Handbook of Clinical Neurology, Vol. 110 (3rd series)
Neurological Rehabilitation
M.P. Barnes and D.C. Good, Editors

Chapter 6

Brain–computer interfaces

JONATHAN R. WOLPAW*

Wadsworth Center, Laboratory of Neural Injury and Repair, New York State Department of Health and State University of New York, Albany, NY, USA

INTRODUCTION

Direct communication from the brain to computers or robots has long been a subject of speculation. In the past several decades, this possibility has evolved into one of the fastest growing areas of neuroscience research and development. Brain−computer interfaces (BCIs) (also called brain−machine interfaces, BMIs) allow their users to communicate or to control devices without using the brain's normal output channels of peripheral nerves and muscles. A BCI recognizes the user's intent by analyzing in real-time electrophysiological or other measures of brain activity. As illustrated in Fig. 6.1, electrical signals may be recorded by electrodes on the scalp (as EEG), on the cortical surface (as electrocorticographic activity, ECoG), or within the brain (as neuronal action potentials or local field potentials, LFPs). Other measures may be recorded by magnetic sensors or other devices. These measures are translated in real-time into commands that accomplish the user's intentions. The archetypal example is BCI control of a computer cursor by scalp-recorded EEG. This chapter provides a succinct overview of BCI research and development. A comprehensive, detailed, and didactic treatment of all aspects of BCI research and development is available (Wolpaw and Wolpaw, 2012a).

Less than 20 years ago, there were only three or four BCI research groups in the world. At present, there are more than 500, and the number continues to rise rapidly. More than half of the peer-reviewed BCI research articles have been published in the past 5 years. This explosive growth is due mainly to four factors. The first is greater appreciation of the needs and abilities of those paralyzed by cerebral palsy, spinal cord injury, brainstem stroke, amyotrophic lateral sclerosis (ALS), muscular dystrophies, and other chronic neuromuscular disorders. Life-support technology such as home ventilators now enables even those most severely disabled to live for many years. In addition, it is now apparent that even those with little or no voluntary muscle control, who may be essentially "locked-in" to their bodies, deprived of the ability to communicate, can lead lives that are enjoyable and productive if they can be provided with even the most basic communication capacity (e.g., Robbins et al., 2001). The second factor is the greater understanding of the origins and functional correlates of EEG and other brain signals that has come from animal and human research, and the greatly improved methods for recording and analyzing these signals. The third factor is the ready availability of powerful inexpensive computer hardware capable of the complex real-time signal analyses required by BCIs. Until quite recently, much of the essential hardware either did not exist or was prohibitively expensive. The fourth factor responsible for the rapid growth in BCI research is new recognition of the nervous system's remarkable adaptive capacities, both in normal life and in response to disease or trauma. This recognition has engendered tremendous enthusiasm for the possibility of using BCIs to create novel interactions between the brain and computer-based devices. Such interactions might replace neuromuscular functions lost to injury or disease, or might help to guide plasticity that maximizes the function of remaining neural structures and pathways.

THE DEFINITION OF A BRAIN–COMPUTER INTERFACE

According to current understanding, the function of the CNS is to respond to external or internal events by producing outputs that serve the organism. The natural CNS outputs are neuromuscular or hormonal. A BCI gives the

*Correspondence: Jonathan R. Wolpaw, M.D., Wadsworth Center, New York State Department of Health, P.O. Box 509, Empire State Plaza, Albany, NY 12201-0509, USA. Tel: +1-518-473-3631, Fax: +1-518-486-4910, E-mail: wolpaw@wadsworth.org

