Chapter 2
Neural Control Interfaces

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Abstract The *control interface* is the primary component of a Brain-Computer Interface (BCI) system that provides user interaction. The control interface supplies cues for performing mental tasks, reports system status and task feedback, and often displays representations of the user's brain signals. Control interfaces play a significant role in determining the usability of a BCI, and some of the traditional human-computer interaction design methods apply. However, the very specialized input methods and display paradigms of a BCI require consideration to create optimal usability for a BCI system. This chapter outlines some of the issues and challenges that make designing control interfaces for BCIs unique.

2.1 Introduction

The *Control Interface* of a Brain-Computer Interface (BCI) system is described in (Mason and Birch 2003) as the component that translates the logical control signals produced by a neural signal classifier into semantic control signals to operate a device. Put more simply, the Control Interface (CI) is the component of the BCI system that the user observes during interaction to perform mental tasks and obtain performance feedback. Control Interfaces serve three main functions:

1. Making the state of the controlled device or application visible with a *Control Display*
2. Making the state of the user's neural signals visible via a *Neural Display*
3. Providing a representation of control tasks for the BCI

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Fig. 2.1 A binary speller
Control Display
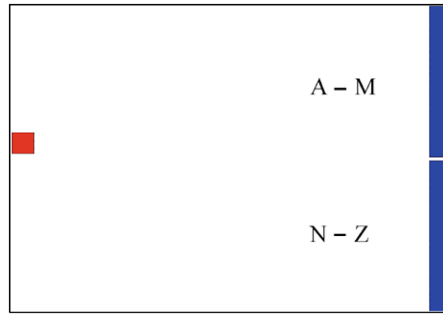
A control display provides visual and/or auditory cues for a control task as well
as performance feedback for a BCI user. Control displays reflect the current state of
the application or the device; for example, in a spelling program the control display
contains the letters available for selection, and typically lists letters already selected.
Figure 2.1 shows a binary speller such as described in Vaughan et al. (2001) and
similar to Perelmouter and Birbaumer (2000). The two target alphabet ranges on
the right side of the screen represent the control task (to select one of the ranges).
The vertical position of the small square represents the normalized instantaneous
amplitude of the targeted brain signal as the "cursor" moves horizontally across the
screen at a constant rate. The selection occurs when the "cursor" reaches one of
the targets, and the chosen target flashes to confirm. This simple control interface
incorporates the control task, the state of the application, and a representation of
neural activity for performance feedback.

This chapter provides an overview of control interface approaches, beginning
with control tasks and their associated control and neural displays. We propose a
classification of control interfaces and the types of information used to improve
usability and performance in BCIs. We discuss traditional models of measuring us-
ability of graphical interfaces and how they can apply in the context of BCI. The
chapter concludes with the implications for designing control interfaces for general-
use BCIs.

2.2 Background-Biofeedback

Control interface research began over a decade ago as biofeedback research; testing
the hypothesis that operant conditioning of autonomic processes could be accom-
plished by providing physiological process information. The motivation for early
biofeedback research was to explore whether displaying real-time physiological
information such as blood pressure and heart rate would be sufficient to condi-
tion physiological processes. Controlling autonomic processes through conditioning
suggested that behavioral therapies could be effective in treating chronic illnesses
such as migraine headaches and hypertension.

While initial experiments showed great promise, validation studies were never
successful, and biofeedback as the sole instrument for therapy was abandoned

(Roberts 1985). Today, BCIs routinely incorporate biofeedback in the form of neural signal representations. This neural biofeedback is essential for BCIs that require a user to learn to alter a particular brain signal (such as increasing the amplitude of motor cortical signals, Wolpaw et al. 2003) or to indicate the relative status of a brain signal (such as with functional Near Infrared based systems (Naito et al. 2007)).

Recent work has shown that biofeedback displays incorporated with BCIs show promise for new rehabilitation therapies. The barrier between autonomic and voluntary responses using respondent and operant conditioning is being challenged in areas like stroke rehabilitation and seizure management (Birbaumer 2006).

