.g., McFarland and Wolpaw, 2005; Schlogl et al., 2005). There are many other possible ways of performing spectral analysis. For example in our initial work, we used FFT-based spectral analysis (Wolpaw et al., 1991). More recently, we have explored the use of a matched-filter approach (Krusienski et al., in press). This approach allows for more accurate characterization of the mu rhythm in terms of phase-coupled alpha and beta components.

Feature translation

The translation algorithm could be based on either a classifier or a regression function. We use a regression function since the regression approach is simpler given multiple targets and it generalizes more readily to different target configurations (McFarland and Wolpaw, 2005).

Figure 4 compares the classification and regression approaches. For the two-target case, both the regression approach and the classification approach require that the parameters of a single function be determined. For the five-target case, the regression approach still requires only a single function when the targets are distributed along a single dimension (e.g., vertical position on the screen). In contrast for the five-target case, the classification approach requires that four functions be parameterized. With even more and variable targets, the advantage of the regression approach becomes more apparent. For example, the positioning of icons in a typical mouse-based graphical user interface would require a bewildering array of classifying functions, while with the regression approach, two dimensions of cursor movement and a button selection serves all cases.

Model adaptation

There are at least three distinct orientations toward BCI training. The first of these, expressed best by the statement "let the machines learn" (Blankertz et al., 2003), views BCI to be mainly a problem of machine learning. This view implicitly sees the user as producing a predictable signal that needs to be discovered. A second view sees BCI as an operant-conditioning paradigm (Birbaumer et al., 2003). This view sees the process as one in which the experimenter, or trainer, encourages the desired output by means of reinforcement. The training process then consists of guiding or leading the user. A third possibility views the user and system as the interaction of two dynamic processes

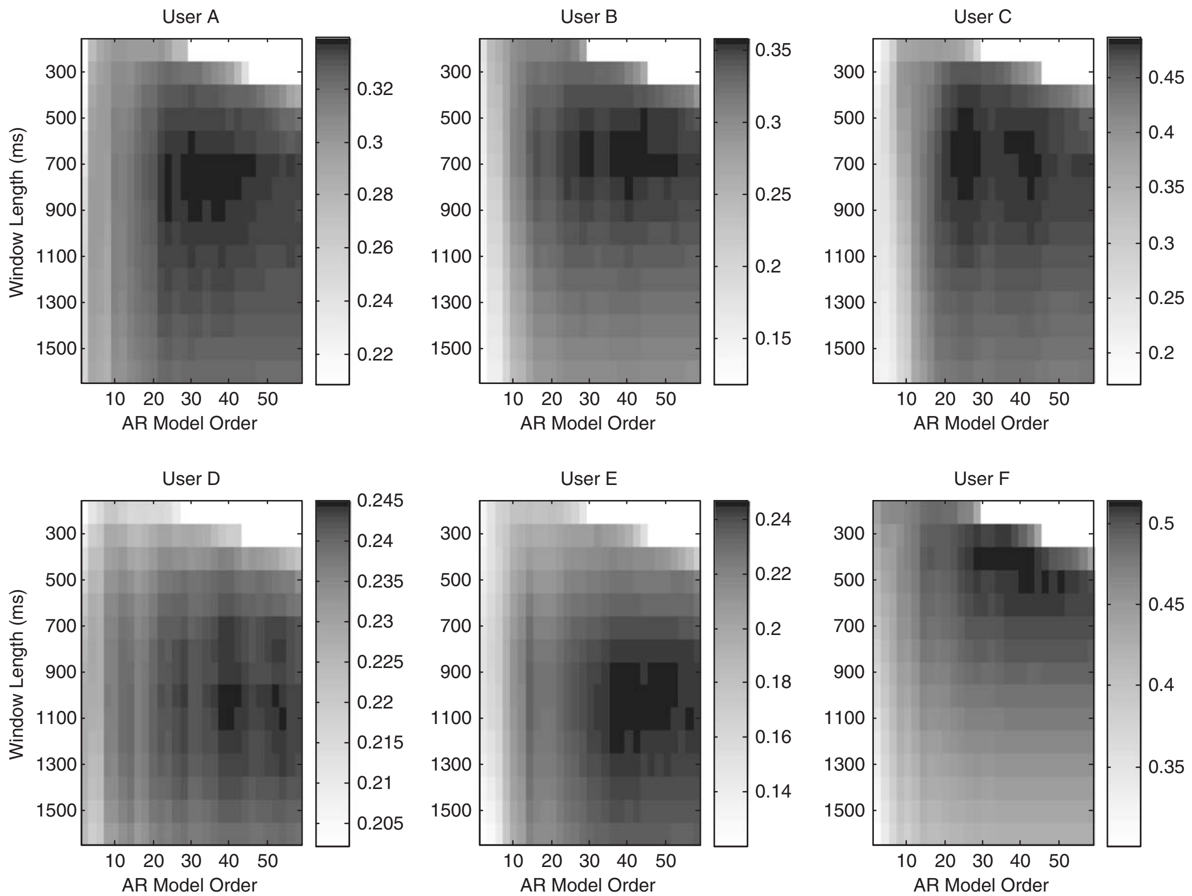

Fig. 3. Parametric offline evaluation of AR model order and window length in six BCI users. Larger r^2 values are darker. Note that model orders >30 and window lengths >500 ms produce the best results in all users.