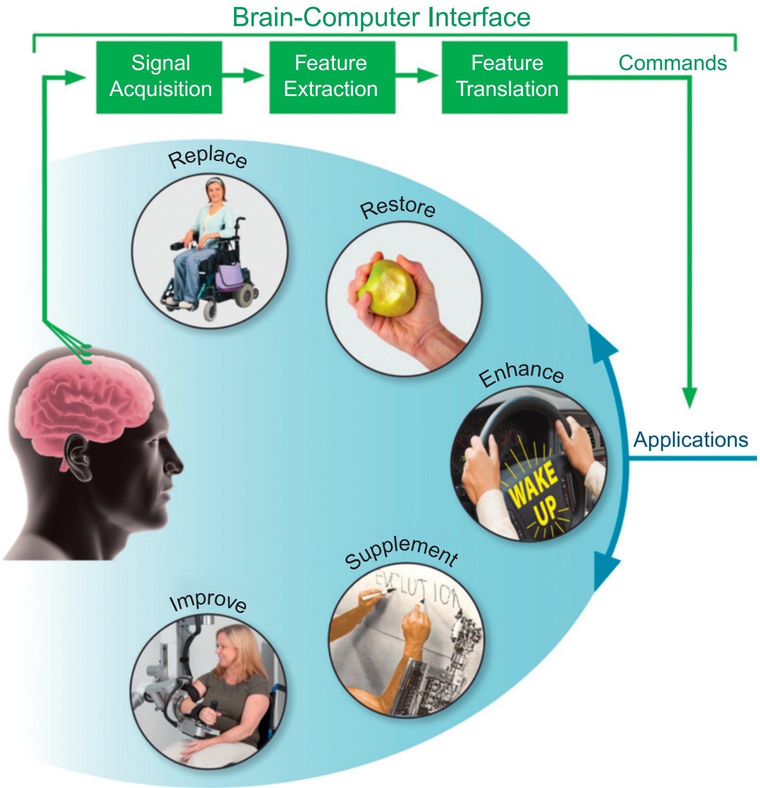

Fig. 6.1. Basic design and operation of a brain–computer interface (BCI) system. Signals reflecting brain activity are recorded from the scalp, the cortical surface, or within the brain. They are analyzed to measure signal features (e.g., amplitudes of EEG rhythms or firing rates of individual neurons) that reflect the user's intent or other aspects of current brain function (e.g., state of alertness). The features are translated into commands that control applications that replace, restore, enhance, supplement, or improve natural CNS outputs. (From Wolpaw and Wolpaw, 2012b.)

CNS new output that is neither neuromuscular nor hormonal. A BCI can be defined as "a system that measures CNS activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment" (Wolpaw and Wolpaw, 2012b).

A BCI creates a real-time interaction between its user and the world. The user receives feedback as to the results of the BCI's output, and that feedback may influence the user's intention and the brain signals that encode that intention. For example, if the BCI controls the movements of a cursor on a screen, the cursor's location after each movement influences the user's intention for the next movement and the brain signals that encode it. (Thus, a system that simply records and analyzes brain signals, without providing the results of analysis to the user in real-time, is not a BCI.) Figure 6.1 illustrates the basic design and possible applications of any BCI (see Wolpaw and Wolpaw (2012b) for full discussion).

BCIs are frequently seen as "mind-reading" or "wire-tapping" technology, systems that listen in on the brain, determine its intent, and then accomplish that intent. This misconception ignores a key feature of the brain's interactions with the world. The actions that achieve a person's intention, whether to walk across a room, speak certain words, or play a specific piece on the piano, are mastered and maintained by continual adaptive changes in brain function. During development and throughout subsequent life, neurons and synapses change continually to acquire new skills and to preserve those already acquired. Such adaptive plasticity, which is responsible for standard skills such as walking and talking and more esoteric skills such as ballet, is guided by the outcomes that are produced. Thus, for example, as body size, strength, and weight change throughout life, the nervous system continually modifies its outputs so as to preserve motor skills.

This need for initial and continuing adaptation is present whether a person's intent is accomplished normally, that is, by muscles, or through a BCI, which uses brain signals instead of muscles. BCI operation depends on the interaction of two adaptive controllers: the user, who must produce brain signals that encode intent, and the BCI, which must translate these signals into commands that achieve the user's intent (e.g., Wolpaw et al., 2002; Rossini, 2009; Sanchez et al., 2009). As a result, BCI usage is basically a skill that user and system together acquire and maintain. The user encodes intent in signal features that the BCI can measure; and the BCI measures these features and translates them into output commands. This ongoing dependence on the mutual adaptation of user to BCI and BCI to user is a fundamental principle of BCI operation, and its management is one of the main challenges of BCI development.

THE BRAIN SIGNALS USED IN BCIs

A variety of technologies measure brain activity. These include EEG, ECoG, intracortical recording, magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared (fNIR) imaging, and positron emission tomography (PET). However, MEG, fMRI, and PET are at present not suited for everyday use due to their technical demands, expense, and/or limited real-time capacities. Only electrical field recording and possibly fNIR imaging are likely to be practical for BCI applications in the foreseeable future.

Each electrical recording method has advantages and disadvantages. EEG is easy and non-invasive, but has limited topographical resolution and frequency range, and may be obscured by electromyographic (EMG) activity from head muscles or other artifacts. ECoG has better topographical resolution and frequency range, but requires that electrode arrays be implanted on the cortical surface. Recording within the cortex (or other brain areas) provides signals with the highest resolution, but requires that multielectrode arrays be inserted in brain tissue, and faces unresolved issues concerning tissue damage and scarring and long-term recording stability.

