Selzer-33.qxd 21/10/2005 06:42 PM Page 602

33

Brain–computer interfaces for communication and control

Jonathan R. Wolpaw[1] and Niels Birbaumer[2]

[1]Laboratory of Nervous System Disorders, Wadsworth Center, NYS Department of Health, Albany, NY, USA and
[2]Institute Behavioural Neuroscience, Eberhard-Karls-University, Tubingen, Germany

33.1 Introduction

Early speculation

Electrical signals produced by brain activity were first recorded from the cortical surface in animals by Richard Caton in 1875 (Caton, 1875) and from the human scalp by Hans Berger in 1929 (Berger, 1929). In the 75 years since Berger's first report, electroencephalographic (EEG) activity has been used mainly for clinical diagnosis and for exploring brain function. Nevertheless, throughout this period, scientists and others have speculated that the EEG or other measures of brain activity might serve an entirely different purpose, that they might provide the brain with another means of conveying messages and commands to the external world. While normal communication and control necessarily depend on peripheral nerves and muscles, brain signals such as the EEG suggested the possibility of non-muscular communication and control, achieved through a brain–computer interface (BCI).

Recent interest and activity

Despite long interest in this possibility, and despite isolated demonstrations (e.g., Vidal, 1973; 1977) it has only been in the past two decades that sustained research has begun, and only in the past 10 years that a recognizable field of BCI research, populated by a rapidly growing number of research groups, has developed (see Wolpaw et al. (2002) for review). This recent interest and activity reflect the confluence of four factors.

The first factor is the greatly increased appreciation of both the needs and the abilities of people severely affected by motor disorders such as cerebral palsy, spinal cord injury, brain stem stroke, amyotrophic lateral sclerosis (ALS), and muscular dystrophies. Modern life-support technology (e.g., home ventilators) now enables the most severely disabled people to survive for many years. Furthermore, it is now clear that even people who have little or no voluntary muscle control, who may be totally "locked-in" to their bodies, unable to communicate in any way, can lead lives that are enjoyable and productive if they can be provided with even the most minimal means of communication and control (Simmons et al., 2000; Maillot et al., 2001; Robbins et al., 2001).

The second factor is the greatly increased understanding of the nature and functional correlates of EEG and other measures of brain activity, understanding that has come from animal and human research. In tandem with this new knowledge have come better methods for recording these signals, both in the short and the long term. This new knowledge and technology are guiding and supporting increasingly sophisticated and effective BCI research and development.

The third factor is the availability of powerful low-cost computer hardware that allows complex real-time analyses of brain activity, which is essential for effective BCI operation. Much of the online signal processing used in present-day BCIs was impossible or prohibitively expensive until recently.

The fourth factor responsible for the recent surge in BCI research is new recognition of the remarkable adaptive capacities of the central nervous system (CNS), both in normal life and in response to damage or disease. This recognition has generated great excitement and interest in the possibility of engaging these adaptive capacities to establish new interactions between brain tissue and computer-based devices, interactions that can replace or augment the brain's normal neuromuscular interactions with the world.

33.2 What a BCI is, and what it is not

The definition of a BCI

A BCI is a communication and control system that does not depend in any way on the brain's normal neuromuscular output channels. The user's intent is conveyed by brain signals (such as EEG) rather than by peripheral nerves and muscles, and these brain signals do not depend for their generation on neuromuscular activity. (Thus, e.g., a device that uses visual evoked potentials to determine eye-gaze direction is not a true BCI, for it relies on neuromuscular control of eye position, and simply uses the EEG as a measure of that position.)

Furthermore, as a communication and control system, a BCI establishes a real-time interaction between the user and the outside world. The user receives feedback reflecting the outcome of the BC'Is operation, and that feedback can affect the user's subsequent intent and its expression in brain signals. For example, if a person uses a BCI to control the movements of a robotic arm, the arm's position after each movement is likely to affect the person's intent for the next movement and the brain signals that convey that intent. Thus, a system that simply records and analyzes brain signals, without providing the results of that analysis to the user in an online interactive fashion, is not a BCI. Figure 33.1 shows the basic design and operation of any BCI.

The fundamental principle of BCI operation

Much popular speculation and some scientific endeavors have been based on the fallacious assumption that BCIs are essentially "wire-tapping" or "mind-reading" technology, devices for listening in on the brain, detecting its intent, and then accomplishing that intent directly rather than through muscles. This misconception ignores the central feature of the brain's interactions with the external world: that the motor behaviors that achieve a person's intent, whether it be to walk in a certain direction, speak certain words, or play a certain piece on the piano, are acquired and maintained by initial and continuing *adaptive changes* in CNS function. During early development and throughout later life, CNS neurons and synapses continually change both to acquire new behaviors and to maintain those already acquired (Salmoni et al., 1984; Ghez and Krakauer, 2000). Such CNS plasticity underlies acquisition of standard skills such as locomotion and speech and more specialized skills as well, and it responds to and is guided by the results achieved. For example, as muscle strengths, limb lengths, and body weight change with growth and aging, the CNS adjusts its outputs so as to maintain the desired results.