(Wolpaw et al., 2000; Taylor et al., 2002). By this view, the goal of the BCI system is to vest control in those signal features that the user can best control and optimize the translation of these signals into device control. This optimization facilitates further learning by the user. Figure 5 illustrates these three views of BCI.

We use adaptive estimates of the coefficients in the regression functions. The cursor movement problem is modeled as one of minimizing the squared distance between the cursor and the target for a given dimension of control. For one-dimensional movement we use a single regression function and for two-dimensional movement we use separate functions for horizontal and vertical movements. These functions for vertical and horizontal movements are as follows:

$$\Delta V = b_V(S_V - a_V) \tag{1}$$

$$\Delta H = b_H(S_H - a_H) \tag{2}$$

where S is the control signal (weighted sum of features), a is the estimated mean of the control signal, and b is the gain term that controls the size of the cursor step. The intercept, a, can be expressed as

$$a = c\mu \tag{3}$$

where μ is the mean of the signal and c is a proportion. The slope, b, can be expressed as

$$b = g\sigma \tag{4}$$

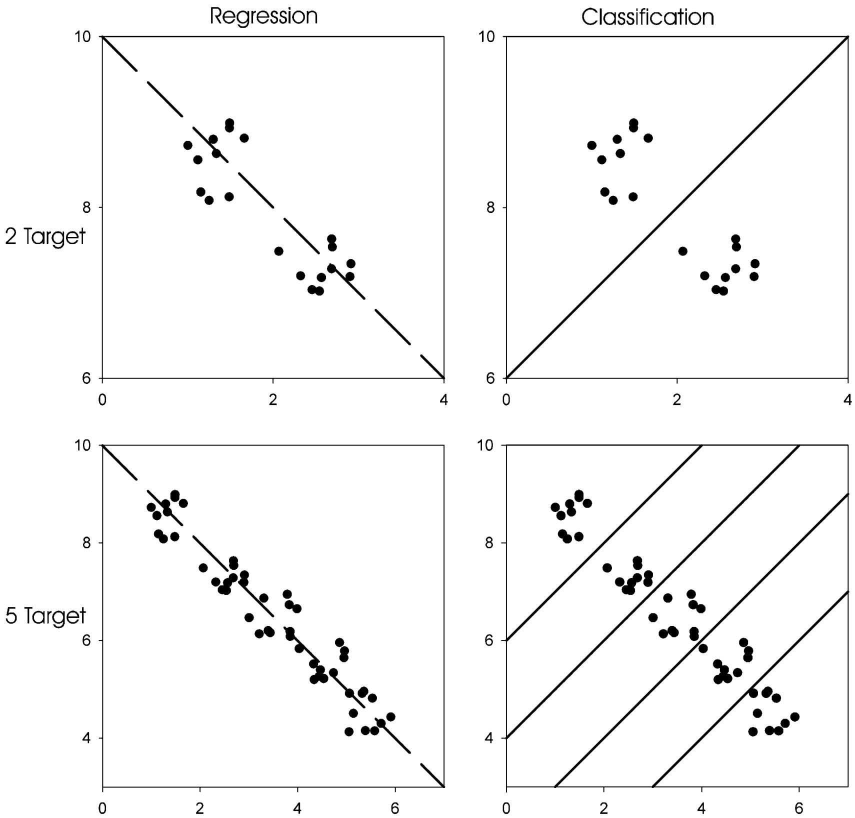

Fig. 4. Comparison of regression and classification algorithms. For the two-target case, both methods require only one function. For the five-target case, the regression approach still requires only a single function, while the classification approach requires four functions.

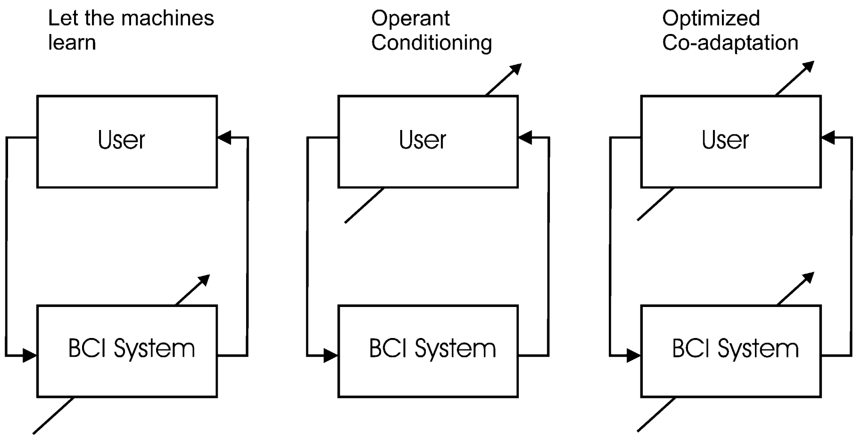

Fig. 5. Three approaches to adaptation in BCI design. The arrows through the user and/or the BCI system indicate which elements are adapted upon with each approach.

where σ is the standard deviation of the signal and g is a proportion. Finally, S can be expressed as

$$S = \Sigma w_i f_i \quad (5)$$

where f_i represents the ith feature and w_i is an associated weight. The expansions in Eqs (3), (4), and (5) provide means to adapt to three distinct aspects of BCI performance. These are summarized in Table 1 and discussed below.