2.3 Control Tasks

A *control task* is a mental effort performed by a BCI user to voluntarily produce changes in brain signals. Control tasks take many forms, including imagined or physical movement, object visualization, focused attention, silent singing or counting, or calming thoughts. Control tasks can be divided into two main categories:

1. *Exogenous* (evoked) paradigms—the user focuses attention on a set of stimuli, which produce an autonomic response that can be detected by a BCI, and
2. *Endogenous* (self-generated) paradigms—the user performs a mental task, such as imagined movement or sub-vocal counting, to create changes in brain signals that can be detected by a BCI.

2.3.1 Exogenous Control Task Paradigms

In exogenous or evoked-response control, an external stimulus is required to cause brain signal changes. For example, the P300 response is activated in the parietal region of the brain 300 ms after the presentation of a visual or auditory stimulus (such as flashing the letters of the alphabet). The activation of the P300 response depends on attention, and a user indicates intent by attending to a particular stimulus (target letter) from a set of stimuli (the entire character set). The original interface paradigm for evoked responses that is still dominant in P300-based BCIs today is the Farwell and Donchin matrix for spelling (Farwell and Donchin 1988). The Farwell-Donchin BCI presents a user with an alphabet arranged in a square matrix. The system evokes a P300 response by randomly highlighting rows and columns of the matrix while measuring parietal responses. The user focuses attention on the desired letter, and each time the row or column containing that letter flashes, the P300 response occurs. At the end of a number of flashes, the intersection of the row and column in the matrix with the highest P300 response will indicate the desired target. P300-based BCI accuracies can reach 100% and many research groups have explored the nuances of optimally presenting stimuli (Allison and Pineda 2006;

Sellers and Donchin 2006). Current research in processing P300 aims to recognize single-trial P300 responses to decrease selection time (Salvaris and Sepulveda 2009; Solis-Escalante et al. 2006).

Another evoked-response approach for BCIs is Steady-state evoked potentials (SSVEPs). The SSVEP response is measured over visual cortex in response to steadily flashing stimuli. For example, an SSVEP control interface might consist of two checkerboxes displayed on a computer screen, one flashing at 10 Hz (representing the response "yes") and one flashing at 15 Hz (representing the response "no"). The user focuses attention on the checkerbox representing the desired response, and the corresponding oscillation can be detected in visual cortex. If the user attends to the 10 Hz checkerbox, after a number of samples the BCI will recognize the 10 Hz oscillations in visual cortex and choose the response "yes". Control interfaces using steady-state evoked potentials benefit from more differentiable states than the P300 response (Allison and Moore Jackson 2005; Bin et al. 2009) and have been applied to interfaces requiring multiple degrees of freedom such as gaming (Lalor et al. 2005; Moore Jackson et al. 2009).

Exogenous systems typically do not need to display any biofeedback; they typically only report task performance (i.e. the control outcome or selection itself). Sensory responses are autonomic, and therefore operant conditioning does not improve performance. Learned effects in exogenous control interfaces are usually a result of experience with the interface itself rather than a modulation of the observed response potentials.

2.3.2 Endogenous Control Task Paradigms

In an endogenous control interface, the user voluntarily performs a mental task that activates a particular part of the brain, such as silently singing or imagining hand movements. Endogenous responses do not require a stimulus, although prompts and cues may be used to improve response characteristics. Users can learn to improve brain signal responses; conditioning these voluntary responses is accomplished with biofeedback mechanisms.