This dependence on initial and continuing CNS adaptation is present whether the person's intent is accomplished in the normal fashion, that is, through peripheral nerves and muscles, or through an artificial interface, a BCI, that uses brain signals rather than nerves and muscles. BCI use depends on the interaction of two adaptive controllers: the user, who must generate brain signals that encode intent; and the BCI system, that must translate these signals into commands that accomplish the user's intent. Thus, BCI use is a skill that both user and system must acquire and maintain. The user must encode intent in signal features that the BCI system can measure; and the BCI system must measure these features and translate them into device commands. This dependence, both initially and continually, on the adaptation of user to system and system to user is the fundamental principle of BCI

Selzer-33.qxd 21/10/2005 06:42 PM Page 604

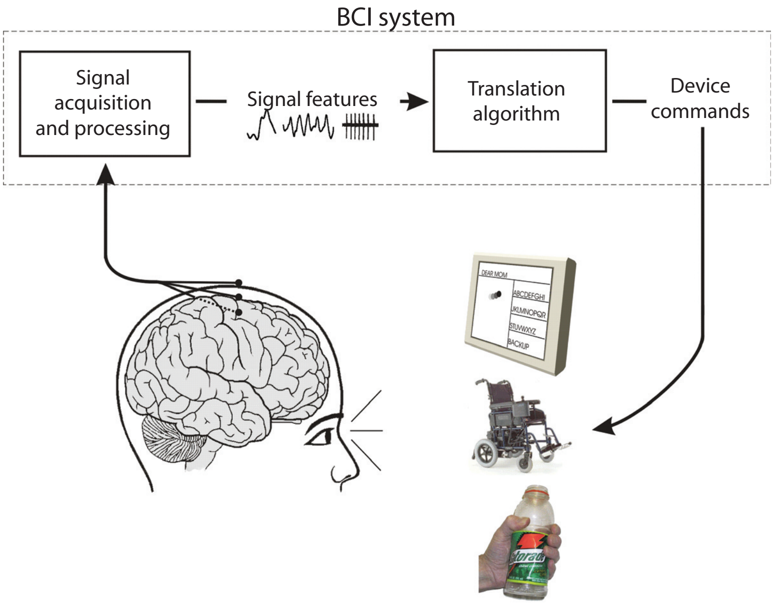

Figure 33.1. Design and operation of a BCI system (modified from Wolpaw et al., 2002; head image from www.BrainConnection. com). Electrophysiological signals reflecting brain activity are acquired from the scalp, from the cortical surface, or from within the brain and are processed to measure specific signal features (such as amplitudes of evoked potentials or EEG rhythms or firing rates of single neurons) that reflect the user's intent. These features are translated into commands that operate a device, such as a word-processing program, a wheelchair, or a neuroprosthesis.

operation; and its effective management is the principal challenge of BCI research and development.

33.3 Brain signals that can or might be used in a BCI

In theory, brain signals recorded by a variety of methodologies might be used in a BCI. These methodologies include: recording of electrical or magnetic fields; functional magnetic resonance imaging (fMRI); positron emission tomography (PET); and infrared (IR) imaging. In reality, however, most of these methods are at present not practical for clinical use due to their intricate technical demands, prohibitive expense, limited real-time capabilities, and/or early stage of development. Only electrical field recording is likely to be of significant practical value for clinical applications in the near future.

Alternative recording methods for electrical signals

The electrical fields produced by brain activity can be recorded from the scalp (EEG), from the cortical surface (electrocorticographic activity, (EcoG)), or from within the brain (local field potentials (LFPs)) or neuronal action potentials (spikes)). These three alternatives are shown in Fig. 33.2. Each recording method has advantages and disadvantages. EEG recording is easy and non-invasive, but EEG has limited topographical resolution and frequency range and may be contaminated by artifacts such as electromyographic (EMG) activity from cranial muscles or electrooculographic (EOG) activity. ECoG has better topographical resolution and frequency range, but requires implantation of electrode arrays on the cortical surface, which has as yet been done only for short periods (e.g., a few days or weeks) in humans. Intracortical recording (or recording within other brain structures) provides the highest resolution signals, but requires insertion of multiple electrode arrays within brain tissue and faces as yet unresolved problems in minimizing tissue damage and scarring and ensuring long-term recording stability.

The ultimate practical value of each of these recording methods will depend on the range of communication and control applications it can support and the extent to which its limitations can be overcome.

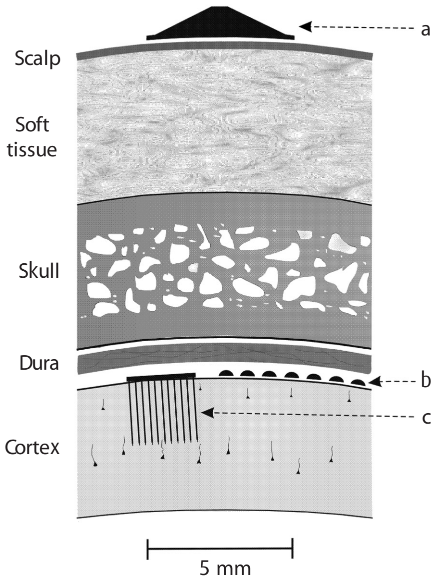

Figure 33.2. Recording sites for electrophysiological signals used by BCI systems. (a) EEG is recorded by electrodes on the scalp. (b) ECoG is recorded by electrodes on the cortical surface. (c) Action potentials from single neurons or LFPs are recorded by electrode arrays inserted into the cortex or other brain areas.