The practical value of each of these methods depends on the BCI applications it can support and on the degree to which its disadvantages can be reduced. The issue of the relative value of noninvasive (EEG) methods, moderately invasive (ECoG) methods, and most invasive (intracortical) methods remains unresolved. Practical, stable, and safe methods for long-term recording within brain tissue may prove relatively easy to develop. On the other hand, the BCI capacities of intracortical recording may turn out to be no greater than those of ECoG, or even EEG (Wolpaw, 2010). It is very possible that different methods will prove best for different applications and/or for different users. Careful and comprehensive studies of the characteristics and capacities of each method are needed to resolve these questions.

CURRENT BCIs

Human BCI studies to date have been mainly EEG-based. Several short-term ECoG studies have been published, as have a few reports of data obtained from a small number of people implanted with intracortical microelectrode arrays. Most intracortical BCI studies have been in animals, primarily monkeys. EEG-based BCIs can clearly support simple applications and may be able to support more complex ones. Invasive methods could probably support complex applications; however, issues of risk and long-term performance remain to be resolved.

Several types of EEG-based BCI have been tested in humans. They are distinguished by the specific EEG features from which they derive the user's intent. Figure 6.2A (top) shows a BCI that uses the P300 component of the event-related brain potential (Farwell and Donchin, 1988). This component appears in the EEG over central areas about 300 ms after a stimulus that has special significance. Almost all P300-based BCIs described to date use visual stimuli. In a typical design, letters, numbers, or other possible choices are presented in a matrix, and the rows and columns of the matrix flash rapidly in succession. Only the row and column that include the item the user wants to select elicit P300 potentials. By recognizing these P300 potentials, the BCI determines what item the user wants to select. P300-based BCIs can, for example, operate a simple word-processing program that enables users to communicate up to several words/minute. Improvements in analysis and other aspects of the system might substantially augment this rate.

Figure 6.2A (bottom) shows a BCI that uses EEG sensorimotor rhythms (SMRs) (e.g., Wolpaw et al., 1991; Pfurtscheller et al., 2006). SMRs are 8–12 Hz (mu) and 18–26 Hz (beta) oscillations recorded from the scalp over sensorimotor cortices. Changes in mu and beta rhythm amplitudes typically accompany movement and sensation, and motor imagery as well. Studies indicate that people can learn to control mu or beta rhythm amplitudes in the absence of movement or sensation, and can use this control to move a cursor to select items on a screen or to operate an orthotic device. One-, two-, and three-dimensional cursor control are achievable (e.g., Wolpaw and McFarland, 2004; McFarland et al., 2010; Doud et al., 2011). SMR BCIs, like P300 BCIs, can support word-processing or other basic applications. In addition, they might also enable multidimensional control of a neuroprosthesis, a robotic arm, or other device.

Current BCIs rely mainly on visual stimuli and visual feedback. However, those who are severely disabled may not have the vision or gaze control necessary for perceiving visual stimuli, particularly when the stimuli change