Two of the first and most thoroughly studied endogenous control interface paradigms are Slow Cortical Potentials (SCPs) (Birbaumer 2006) and the mu-rhythm response (Wolpaw et al. 2003). These endogenous BCIs are based on voluntary, conditioned responses from users. SCP-based systems rely on operant conditioning to train users to shift the polarity (positive or negative) of their SCPs. Mu-based systems operate on actual or imagined movement reflected in the motor cortex; a mu-based BCI system measures the amplitude of the mu-band signal to effect control. Both SCP based and Mu-rhythm based BCIs have been demonstrated for cursor control and target selection (Birbaumer 2006; Schalk et al. 2008; Wolpaw et al. 2003). SCP and Mu-based BCIs are often used for target selection, such as spelling. In visual target acquisition tasks, the position of a pointer or cursor is manipulated using the endogenous input (such as a user imagining hand movement). The "right justified box" (RJB) task illustrated in Fig. 2.1 is a well-studied

paradigm of target acquisition control used both for screening and testing (Schalk et al. 2004). In the one-dimensional case, the cursor moves across the screen at a constant rate of speed. Target areas are discretized regions of the right edge of the screen, each representing a selection alternative. The BCI user either performs or imagines movements such as finger tapping, which influences the y-position (height) of the cursor on the screen. The trial concludes when the cursor reaches the end of the screen, completing the selection based on the y-position of the cursor. Several manipulations of the task are regularly used in research. A similar paradigm allows selection in two and three dimensions, employing different imagined movement tasks. The size and number of targets can be manipulated as well. The effectiveness of the selection interface is also influenced by the relative sizes of the cursor and the targets, where Fitts's law appears to predict task performance (Felton et al. 2009). In the one-dimensional case, performance is affected by the rate of motion in the fixed x-direction as well as the target and cursor size. In the two-dimensional case, accuracy is determined by target and cursor size.

The mental task for indicating intent can also be varied. In a mu-rhythm motor imagery control setting, users may be instructed to imagine left hand movement to move the cursor left and right hand movement to move the cursor right. There are several aspects of an endogenous control interface that influence performance. Target regions may be placed in the middle of the screen, and the task is to maintain a cursor within a target for a predetermined time interval to indicate selection (a *dwell* task). The design of these interfaces has significant impact on performance (Felton et al. 2009). In the RJB task, the cursor moves across the screen; when the cursor reaches the end of the screen, the position of the cursor indicates the selection. The relative size of the destination regions affects the performance: smaller objective regions reduce overall performance but can provide higher confidence in ascertaining user intent.

Biofeedback plays a large role in shaping response performance in endogenous control interfaces. Operant conditioning of these responses determines performance accuracy for voluntary responses, and biofeedback positively affects training time. Feedback in these cases consists of performance information, task-related neural activity, and a reinforcement signal. Behavioral theory predicts the optimal schedule of reinforcement signals for training to improve task performance.

2.4 Cognitive Models of Interaction

How can we quantify the usability of a BCI? For graphical interfaces, cognitive models offer a means of assessing and predicting usability. Cognitive models predict the difficulty of interaction tasks by decomposing an interaction task into cognitive process components. For graphical interface interactions, component cognitive processes are measured in terms of response time. These components are well studied; their individual response times have relatively low between-subject variance, and therefore the sum of components represents total interaction response time and serves as a predictor for interaction difficulty where higher response time

is positively correlated with task difficulty. Several task decomposition approaches exist today: the Human Information Processor (Card et al. 1986), activity theory (Nardi 1996), situated cognition (Clancey 1997), and goals, operators, methods, selection (GOMS) (John and Kieras 1996). While there is considerable empirical evidence for these approaches in traditional mouse-and-keyboard interaction assessment, there has been little validation of these methods in brain-computer interfaces. Perhaps the largest barrier to applying these methods to interface assessment is finding representations of component cognitive tasks in the sensing modality of the interface.

Consider the human information processor model of interaction, where the model of the brain is conceptually a collection of independent, task-specialized processors: cognitive, perceptual, and motor. These processors receive information from the visual image, working memory and long-term memory stores as they execute tasks. For example, the perceptual processor uses the visual image, which is information obtained from the visual sensory system. During task execution, processors access information from the information sources. Each processor has a cycle time and information stores each have a decay time. In the context of this model, BCIs directly measure these processors, so the task decomposition should provide predictions about the measurable differences in how these processors handle information. The problem with this model is that these processors are task-defined; a functional definition is required in terms of a BCI sensing modality. Anatomically, these processors represent integrations of disparate brain regions and therefore represent too coarse a model for BCI.