The issue of the relative value of non-invasive (i.e., EEG) methods, moderately invasive (e.g., ECoG) methods, and maximally invasive (e.g., intracortical) methods remains unresolved. On the one hand, stable, practical, and safe techniques for long-term recording within the brain may not prove that difficult to develop. On the other hand, despite expectations to the contrary (e.g., Donoghue, 2002), for actual practical applications, the information transfer rates possible with intracortical methods may turn out to be no greater than those achievable with less invasive methods (e.g., ECoG). Thorough evaluations of the characteristics and capacities of each recording method are needed.

33.4 Present-day BCIs

Human BCI experience to date has been confined almost entirely to EEG studies and short-term ECoG studies. Intracortical BCI data come mainly from animals, primarily monkeys. The available human data indicate that EEG-based methods can certainly support simple applications and may be able to support more complex ones. Invasive methods appear able to support complex applications, but the issues of risk and long-term recording stability are not yet resolved.

EEG-based BCIs

Three different kinds of EEG-based BCIs have been tested in humans. They differ in the particular EEG features that serve to convey the user's intent. Figure 33.3(a) illustrates a P300-based BCI (Farwell and Donchin, 1988; Donchin et al., 2000). It uses the P300 component of the event-related brain potential, which appears in the centroparietal EEG about 300 ms after presentation of a salient or attended stimulus. The P300 BCI system described by Donchin's group flashes letters or other symbols in rapid succession. The letter or symbol that the user wants to select produces a P300 potential. By detecting this P300 potential, the BCI system can determine the user's choice. This BCI method appears able to support operation of a simple word-processing program that enables users to write words at a rate of one or a few letters per minute. Improvements in signal analysis may substantially increase its capacities. At the same time, the effects of long-term usage of a P300-based BCI on its communication performance remain to be determined: P300 size and reliability may improve with continued use so that performance improves, or P300 may habituate so that performance deteriorates.

Figure 33.3(b) illustrates a BCI based on slow cortical potentials (SCPs), which last from 300 ms to several seconds (Birbaumer et al., 1999; 2000; Kübler et al., 2001). In normal brain function, negative SCPs reflect preparatory depolarization of the underlying cortical network, while positive SCPs are usually interpreted as a sign of cortical disfacilitation or inhibition. Birbaumer and his colleagues have shown that, with appropriate training, people can learn to control SCPs so as to produce positive

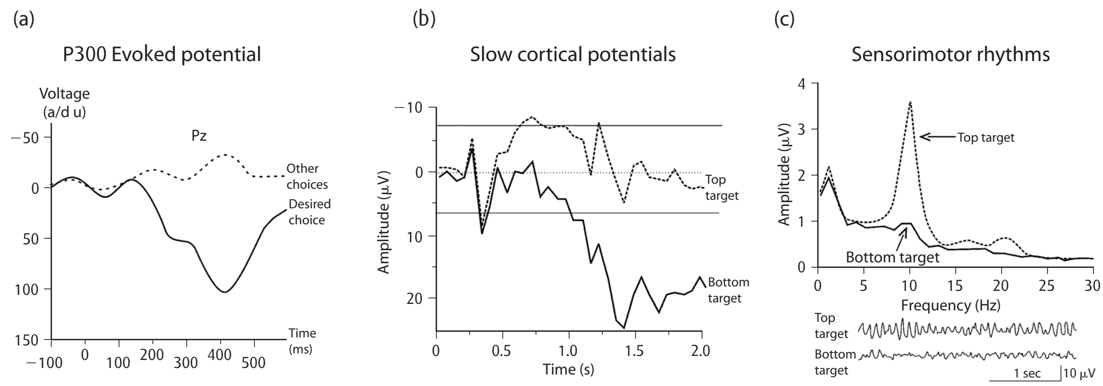

Figure 33.3. Non-invasive EEG-based BCI methods demonstrated in humans (modified from Kübler et al., 2001). These methods use EEG recorded from the scalp. (a) P300 evoked potential BCI (Farwell and Donchin, 1988; Donchin et al., 2000). A matrix of possible selections is shown on a screen. Scalp EEG is recorded over centroparietal cortex while these selections flash in succession. Only the selection desired by the user evokes a large P300 potential (i.e., a positive potential about 300ms after the flash). (b) Slow cortical potential BCI (Birbaumer et al., 1999; 2000; Kübler et al., 2001). Users learn to control SCPs to move a cursor to a target (e.g., a desired letter or icon) at the bottom (more positive SCP) or top (more negative SCP) of a computer screen. (c) Sensorimotor rhythm BCI (Wolpaw and McFarland, 1994; 2003; Wolpaw et al., 2002; 2003). Scalp EEG is recorded over sensorimotor cortex. Users control the amplitude of a 8–12Hz mu rhythm (or a 18–26 Hz beta rhythm) to move a cursor to a target at the top of the screen or to a target at the bottom (or to additional targets at intermediate locations). Frequency spectra (top) for top and bottom targets indicate that this user's control is clearly focused in the mu-rhythm frequency band. Sample EEG traces (bottom) also show that the mu rhythm is prominent with the top target and minimal with the bottom target. Trained users can also control movement in two dimensions.

or negative shifts. Furthermore, they can use this control to perform basic word-processing and other simple control tasks such as accessing the Internet. Most important, people who are severely disabled by ALS, and are otherwise unable to communicate, are capable of achieving SCP control and using it for effective communication.