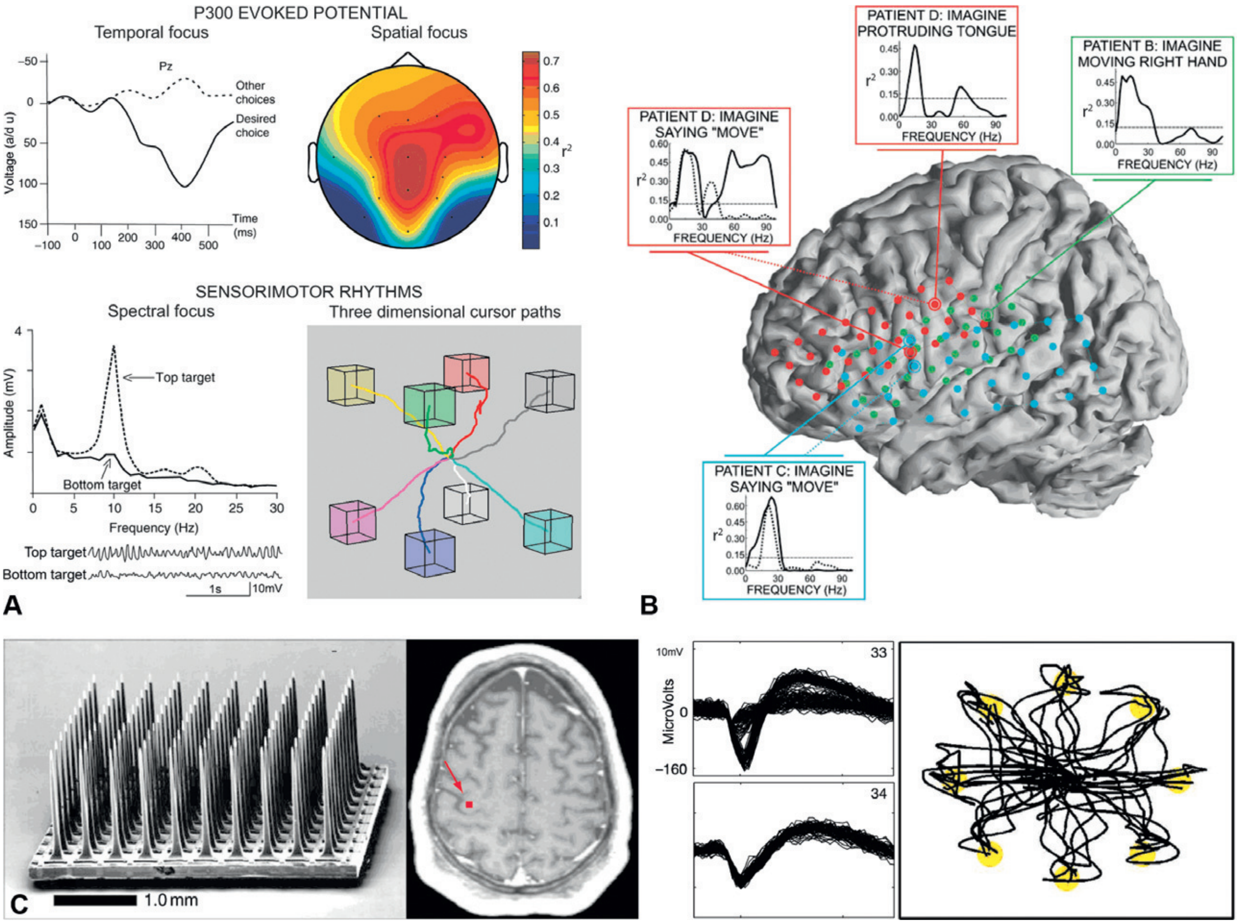

Fig. 6.2. Types of BCI system. (**A**) Two EEG-based BCI systems. Top: P300 evoked potential BCI. A matrix of possible choice appears on a screen. EEG is recorded over centroparietal cortex (location Pz) while these choices flash in rapid succession. Only the choice desired by the user evokes a large P300 potential (i.e., a positive potential about 300 ms after the flash). r^2 is the coefficient of variation; a/d u are the analog-to-digital voltage conversion units. Bottom: sensorimotor rhythm BCI. EEG is recorded over sensorimotor cortex. Users control the amplitudes of one or more 8–12 Hz mu rhythms or 18–26 Hz beta rhythms to move a cursor to a desired target located somewhere on a computer screen. Frequency spectra (top left) for top and bottom targets indicate that this user's control of vertical cursor movement is sharply focused in the mu-rhythm frequency band. Sample EEG traces (bottom left) also show that the mu rhythm is large with the top target and small with the bottom target. Trained users can also control movement in two or three dimensions. (Adapted from Kübler et al., 2001.) Right: a person uses sensorimotor rhythms in scalp-recorded EEG to move a cursor in three dimensions from the center of a virtual cube to targets at the eight different corners. The figure shows the average path of the EEG-controlled cursor to each target. The green and purple targets are in the front corners. (From McFarland et al., 2010.) (**B**) An ECoG-based BCI system. ECoG control of vertical cursor movements using specific motor imagery to move the cursor up and using rest (i.e., no imagery) to move it down. The electrodes used for control are circled, and the spectral correlations of their ECoG with target position (i.e., top or bottom of screen) are shown. The electrode arrays for Patients B, C, and D are green, blue, and red, respectively, and the specific imagined actions used are indicated. The substantial levels of control achieved with different kinds of imagery are evident. (The dashed lines indicate significance at the $P < 0.01$ level.) For Patients C and D, the solid and dotted r^2 spectra correspond to the electrodes indicated by the dotted and solid line locators, respectively. (From Leuthardt et al., 2004.) (**C**) An intracortical BCI system. Left: A 100-microelectrode array for chronic implantation in human motor cortex to record neuronal action potentials and/or local field potentials. Left middle: the arrow points to an electrode array implanted in human motor cortex. Right middle: multiple superimposed neuronal action potentials (spikes) recorded from two microelectrodes (33 and 34) in an array implanted in human motor cortex 90 days earlier. Spikes from two different neurons are evident in electrode 33. Electrode 34 shows spikes from a single neuron. (Last three figures adapted from Hochberg et al., 2006.) Right: a person uses neuronal action potentials (spikes) recorded by an array in motor cortex to move a cursor in two dimensions from the center of the screen to targets at eight different locations, select the target, and then move back to the center. The figure shows the path of the neurally controlled cursor for a continuous series of trials. (Adapted from Kim et al., 2007.)

rapidly. Thus, BCI systems that use auditory stimuli could be valuable, and are under study (e.g., Klobassa et al., 2009).