The GOMS model of interaction uses Goals, Operators, Methods and Selection to derive a response-time based representation of usability. In this method, the response times of tasks are gathered from population studies of activities. For instance, typing is a skill where the mean time to press a key depends on the relative skill level of the typist, and there is large variance between groups. "Typing" with a BCI may require a series of tasks, such as a binary selection, which could take up to five steps. The GOMS method represents too coarse of a level of model with respect to BCI, and therefore has little predictive power in the context of BCI usability.

2.5 Interaction Task Frameworks

A classic approach to classifying interaction tasks is rooted in differentiating the interaction tasks themselves. For graphical interfaces, Foley groups graphical interactions into basic interaction tasks and compound interaction tasks (Foley and Van Dam 1982). The basic interaction tasks are selection, text, quantify, and position. For graphical interfaces, these represent the set of possible actions a user can make with traditional input devices such as mice and keyboards.

2.5.1 Selection

Selection represents discrete choices from a set of possibilities. Typically, these possibilities are grouped and presented simultaneously, and the user interacts with the interface to select one of the finite set. In BCIs, selection is the most ubiquitous interaction task; selection is often employed to implement the other three interaction tasks. The most basic control tasks are the *binary selection*, which is a choice between one of two alternatives, and *n-ary selection*, a choice from several alternatives. In BCIs there are two common control tasks for binary selection. The first takes advantage of two spatially separate mental tasks causing differentiable activity in the brain. The second measures the activity level over one area of the brain, such as motor cortex, which can be increased and decreased with motor imagery. The second method can also be used for n-ary selection.

In the first approach, one of the mental tasks evokes brain activity in a target region of observation; the other task evokes activity in a spatially separate region, where the second task does not overlap activity with the first. A typical example of this design is language production versus mental rotation. Language production, while evoking activity in many cortical regions, is best measured over Broca's area (usually near the left temple). This activation pattern is contrasted with mental rotation, best measured over the parietal region on the top of the head. Users perform a sequence of these two tasks to indicate yes/no decisions. To indicate a positive response, the user performs a language production task such as sub-vocal counting or silently singing. To indicate a negative response, the user envisions a shape such as a Rubik's cube rotating in space. Each of these tasks is performed for a fixed time interval, sufficient to capture the activation patterns of the two tasks given the sensing modality. Typically, first order properties of the activation signals are used to determine which pattern is executed, and therefore which response the user makes.

There are several drawbacks to the binary selection method. First, the binary nature of the response sequence does not scale to more sophisticated communication. A user may indicate a number of symbols with these alternating sequences, but longer sequences are required to indicate intent. The symbol set must also have an ordering so that it can be predictably divided (a set of icons for, say, web browser controls would not work well in a binary selection interface). The fixed task time intervals themselves limit the speed with which a user may generate a symbol. These simple interfaces are often used with single channel sensor arrays.

N-ary selection can be implemented by measuring the amplitude of a signal (such as the mu signal generated by movement imagery), discretizing the signal with a number of progressive thresholds. This approach requires the user to be much more accurate with signal production, and relies heavily on biofeedback. However, the increased efficiency of selection makes this method more appealing than binary selection (Schalk et al. 2008).

Selections with evoked response BCIs such as P300 and SSVEP are similar to selections on a touch screen; by definition they require one selection step and therefore are more efficient than endogenous-response systems. Another advantage is that the entire selection space is displayed at once; no ordering is required as in binary selections.

2.5.2 Text and Quantify

Text and quantify in a BCI are both subsets of selection, where each alphanumeric character entered is a discrete choice of the character set represented on the input device. For graphical interfaces, typically the keyboard is the input device used to enter text or numeric values. Graphical controls for quantification are typically dials or sliders and often augmented with selection and text controls. Because there is no "typing" with a BCI, the methods for selection described above are employed to enter selections from an alphanumeric character set to implement text entry and quantify tasks.