Figure 33.3(c) illustrates a BCI based on sensorimotor rhythms (Wolpaw et al., 1991; 2003; Wolpaw and McFarland, 1994; 2003; Kostov and Polak , 2000; Roberts and Penny, 2000; Pfurtscheller et al., 2003a). Sensorimotor rhythms are 8–12 Hz (mu) and 18–26 Hz (beta) oscillations in the EEG recorded over sensorimotor cortices. In normal brain function, changes in mu and/or beta rhythm amplitudes are associated with movement and sensation, and with motor imagery as well. Several laboratories have shown 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 letters or icons on a screen or to operate a simple orthotic device. Both one- and two-dimensional control are possible. Like the P300- and SCP-based BCIs, sensorimotor rhythm-based BCIs can support basic word-processing or other simple functions. They may also support multi-dimensional control of a neuroprosthesis or other device such as a robotic arm.

These present-day BCI methods all rely on selection protocols that begin at fixed times set by the system. However, in real-life applications, BCIs in which the onset and timing of operation are determined by the user may be preferable. Efforts to develop such user-initiated methods, based on detection of certain features in the ongoing EEG, have begun (Mason and Birch, 2000). Present-day BCIs also depend on visual stimuli. People who are severely disabled (e.g., locked-in) may not be able to follow such stimuli, especially if they change rapidly. In this case, BCI systems (e.g., P300-based) that use auditory rather than visual stimuli may prove effective.

ECoG-based BCIs

Figure 33.4(a) illustrates a BCI based on sensorimotor rhythms in ECoG recorded by electrode arrays placed on the cortical surface. ECoG has much higher spatial and temporal resolution than scalp-recorded EEG. It can resolve activity limited to a few mm^2 of cortical surface, and it includes not only mu and beta rhythms, but higher-frequency gamma ($>$30 Hz) rhythms, which are very small or absent in EEG. ECoG studies to date have been limited to short-term experiments in individuals temporarily implanted with electrode arrays prior to epilepsy surgery. They reveal sharply focused ECoG activity associated with movement and sensation and with motor imagery (Pfurtscheller et al., 2003b; Leuthardt et al., 2004). Furthermore, with only a few minutes of training, people can learn to use such imagery to control cursor movement (Fig. 33.4(a)) (Leuthardt et al., 2004).

The rapidity of this learning, which occurs much faster than that typically found with scalp-recorded sensorimotor rhythms, combined with the high topographical resolution and wide spectral range of ECoG and its freedom from artifacts such as EMG, suggests that ECoG-based BCIs might support communication and control superior to that possible with EEG-based BCIs. Their clinical use will depend on development of fully implanted systems (i.e., systems that do not require wires passing through the skin) and on strong evidence that they can provide safe and stable recording over periods of years.

Intracortical BCIs

Figure 33.4(b) shows data from a BCI based on the firing rates of a set of single cortical neurons recorded by a fine-wire array chronically implanted in monkey motor cortex. Intracortical BCIs studied to date have used such neuronal activity (Kennedy and Bakay, 1998; Chapin et al., 1999; Kennedy et al., 2000; Taylor et al., 2002; 2003; Serruya et al., 2002; Carmena et al., 2003; Musallam et al., 2004) and have shown that it can support rapid and accurate control of cursor movements in one, two, or even three dimensions. Related data suggest that LFPs, which can be recorded by the same electrode arrays and reflect nearby synaptic and neuronal activity, might also support BCI operation (Pesaran et al., 2002). The basic strategy in the single-neuron studies has been to define the neuronal activity associated with standardized limb movements, then to use this activity to simultaneously control comparable movements of a cursor, and finally to show that the neuronal activity can continue to control cursor movements in the absence of actual limb movements. In the most thorough and successful study to date (Taylor et al., 2002), in which neuronal control of three-dimensional cursor movement was observed over many sessions, neuronal activity was found to adapt over sessions so as to improve cursor control. Figure 33.4(b) illustrates this adaptation. Like the comparable adaptations seen with EEG- and ECoG-based BCIs, it reflects the fundamental BCI principle described above: dependence on initial and continuing adaptation of system to user and user to system.

The major issues that must be resolved prior to clinical use of intracortical BCIs include their long-term safety, the stability of their signals in the face of cortical tissue reactions to the implanted electrodes, and whether their capabilities in actual practical applications (e.g., in neuroprosthesis control) substantially exceed those of less invasive BCIs.

33.5 Signal processing

A BCI records brain signals and processes them to produce device commands. This signal processing has two stages. The first stage is feature extraction, the calculation of the values of specific features of the signals. These features may be relatively simple measures such as amplitudes or latencies of specific potentials (e.g., P300), amplitudes, or frequencies of specific rhythms (e.g., sensorimotor rhythms), or