Figure 6.2B shows a BCI that uses sensorimotor rhythms in ECoG recorded from the cortical surface (e.g., Leuthardt et al., 2004). ECoG signals are much larger than scalp-recorded EEG signals, have higher spatial and temporal resolution, and are less susceptible to contamination by EMG or other nonbrain activity. In addition to mu and beta rhythms, ECoG includes higher-frequency gamma (> 30 Hz) rhythms, which are very small or entirely absent in EEG. With adequate interelectrode spacing, ECoG can resolve activity limited to only a few square millimeters of cortical surface. ECoG studies to date have been limited to short-term experiments in patients temporarily implanted with electrode arrays in preparation for surgery to remove an epileptic focus or other lesion. This work has revealed highly focused ECoG activity associated with movement and sensation and with motor imagery. Furthermore, with a few minutes of training, people can learn to control cursor movement by using motor imagery to produce appropriate ECoG activity.

The speed of this learning, which may be faster than that typically found with sensorimotor rhythms in scalp-recorded EEG, combined with ECoG's superior topographical resolution, broader spectral range, and absence of contamination, suggests that ECoG-based BCIs could support communication and control better than that provided by EEG-based BCIs. Long-term use of ECoG-based BCIs will depend on development of completely implanted systems (i.e., systems that do not have wires passing through the skin) and strong evidence that they function safely and reliably for many years.

Figure 6.2C shows a microelectrode array for intracortical recording and its placement in human motor cortex. Intracortical studies in monkeys and a few humans have shown that neuronal activity recorded by such arrays can control cursor movement in one, two, or even three dimensions (Fig. 6.2C) (e.g., Taylor et al., 2002; Hochberg et al., 2006, 2012). Local field potentials (LFPs) recorded by the same arrays reflect nearby synaptic and neuronal activity and might provide comparable control. In these intracortical neuronal and LFP studies, the typical strategy is to define the neuronal activity associated with standard limb movements, to apply this activity to control comparable cursor movements simultaneously, and finally to establish that the cortical activity alone, in the absence of actual limb movements, can control cursor movements. The correlations between neuronal activity and intended movements change over time, hopefully in a fashion that improves cursor control. Such changes, like those seen with usage of EEG- and ECoG-based BCIs, indicate the need for initial and ongoing adjustments of BCI to user, and of user to BCI.

The main issues that must be resolved prior to widespread clinical use of intracortical BCIs include their long-term safety, the persistence and stability of the signals they record in the face of tissue reactions to the implanted electrodes, the long-term usefulness of these signals, and the degree to which their capacities (e.g., for neuroprosthesis control) substantially exceed those of less invasive BCIs. Indeed, as a comparison of the videos at the first two websites listed below illustrates, in human studies to date, the cursor control provided by a noninvasive EEG-based BCI that uses sensorimotor rhythms is comparable in speed and accuracy to that achieved with intracortical methods.

SIGNAL PROCESSING

BCIs record brain signals and analyze them to determine the outputs desired by the user. This signal processing has two components. The first component is feature extraction, the measurement of those signal features that encode the user's intent. These features can be simple measures such as the amplitudes or latencies of specific evoked potentials (e.g., P300), the amplitudes or frequencies of specific rhythms (e.g., sensorimotor rhythms), or the firing rates of single cortical neurons; or they can be complex measures such as spectral coherences or weighted combinations of simple measures. To function effectively, feature-extraction must focus on features that encode the user's intent, and must measure those features accurately.

The second component of BCI signal processing is a translation algorithm that translates these features into outputs. Features such as rhythm amplitudes or neuronal firing rates are translated into output commands that specify cursor movements, icon selections, or prosthesis operations. Translation algorithms range from simple (e.g., linear equations) to complex (e.g., neural networks, support vector machines).

An effective translation algorithm ensures that the BCI user's range of control of the signal features covers the full range of output commands. Imagine, for example, that the feature is the amplitude of a 10 Hz mu rhythm in the EEG over right sensorimotor cortex, that the user can vary this feature over a range of 1–4 μV, and that the output is vertical cursor movement. In this example, the translation algorithm needs to ensure that the 1–4 μV range allows the user to move the cursor to both the top and bottom edges of the screen, and at a rate appropriate to the speed and maximum duration of the user's mu-rhythm control. In addition, the algorithm needs to adjust for spontaneous changes in the user's control range (i.e., due to fatigue, diurnal variation, or other factors). Furthermore, the translation algorithm should at least adapt to, and preferably encourage, increases in the user's control over the signal features. For example, if the user's control range increases from $1-4\,\mu V$ to $0-6\,\mu V$, the algorithm should use this improvement to increase the speed and/or precision of vertical cursor movement.