2.5.3 Position

Position in a graphical interface means to move a cursor to a desired position. Position is used to implement drawing and other continuous (non-selection) tasks. In BCI systems, the position task could translate to more esoteric tasks, such as driving a wheelchair. The position interaction task for BCIs has not been fully explored. Although arguments can be made that evoked-response systems selection mechanism such as a Farwell-Donchin matrix indicates a position on a screen, the P300 paradigm cannot be used for drawing. The SSVEP response has been incorporated into a continuous-control BCI for a gaming environment (Moore Jackson et al. 2009) where the user positions an avatar by focusing attention on flashing stimuli in the desired direction of movement. A simple drawing system based on functional Near Infrared (fNIR) imaging provided positional control in a letter-drawing study (Mappus et al. 2009). More exploration of this control task for BCIs is needed to implement position requirements for creative expression and navigation.

2.6 Dialog Initiative

In user interface design, the *dialog initiative* determines whether the system initiates a control interaction, or the user does. Most command-line systems are system-initiated (the system prompts the user for a response); most graphical user interfaces are user-initiated (the user clicks on an icon to open an application). BCI systems have an additional issue: the brain generates signals constantly, such as the mu rhythm, and therefore a BCI system must know when the user intends to control the system. This issue is known as the "Midas touch problem"; as with King Midas, who turned everything to gold on his touch, BCIs interpret all brain signals in a specified domain as user intent. The ability to turn off neural input when the user does not wish to interact is a primary challenge in the field of BCI research.

In order to address this challenge, the BCI field makes a distinction between *synchronous* and *asynchronous* interaction. This differentiates systems that allow

interaction in consistent, fixed time windows and those that are "interrupt driven" (initiated by the user). The distinction parallels the distinctions between exogenous and endogenous inputs.

2.6.1 Synchronous Interfaces

A *synchronous* interface allows interactions only in fixed time windows determined by the BCI system (system initiation). Exogenous control interfaces fit well in synchronous paradigms; evoking activity from a stimulus implies that the stimulus onset time is known and correlated with brain activity. Most BCI systems using evoked responses rely on this correlation, implementing synchronous paradigms where the stimulus onset times and display durations are fixed. This is not always the case for evoked responses, as animated stimuli can be displayed continuously and by attending to the animation the user evokes a response. Endogenous inputs may also be used in synchronous paradigms where precise event correlation is not needed. For example, the RJB paradigm requires the user to perform a mental task within a time window in order to make a selection, although the mu response is endogenous. Heuristically, synchronized interfaces are best suited for interactions involving selection; where a discrete choice from a set of possibilities is made within a time frame.

2.6.2 Asynchronous Interfaces

An *asynchronous* interface does not impose time windows for interaction; the user performs a mental task that initiates the interaction (user-initiation). Endogenous inputs fit well in asynchronous paradigms, where self-paced interaction is needed. In these cases, endogenous inputs with high recognition rates are critical. The mental task must be unique enough that it is unlikely to be detected by the BCI accidentally (such as imagining a rotating Rubik's cube). Mental tasks such as language production are poor for asynchronous control because of the likelihood of language processing evoked by the environment. Asynchronous paradigms are showing promise in general-purpose problems (Mason et al. 2006). Research focusing on BCI in the wild relies on asynchronous interaction; initiating and concluding interaction as well as eliminating "false positive" errors are essential for acceptable use.

2.6.3 User Autonomy

One barrier to adoption of BCI in general-use situations has to do with autonomy; for the user, this means when and at what rate to interact with the system.

In a setting where a sensor array is constantly sampling brain state and there is no fixed time course of interaction, the BCI must be able to differentiate intentful interaction from no interaction. Asynchronous interfaces address the problem of variable periods of inactivity during an interaction session (Borisoff et al. 2006; Scherer et al. 2008). Asynchronous interfaces improve BCI autonomy; as more sophisticated applications are adapted to BCI usage constraints and as BCI developers target more assistive technology settings, asynchronous interfacing becomes higher demand (Scherer et al. 2007).