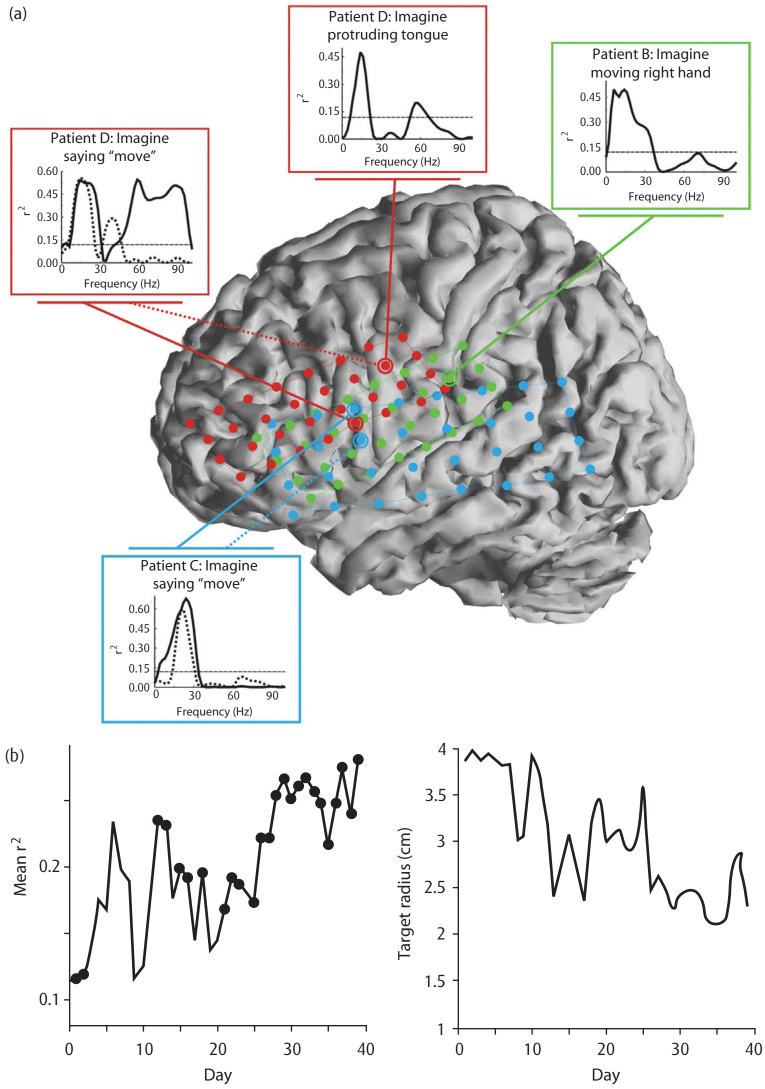

Figure 33.4. Invasive BCI methods. (a) Electrode arrays on the cortical surface. Human ECoG control of vertical cursor movement using specific motor imagery to move the cursor up and rest (i.e., no imagery) to move it down (from Leuthardt et al., 2004). The electrodes used for online control are circled and the spectral correlations of their ECoG activity with target location (i.e., top or bottom of screen) are shown. Electrode arrays for Patients B, C, and D are green, blue, and red, respectively. The particular imagined actions used are indicated. The substantial levels of control achieved with different types of imagery are evident. (The dashed lines indicate significance at the 0.01 level). For Patients C and D, the solid and dotted r^2 spectra correspond to the sites indicated by the dotted and solid line locators, respectively. (b) Control of three-dimensional cursor movements by single neurons in motor cortex of a monkey (from Taylor et al., 2003). The left graph shows the improvement over training sessions of the average correlation between the firing rate of an individual cortical neuron and target direction. The right graph shows the resulting improvement in performance (measured as the mean target radius needed to maintain a 70% target hit rate). As the firing rates of the neurons that are controlling cursor movement become more closely correlated with target direction, the size of the target can be steadily reduced.

firing rates of individual cortical neurons, or they may be more complex measures such as spectral coherences. To support effective BCI performance, the feature-extraction stage of signal processing must focus on features that encode the user's intent, and it must extract those features as accurately as possible.

The second stage is a translation algorithm that translates these features into device commands. Features such as rhythm amplitudes or neuronal firing rates are translated into commands that specify outputs such as cursor movements, icon selection, or prosthesis operation. Translation algorithms may be simple (e.g., linear equations), or more complex (e.g., neural networks, support vector machines) (Müller et al., 2003).

To be effective, a translation algorithm must ensure that the user's range of control of the chosen features allows selection of the full range of device commands. For example, suppose that the feature is the amplitude of a 8–12 Hz mu rhythm in the EEG over sensorimotor cortex; that the user can vary this feature over a range of 2–10 μV; and that the application is vertical cursor movement. In this case, the translation algorithm must ensure that the 2–10 μV range allows the user to move the cursor both up and down. Furthermore, the algorithm must accommodate spontaneous variations in the user's range of control (e.g., if diurnal change, fatigue, or another factor changes the available voltage range) (e.g., Ramoser et al., 1997). Finally the translation algorithm should have the capacity to at least accommodate, and at best encourage, improvements in the user's control. For example, if the user's range of control improves from 2–10 to 1–15 μV, the translation algorithm should take advantage of this improvement to increase the speed and/or precision of cursor movement control.

This need for continual adaptation of the translation algorithm to accommodate spontaneous and other changes in the signal features is in accord with the fundamental principle of BCI operation (i.e., the continuing dependence on system/user and user/system adaptation), and has important implications. First, it means that new algorithms cannot be adequately evaluated simply by offline analyses. They must also be tested online, so that the effects of their adaptive interactions with the user can be assessed. This testing should be long term as well as short term, for important adaptive interactions may develop gradually. Second, the need for continual adaptation means that simpler algorithms, for which adaptation is usually easier and more effective, have an inherent advantage. Simple algorithms (e.g., linear equations) should be abandoned for complex alternatives (e.g., neural networks) only when online as well as offline evaluations clearly show that the complex alternatives provide superior performance.