The need for ongoing algorithm adjustments that accommodate spontaneous and other changes in the features illustrates the continuing importance of system/user and user/system adaptations, and has major implications. First, it means that promising new algorithms cannot be fully evaluated by offline analyses alone. They also need to be tested online, so that the impact of their ongoing adaptive interactions with the user can be assessed. Both long-term and short-term evaluation is essential, since important adaptive interactions often occur gradually. Second, the need for continual adaptation means that simpler algorithms, for which adaptation is usually easier and more successful, have an advantage. Simple algorithms, such as linear equations, should be replaced by complex algorithms, such as neural networks, only when online as well as offline tests show that the complex algorithms provide better long-term performance without needing frequent time-consuming recalibration routines.

BCI USERS

At their present early level of development, BCIs are likely to be of substantial value mainly for those with very severe neuromuscular disabilities, people for whom conventional assistive communication systems, all of which need some consistent voluntary muscle control, are not suitable options. Included in this group are people with ALS who elect to accept artificial ventilation as their disease progresses, children and adults with severe cerebral palsy who lack any useful muscle control, people with brainstem strokes who are left with only minimal eye movement control, people with severe peripheral neuropathies or muscular dystrophies, and perhaps people with short-term disorders accompanied by extensive paralysis (e.g., Landry–Guillain–Barré syndrome). Those with somewhat less severe disabilities, such as people with high-cervical spinal cord injuries, might also prefer BCIs to conventional assistive communication systems that coopt their residual muscle control (such as systems that use gaze direction or facial muscle EMG). The degree to which BCIs become useful to people with less severe disabilities will hinge on the rapidity and precision of the control the BCIs provide and on their reliability and convenience.

People with different kinds of disability might differ in the BCIs most useful for them. For some, the damage or disease responsible for their disabilities may also impair their ability to control some brain signal features but not others. For example, the cortical pathology that may accompany ALS or subcortical damage in cerebral palsy might impair the generation or voluntary control of sensorimotor rhythms or single-neuron firing rates. In this event, other signal features (such as P300 potentials or neuronal activity in other brain areas) might be viable alternatives. Relevant to this consideration, it is promising that some ability to control sensorimotor rhythms in sensorimotor cortex appears to be retained in people with advanced ALS (Kübler et al., 2005).

Factors that may seem trivial can affect the clinical usefulness of BCI applications. The complexity and convenience of the procedures for donning and doffing electrodes or for initiating BCI operation, or how the user looks when operating the BCI, can affect how likely people are to adopt a BCI system and the extent to which they use it in their lives.

BCI APPLICATIONS

BCIs have a wide range of potential uses, from very basic to very complex. Simple applications have been demonstrated in the laboratory and in limited clinical testing. These include BCIs for answering Yes/No queries, handling environmental control (e.g., temperature, lights), operating a television, or opening and closing a hand orthosis. BCIs can also provide basic word-processing, e-mail capability, or Internet access. Such simple BCI applications can make it possible for people who lack any useful muscle control to lead lives that they find pleasant and productive. In fact, many recent studies show that, with supportive care and the capacity for basic communication, severely paralyzed people can enjoy what they consider to be a reasonable quality of life and are not much more likely to be depressed than those without physical disabilities (e.g., Lule et al., 2009). Thus, simple BCI applications have a viable future in their capacity to improve the lives of those most severely disabled. Indeed, a few such individuals are already using EEG-based BCIs for important purposes in their daily lives (e.g., Sellers et al., 2010).

BCIs might also control a motorized wheelchair, a robotic arm, a neuroprosthesis that provides multidimensional movement to a paralyzed limb, or other complex devices. Both invasive and noninvasive BCI systems offer the possibility of such control. The value of such BCI applications will depend on their capabilities, practicality, and reliability, their acceptance by particular user groups, and the degree to which they have significant advantages over conventional assistive technologies.