Synchronous interfaces do not necessarily address the issue of indicating the beginning of interaction (i.e. turning on the system to begin with) or indicating the end of an interactive session. Two primary means of addressing this problem are using additional sensing channels and orthogonal mental tasks to recognize initiation and termination sequences of activity. Additional channels of interaction directly address asynchronous activity, but add complexity to the sensing system as well as cognitive load to the user. Work with asynchronous interfaces focuses on recognizing patterns of activity designated as initiation and termination sequences (Mason and Birch 2000).

Both cases improve autonomy; however, there is growing evidence from usability surveys and studies that these asynchronous switches must be accurate to be useful; users will not tolerate more than one false positive over several hours and will not use a system that makes it difficult to initiate interactions (high false negative rate) (Mason et al. 2006; Millán and Mouriño 2003; Scherer et al. 2007, 2008).

2.7 Improving BCI Control Interface Usability

Control interface design can be a critical factor in increasing the throughput of BCIs (Van Gerven et al. 2009). In a character selection task, character layout in conjunction with auto-completion and spell checking improves accuracy and lowers the key selection count for words (Felton et al. 2007). In target acquisition, relative area of cursor and target as well as rates of motion all affect task performance, particularly in dwell selection cases (McFarland et al. 2003).

McFarland and Wolpaw studied considerations between speed and accuracy tradeoffs in BCIs (McFarland and Wolpaw 2003). In this study, five participants manipulated a cursor in one- or two-dimensions. Target locations were one of four boxes arranged in a horizontal line. The task was to manipulate the cursor to the target box (bold outlined, while other boxes were light gray outlined) and dwell within the target for a fixed amount of time. The results of the study indicate performance in terms of achieving target locations is optimal when the distribution of target box selections is uniform.

Adaptive interfaces represent a novel approach to addressing BCI system throughput (Shenoy et al. 2006). By adaptively learning users' response characteristics, the BCI is able to better maintain a high level of performance accuracy. The drawback of adaptive systems is that they require repeated calibration sessions with a guided task, because in order to automatically "tune" the BCI system, perfect knowledge of the user's intent is required.

2.7.1 User Training

A subject-specific factor that affects user performance is the type and amount of training they receive (McFarland et al. 2005). The training process serves two purposes; first to make users aware of the interface dynamics and introduce them to the control paradigm, second to provide sufficient training data for a supervised learning method to classify input with sufficient accuracy to be a responsive interface for users. Conditioning in asynchronous, endogenous interfaces has a positive effect on enhancing generative responses. Finally, a converging set of evidence seems to indicate that directed conditioning affects synaptic plasticity in certain tasks and under certain neural conditions. The results of this work are challenging previous notions of the separation between operant and respondent conditioning. Achtman et al. presents usability results for Electrocorticographic (ECoG) data in an asynchronous task (Achtman et al. 2007). BCI applications in stroke rehabilitation show that BCI training produces lasting changes in neural responses where functionality is limited (Daly and Wolpaw 2008). In these cases the interface links brain activity with robotic control that serves as an assistive trainer for rehabilitation.

2.8 Conclusions

Control interfaces are a critical area of research in order for BCIs to be viable as general-purpose interaction methods. Studies have shown that the design and organization of a BCI control interface can significantly impact the usability of a BCI system. Many of the traditional design paradigms for interactive graphical systems have relevance to BCI control interfaces; however BCIs have additional unique challenges that make their control interfaces difficult to design. More studies are needed to solidify methods of user initiation for BCI interaction, and to solve the "Midas Touch" problem. More accurate classifiers are needed to improve selection accuracy. The area of continuous control needs much more work in order for BCIs to implement applications such as drawing or driving a vehicle. BCI control interfaces are even projected to impact rehabilitation by directing neural plasticity to "re-wire" the brain. BCIs have significantly improved the quality of life for people with severe physical disabilities by allowing them to communicate and control their environments. BCIs also have great potential as the ultimate hands-free control interface for mainstream applications. Although the BCI field has enjoyed dramatic progress in the last two decades, there is great promise and much work to be accomplished in the future as we strive to perfect our interaction methods through control interface research.

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