33.6 Potential users

In their present early state of development, BCIs are likely to be of practical value mainly for those with the most severe neuromuscular disabilities, people for whom conventional assistive communication technologies, all of which require some measure of voluntary muscle control, are not viable options. These include people with ALS who elect to accept artificial ventilation (rather than to die) as their disease progresses, children and adults with severe cerebral palsy who lack any useful muscle control, patients with brain stem strokes who are left only with minimal eye movement control, those with severe muscular dystrophies or chronic peripheral neuropathies, and possibly people with short-term disorders associated with extensive paralysis (such as Landry-Guillain-Barré syndrome). It is also possible that people with less severe disabilities, such as those with high-cervical spinal cord injuries, may find BCI technology preferable to conventional assistive communication methods that co-opt remaining voluntary muscle control (e.g., methods that depend on gaze direction or EMG of facial muscles). BCIs might eventually also prove useful for those with less severe motor disabilities. The eventual extent and impact of BCI applications will depend on the speed and precision of the control that can be achieved and on the reliability and convenience of their use.

People with disabilities of different origins are likely to differ in the BCI methods that are of most use to them. For some, the CNS deficits responsible for their disability may affect their ability to control particular brain signals and not others. For example, the motor cortex damage that can be associated with ALS or the subcortical damage of severe cerebral palsy may compromise generation or control of sensorimotor rhythms or neuronal activity. In such individuals, other brain signals, such as P300 potentials or neuronal activity from other brain regions, might provide viable alternatives.

Prosaic and even ostensibly trivial factors are also likely to play significant roles in the eventual practical success of BCI applications. Issues such as the steps involved in donning and doffing electrodes or in accessing a BCI application, or a person's appearance while using it, may greatly affect the number of people interested in the system and the extent to which they actually use it.

33.7 Applications

The range of possible applications

BCIs have a wide range of possible practical applications, from extremely simple to very complex. Simple BCI applications have already been demonstrated in the laboratory and in limited clinical use. They include systems for answering Yes/No questions, managing basic environmental control (e.g., lights, temperature), controlling a television, or opening and closing a hand orthosis (Miner et al., 1998; Birbaumer et al., 1999; Pfurtscheller et al., 2003a). Such simple systems can be configured for basic word-processing or for accessing the Internet (e.g., Mellinger et al., 2003). For people who are totally paralyzed (i.e., "locked-in") and thus cannot use conventional assistive communication devices (see Volume II, Chapter 22), these simple BCI applications may make possible lives that are pleasant and even productive. Indeed, several recent studies indicate that severely paralyzed people, if they have good supportive care and the capacity for basic communication, may enjoy a reasonable quality of life and are only slightly more likely to be depressed than people without physical disabilities (Simmons et al., 2000; Maillot et al., 2001; Robbins et al., 2001). Thus, simple BCI applications appear to have a secure future in their potential to make a difference in the lives of extremely disabled people.

More complex BCI applications might support control of devices such as a motorized wheelchair, a robotic arm, or a neuroprosthesis that enables the multi-dimensional movements of a paralyzed limb. While most present efforts are focused on development of invasive BCI systems to support such applications, non-invasive EEG-based BCIs also appear to offer the possibility of such control (Wolpaw and McFarland, 1994; 2003). The ultimate practical importance of such BCI applications will depend on their capacities and reliability, on their acceptance by specific user population groups, and on whether they provide clear advantages over conventional methodologies.

Process control versus goal selection

Two alternative approaches underlie BCI applications: process control and goal selection. In the process-control approach, the BCI directly controls every aspect of device operation. This approach underlies most current efforts to develop intracortical BCI systems. For neuroprosthesis operation, this approach vests in a specific set of cortical neurons (and/or other brain neurons) ongoing interactive control of all the muscles that move a limb so as to carry out the user's intent. Thus, the approach requires that the BCI supports complex high-speed interactions; and it requires that cortical neurons assume functions normally performed by lower-level (e.g., spinal cord) neurons.

In the alternative approach of goal selection, the BCI simply determines the user's intent, which is then executed by the system. This approach underlies most efforts to develop non-invasive or minimally invasive BCI methods. While it has been most often used for simple applications (e.g., Yes/No), this approach can apply also to the most complex applications, such as multidimensional control of a neuroprosthesis. For example, the user might communicate the command: "pick up the book." The complex control of the shoulder, arm, and hand muscles that execute that command would then be orchestrated by a device that stimulates muscles and simultaneously monitors the resulting movements so as to accomplish the task. This design, in which task execution is delegated to lower-level structures, is similar in principle to normal motor control, in which subcortical and spinal areas play crucial parts, particularly in managing high-speed real-time interactions between the CNS and the limb it is controlling.

The process-control approach clearly requires that the BCI have information transfer rates and capacities for high-speed real-time interaction substantially greater than those required by the goal-selection approach. Which approach can ultimately provide the most flexible, effective, and natural movement control remains to be determined.