Validation of the clinical usefulness and practicality of BCIs requires demonstration: that they are reliable in the long-term; that people actually use them; and that this use benefits mood, quality of life, and productivity. Especially early in BCI development, it will often be important to design applications that meet each user's particular needs, wishes, and physical and social circumstances. While their initial cost is relatively modest (at least for noninvasive systems), current BCIs require significant ongoing expert oversight, which is expensive and is currently available only from a few research laboratories. As a result, these BCIs are now available to only a few users. Wider BCI dissemination will depend on the extent to which their need for ongoing technical support can be reduced. BCIs should be easy to set up, easy to use, and easy to maintain if they are to have substantial impact in improving the lives of those with severe disabilities. Furthermore, wide dissemination of BCIs is impeded at present by the fact that current systems are useful mainly to those with very severe disabilities. Thus, the potential number of users is limited: BCIs are essentially orphan technology, unable to provide commercial entities with adequate financial incentive. This problem has prompted an effort to create a self-sustaining nonprofit alternative for BCI dissemination and support for those who need this new technology (http://www.braincommunication.org).

BCIs IN NEUROREHABILITATION

In addition to providing nonmuscular communication and control, BCIs might also help people disabled by trauma or disease to relearn useful motor function. BCI-based neurorehabilitation could promote functional recovery and might increase quality of life (Dobkin, 2007). This new kind of BCI use seeks to supplement existing rehabilitation methods by reinforcing and thus increasing the effectiveness of damaged brain areas and connections. An initial evaluation of this new rehabilitation strategy using MEG signals in people with stroke found evidence of cortical reorganization after BCI-based training (Buch et al., 2008).

The possible BCI-based motor learning strategies fall into two categories (Daly and Wolpaw, 2008). In the first, people are trained to produce more normal brain activity during motor function. This strategy is based on the assumption that more normal activity will produce more normal CNS function, and will thereby improve motor control. Initial results showing that stroke patients can gain control of specific brain activity patterns (e.g., Birbaumer and Cohen, 2007) suggest that a BCI might further enhance this control by extracting relevant EEG features and translating them into feedback to the user.

The second strategy for using BCIs in improving motor control is to use BCI output to control a device that assists movement. This approach rests on the hypothesis that the CNS plasticity induced by the sensory input associated with the improved movement will lead to improved motor control. Previous studies indicate that neurorehabilitation training with robotic devices that assist movement is effective in stroke patients (Daly et al., 2005). Initial efforts to combine BCI output with functional electrical stimulation or robotics to improve motor relearning in stroke patients are underway (Daly et al., 2008). BCI-based therapy might prove to be a valuable complement to current neurorehabilitation methods, and it might also reduce expense by reducing the need for ongoing therapist involvement.

BCI RESEARCH AND DEVELOPMENT

BCI research and development is necessarily multidisciplinary. It involves neuroscience, engineering, applied mathematics, computer science, psychology, and rehabilitation. The need to choose useful brain signals, to record them appropriately and reliably, to analyze them properly in real-time, to control outputs valuable to people with severe disabilities, to manage the complex short-term and long-term adaptive interactions of user and BCI, and to integrate BCI applications into the lives of their users, means that all these disciplines are essential for success. As a result, BCI research groups must themselves include the essential disciplines, or groups with different expertises must collaborate. Collaborative efforts are being facilitated by the widespread adoption of the general-purpose BCI software platform BCI2000, which easily accommodates different signals, processing methods, applications, operating protocols, and hardware (Schalk et al., 2004; Schalk and Mellinger, 2010; http://www.bci2000.org). Effective collaborations have also been encouraged by meetings drawing people from all relevant disciplines and from throughout the world, by many symposia and collections of BCI presentations at larger general meetings, and by publication of sets of peer-reviewed BCI articles (e.g., Vaughan and Wolpaw, 2011).

ACKNOWLEDGMENTS

Mr. Scott H. Brainard provided invaluable assistance in preparing this chapter. BCI research in the author's laboratory has been supported by the National Institutes of Health (NIH) (Grants HD30146 (NCMRR/NICHD), EB00856 (NIBIB & NINDS), and EB006356 (NIBIB)), the James S. McDonnell Foundation, the NEC Foundation, the Altran Foundation, the ALS Hope Foundation, and the Brain Communication Foundation.

References

Birbaumer N, Cohen LG (2007). Brain−computer interfaces: communication and restoration of movement in paralysis. J Physiol 579: 621–636.

Buch E, Weber C, Cohen LG et al. (2008). Think to move: a neuromagnetic brain−computer interface (BCI) system for chronic stroke. Stroke 39: 910–917.

Daly JJ, Wolpaw JR (2008). Brain−computer interfaces in neurological rehabilitation. Lancet Neurol 7: 1032–1043.

Daly JJ, Hogan N, Perepezko EM et al. (2005). Response to upper-limb robotics and functional neuromuscular stimulation following stroke. J Rehabil Res Dev 42: 723–736.