Adaptation of the feature weights allows for optimization of the use of the information in the EEG when more than one feature predicts a given dimension of cursor movement (McFarland and Wolpaw, 2005). In addition, with two-dimensional cursor movement, the adaptive process aids in making the two signals orthogonal. This is so when the two dimensions of the target positions are orthogonal (i.e., the positions along the x- and y-axes are uncorrelated). Thus with adaptation, if the two dimensions of target positions are orthogonal, the two dimensions that predict target position should tend to become orthogonal, although this is not guaranteed.

In our current system we assume that the cursor is in the center of the screen. One alternative possibility is to take the dynamic cursor position into account. This approach could potentially result in more accurate prediction models, but would add an additional element of complexity. Another possibility, used in many invasive animal experiments, is to generate a model for EEG-based movement from functions that predict actual movement (e.g., Chapin et al., 1999; Taylor et al., 2002). This approach requires that the features used by the prediction algorithm correspond to those produced when these specific movements occur. This imposes a restriction on the features that may be used and requires that the user be able to actually move so that the system can be calibrated.

The use of cursor movement and a regression approach introduces certain problems. Optimal use of cursor movement with multiple targets requires that the targets be equally accessible, which in turn requires that biases in cursor movement be eliminated (McFarland and Wolpaw, 2003). This is accomplished, in part, by proper selection of the slope (i.e., b) and intercept (i.e., a) in Eqs (1) and (2) above. It is always necessary to have a proper estimate of the intercept so that the cursor will move in either direction with equal ease. When the distribution of signal voltages is symmetrical and not skewed (e.g., with a Gaussian distribution), it is sufficient to simply use the mean of the signal over some recent period as the estimate of the intercept. However if the distribution of the signal values is skewed, then an additional adjustment is helpful. We do this with an algorithm that cancels any linear trend in the percentage of targets hit across a dimension of movement. Thus, there are two adaptive controllers for estimation of the intercept: one that estimates the mean over a short time period and one that removes the linear trend in the proportion of targets hit over a longer time period. The estimation of the signal mean is computed from a moving average of the signal and represents feedforward control. The value of c, the proportion of the mean actually used as the intercept, is a value that minimizes the quantity l:

$$l_k = \Sigma T_j P_{jk} \quad (6)$$

where T_j is the proportion of hits for the jth target and P_{jk} the position of jth target in the kth dimension, normalized so that $\Sigma P_{jk} = 0$.

For one-dimensional movement with only two targets, the rate of cursor movement does not

Table 1. Summary of adaptive processes in the Wadsworth mu-based BCI

Parameter	Dependency	Method of adaptation	Algorithm
Signal mean	EEG data	Feedforward	Signal statistic
Proportion of signal mean	Pattern of targets hit	Feedback	LMS
Standard deviation	EEG data	Feedforward	Signal statistic
Gain for standard deviation	Pattern of targets hit	Feedback	LMS
Weighted features	Difference between target position and cursor position	Feedback	LMS

appear to be critical and there is no need to adaptively estimate the gain for the system (i.e., b in Eqs (1) and (2)). However with three or more targets in one dimension, or more than one dimension of cursor movement, this factor becomes important (McFarland and Wolpaw, 2003). This process also involves two adaptive controllers for estimation of the slope: one that estimates the standard deviation of the signal over a short time period and another that removes any quadratic trend in the percentage of targets hit across a dimension of movement over a longer time period. The estimation of the signal standard deviation is computed from a moving average of the signal and represents feedforward control. The value of g, the proportion of the standard deviation actually used as the intercept, is a value that minimizes the quantity q:

$$q_k = \Sigma T_j \, abs(P_{jk}) - \Sigma P_{jk}/n \quad (7)$$

where n is the number of targets.

BCI2000 software

As we noted earlier, a BCI system must operate in real time. We use BCI2000 (Schalk et al., 2004) to accomplish the cascaded series of signal processing steps in addition to signal acquisition and presentation of feedback to the user. This allows us to do this processing with the Windows operating system in a timely fashion and to rapidly develop modifications as we refine the system.

Conclusion

There are many ways to design a BCI system. We have focused mainly on a design that uses mu and beta rhythms. This dictates many of the choices we have made, such as the use of spatial and spectral filtering options. In addition, we use regression for the prediction equation and normalization to make targets equally accessible. These steps are arranged in a cascaded fashion that allows each of these components to be adjusted according to independent criteria and in different time frames. They are summarized in Table 1.

As noted earlier, a BCI system operates in real time as a closed-loop system. It involves the interaction of two dynamic systems: the user and the BCI system. Understanding the dynamics of this interaction and optimizing its performance represents a major challenge for BCI research.

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