Establishing the practical value of BCI applications

The establishment of BCI applications as clinically valuable methods will require comprehensive clinical testing that demonstrates their long-term reliability and shows that people actually use the applications and that this use has beneficial effects on factors such as mood, quality of life, productivity, etc. Especially in the initial stages of their development, this will often entail configuring applications that match the unique needs, desires, and physical and social environments of each user. While the cost of BCI equipment is relatively modest, current systems require substantial and continuing expert oversight, which is extremely expensive and currently limited to a few research laboratories. As a result, these systems are not readily available to most potential users. Thus, the widespread clinical use of BCI applications will also depend on the extent to which the need for such oversight can be reduced. BCI systems must be easy to set up and easy to maintain if they are to have substantial practical impact.

33.8 Nature and needs of BCI research and development

BCI research and development is an inherently multidisciplinary task. It involves neuroscience, engineering, applied mathematics, computer science, psychology, and rehabilitation. BCI research is not merely a signal-processing problem, a neurobiological problem, or a human-factors problem, though it has often been viewed in each of these limited ways in the past. The need to select appropriate brain signals, to record them accurately and reliably, to analyze them appropriately in real time, to control devices that provide functions of practical value to people with severe disabilities, to manage the complex short-term and long-term adaptive interactions between user and system, and to integrate BCI applications into the lives of their users, means that the expertise and efforts of all these disciplines are critical for success. This reality requires either that each BCI research group incorporate all relevant disciplines, or that groups with different expertises collaborate closely. Such interactions have been encouraged and facilitated by recent meetings drawing BCI researchers from all relevant disciplines and from all over the world (Wolpaw et al., 2000; Vaughan et al., 2003), and by comprehensive sets of peer-reviewed BCI articles (see Wolpaw et al., 2000; Vaughan et al., 2003; Nicolelis et al., 2004 for review).

Up to now, BCI research has consisted primarily of demonstrations, of limited studies showing that a specific brain signal processed in a specific way by specific hardware and software and applied to a specific device can supply communication or control of a specific kind. Successful development and widespread clinical use depend on moving beyond demonstrations. They require effective and efficient techniques for comparing, combining, and evaluating alternative brain signals, analysis methods, and applications, and thereby optimizing BCIs and the usefulness of their applications. This requirement has been the impetus for the original and ongoing development of BCI2000, the first general-purpose BCI system (Schalk et al., 2004). Founded on a design made up of four modules (signal acquisition, signal processing, device control, and system operation), BCI2000 can accommodate a wide variety of alternative signals, processing methods, applications, and operating protocols. Thus, it greatly facilitates the comprehensive quantitative comparative studies critical for continued progress. BCI2000, with source code and documentation, is freely available to research laboratories (at http://www. bci2000.org) and is already in use by many laboratories throughout the world.

Summary

The possibility that EEG activity or other electrophysiological measures of brain function might provide new non-muscular channels for communication and control (i.e., BCIs) has been a topic of speculation for many years. Over the past 15 years, numerous productive BCI research and development programs have been initiated. These endeavors focus on developing new augmentative communication and control technology for those with severe neuromuscular disorders, such as ALS, brain stem stroke, and spinal cord injury. The immediate objective is to give these users, who may be totally paralyzed, or “locked-in,” basic communication capabilities so that they can express their desires to caregivers or even operate word-processing programs or neuroprostheses. Current BCIs determine the intent of the user from electrophysiological signals recorded non-invasively from the scalp (EEG) or invasively from the cortical surface (ECoG) or from within the brain (neuronal action potentials). These signals are translated in real-time into commands that operate a computer display or other device. Successful operation requires that the user encode commands in these signals and that the BCI derive the commands from the signals. Thus, the user and the BCI system need to adapt to each other both initially and continually so as to ensure stable performance. This dependence on the mutual adaptation of user to system and system to user is the fundamental principle of BCI operation.

BCI research and development is an inherently interdisciplinary problem, involving neurobiology, psychology, engineering, mathematics, computer science, and clinical rehabilitation. Its future progress and eventual practical impact depend on a number of critical issues. The relative advantages and disadvantages of non-invasive and invasive methods remain to be determined. On the one hand, the full capacities of non-invasive methods are not clear; on the other hand, the long-term safety and stability of invasive methods are uncertain. The optimal signal processing techniques also remain to be determined. On the one hand, simple algorithms facilitate the continuing adaptation that is essential for effective BCI operation; on the other hand, more complex algorithms might provide better communication and control. Appropriate user groups and applications, and appropriate matches of one to the other, remain to be determined. Present BCIs, which have relatively limited capacities, may be most useful for those with the most severe disabilities. At the same time, the CNS deficits associated with some disorders may impair ability to use certain BCI methods. Widespread clinical use depends also on factors that affect the user acceptance and the practicality of augmentative technology, including ease of use, cosmesis, provision of those communication and control capacities that are most important to the user, and minimization of the need for continuing expert oversight. With proper recognition and effective engagement of all these issues, BCI systems could eventually be important new communication and control options for people with motor disabilities and might also provide to people without disabilities as a supplementary control channel or a control channel useful in special circumstances.

ACKNOWLEDGEMENTS

Drs. Dennis J. McFarland and Elizabeth Winter Wolpaw provided valuable comments on the manuscript, and Mr. Scott Parsons provided excellent assistance with illustrations. Work in the authors' laboratories has been supported by NIH (Grants HD30146 and EB00856), the James S. McDonnell Foundation, the ALS Hope Foundation, and the DFG (Grant SFB 550/B5).