Daly JJ, Cheng RC, Hrovat K et al. (2008). Development and testing of non-invasive BCI+FES/robot system for use in motor re-learning after stroke. Proceedings of the 13th Annual Conference of the International Functional Electrical Stimulation Society, Freiburg, Germany [Online] Available at: http://casemed.case.edu/dept/neurology/IFESS%202008%20BCI%20Case%20Series%20JJ%20Daly%20Sept%202008.pdf.

Dobkin BH (2007). Brain−computer interface technology as a tool to augment plasticity and outcomes for neurological rehabilitation. J Physiol 579: 637–642.

Farwell LA, Donchin E (1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr Clin Neurophysiol 70: 510–523.

Hochberg LR, Serruya MD, Friehs GM et al. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature 442: 164–171.

Hochberg LR, Bacher D, Jarosiewicam B et al. (2012). Reach and grasp by people with tetraplegia using a neurally controlled robotic arm. Nature 485: 372–375.

Kim SP, Simeral JD, Hochberg LR et al. (2007). Multi-state decoding of point-and-click control signals from motor cortical activity in a human with tetraplegia. Proceedings of the Third International IEEE EMBS Conference on Neural Engineering, pp. 486–489.

Klobassa DS, Vaughan TM, Brunner P et al. (2009). Toward a high-throughput auditory P300-based brain−computer interface. Clin Neurophysiol 120: 1252–1261.

Kübler A, Kotchoubey B, Kaiser J et al. (2001). Brain−computer communication: unlocking the locked in. Psychol Bull 127: 358–375.

Kübler A, Nijboer F, Mellinger J et al. (2005). Patients with ALS can use sensorimotor rhythms to operate a brain−computer interface. Neurology 64: 1775–1777.

Leuthardt EC, Schalk G, Wolpaw JR et al. (2004). A brain−computer interface using electrocorticographic signals in humans. J Neural Eng 1: 63–71.

Lule D, Zickler C, Hacker S et al. (2009). Life can be worth living in locked-in syndrome. Prog Brain Res 177: 339–351.

McFarland DJ, Sarnacki WA, Wolpaw JR (2010). Electroencephalographic (EEG) control of three-dimensional movement. J Neural Eng 7(3): 036007.

Pfurtscheller G, Muller-Putz GR, Schlogl A et al. (2006). 15 years of BCI research at Graz University of Technology: current projects. IEEE Trans Neural Syst Rehabil Eng 14: 205–210.

Robbins RA, Simmons Z, Bremer BA et al. (2001). Quality of life in ALS is maintained as physical function declines. Neurology 56: 442–444.

Rossini PM (2009). Implications of brain plasticity to brain-machine interfaces operation a potential paradox? Int Rev Neurobiol 86: 81–90.

Sanchez JC, Mahmoudi B, DiGiovanna J (2009). Exploiting co-adaptation for the design of symbiotic neuroprosthetic assistants. Neural Netw 22: 305–315.

Schalk G, McFarland DJ, Hinterberger T et al. (2004). BCI2000: a general-purpose brain−computer interface (BCI) system. IEEE Trans Biomed Eng 51: 1034–1043.

Schalk G, Mellinger J (2010). A Practical Guide to Brain–Computer Interfacing with BCI2000. Springer.

Sellers EW, Vaughan TM, Wolpaw JR (2010). A brain–computer interface for long-term independent home use. Amyotroph Lat Scler 11: 449–455.

Taylor DM, Tillery SI, Schwartz AB (2002). Direct cortical control of 3D neuroprosthetic devices. Science 296: 1829–1832.

Vaughan TM, Wolpaw JR (2011). Special issue containing contributions from the Fourth International Brain–Computer Interface Meeting. J Neur Engin 8: 020201.

Wolpaw JR (2010). Brain–computer interface research comes of age: traditional assumptions meet emerging realities. J Motor Behavior 42: 351–353.

Wolpaw JR, McFarland DJ (2004). Control of a two-dimensional movement signal by a noninvasive brain−computer interface in humans. Proc Natl Acad Sci U S A 101: 17849–17854.

Wolpaw JR, McFarland DJ, Neat GW et al. (1991). An EEG-based brain−computer interface for cursor control. Electroencephalogr Clin Neurophysiol 78: 252–259.

Wolpaw JR, Birbaumer N, McFarland DJ et al. (2002). Brain−computer interfaces for communication and control. Clin Neurophysiol 113: 767–791.

Wolpaw JR, Wolpaw EW (Eds.) (2012a). Brain–Computer Interfaces: Principles and Practice. Oxford University Press.

Wolpaw JR, Wolpaw EW (2012b). Brain–computer interfaces: something new under the sun. In: JR Wolpaw, EW Wolpaw (Eds.), Brain-Computer Interfaces: Principles and Practice. Oxford University Press, pp 3–12.