REFERENCES

Berger, H. (1929). Über das electrenkephalogramm des menchen. *Archiv für Psychiatrie Nervenkrankheiten*, **87**, 527–570.

Birbaumer, N., Ghanayim, N., Hinterberger, T., Iversen, I., Kotchoubey, B., Kübler, A., Perelmouter, J., Taub, E. and Flor, H. (1999). A spelling device for the paralyzed. *Nature*, **398**, 297–298.

Birbaumer, N., Kübler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., Iversen, I., Kotchoubey, B., Neumann, N. and Flor, H. (2000). The thought translation device (TTD) for completely paralyzed patients. *IEEE Trans Rehabil Eng*, **8**, 190–193.

Birbaumer, N., Kübler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., Iversen, I., Kotchoubey, B., Neumann, N. and Flor, H. (2003). The thought translation device (TTD) for completely paralyzed patients. *IEEE Trans Rehabil Eng*, **8**, 190–192.

Carmena, J.M., Lebedev, M.A., Crist, R.E., O'Doherty, J.E., Santucci, D.M., Dimitrov, D.F., Patil, P.G., Henriquez, C.S. and Nicolelis, M.A. (2003). Learning to control a brain-machine interface for reaching and grasping by primates. *PLOS Biol*, **1**(**3**), Online.

Caton, R. (1875). The electric currents of the brain. *Br Med J*, **2**, 278.

Chapin, J.K., Moxon, K.A., Markowitz, R.S. and Nicolelis, M.A. (1999). Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. *Nat Neurosci*, **2**, 664–670.

Donchin, E., Spencer, K.M. and Wijesinghe, R. (2000). The mental prosthesis: assessing the speed of a P300-based brain–computer interface. *IEEE Trans Rehabil Eng*, **8**, 174–179.

Donoghue, J.P. (2002). Connecting cortex to machines: recent advances in brain interfaces. *Nat Neurosci*, **5**, 1085–1088.

Farwell, L.A. and 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.

Ghez, C. and Krakauer, J. (2000). Voluntary movement. In: *Principles of Neural Science* (eds Kandel, E.R., Schwartz, J.H. and Jessell, T.M.) 4th edn, pp. 653–674. McGraw-Hill, NY.

Kennedy, P.R. and Bakay, R.A. (1998). Restoration of neural output from a paralyzed patient by a direct brain connection. *Neuroreport*, **9**, 1707–1711.

Kennedy, P.R., Bakay, R.A.E., Moore, M.M., Adams, K. and Goldwaithe, J. (2000). Direct control of a computer from the human central nervous system. *IEEE Trans Rehabil Eng*, **8**, 198–202.

Kostov, A. and Polak, M. (2000). Parallel man-machine training in development of EEG-based cursor control. *IEEE Trans Rehabil Eng*, **8**, 203–205.

Kübler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J.R. and Birbaumer, N. (2001). Brain–computer communication: unlocking the locked in. *Psychol Bull*, **127**, 358–375.

Leuthardt, E.C., Schalk, G., Wolpaw, J.R., Ojemann, J.G. and Moran, D.W. (2004). A brain-computer interface using electrocorticographic signals in humans. *J Neural Eng*, **1**, 63–71.

Maillot, F., Laueriere, L., Hazouard, E., Giraudeau, B. and Corcia, P. (2001). Quality of life in ALS is maintained as physical function declines.(Correspondence), *Neurology*, **57**, 939.

Mason, S.G. and Birch, G.E. (2000). A brain-controlled switch for asynchronous control applications. *IEEE Trans Biomed Eng*, **47**, 1297–1307.

Mellinger, J., Hinterberger, T., Bensch, M., Schröder, M. and Birbaumer, N. (2003). Surfing the web with electrical brain signals: the brain web surfer (BSW) for the completely paralysed. In: *Proceedings of the 2nd World Congress International Society Physical and Rehabilitation Medicine – ISPRM* (eds Ring, H. and Soroker, N.), pp. 731–738. Monduzzi, Bologna.

Miner, L.A., McFarland, D.J. and Wolpaw, J.R. (1998). Answering questions with an EEG-based brain–computer interface (BCI). *Arch Phys Med Rehabil*, **79**, 1029–1033.

Müller, K.-R., Anderson, C.W. and Birch, G.E. (2003). Linear and nonlinear methods for brain-computer interfaces. *IEEE Trans Neural Sys Rehabil Eng*, **11**, 165–169.

Musallam, S., Corneil, B.D., Greger, B., Scherberger, H. and Andersen, R.A. (2004). Cognitive control signals for neural prosthetics. *Science*, **305**(**5681**), 258–262.

Nicolelis, M.A.L., Birbaumer, N., Müller, K.-R. (2004). Guest editorial (Brain-machine interfaces). *IEEE Trans Biomed Eng*, **51**, 877.

Pesaran, B., Pezaris, J.S., Sahani, M., Mitra, P.P. and Andersen, R.A. (2002). Temporal structure in neuronal activity during working memory in macaque parietal cortex. *Nat Neurosci*, **5**, 805–811.

Pfurtscheller, G., Neuper, C., Müller, G.R., Obermaier, B., Krausz, G., Schlögl, A., Scherer, R., Graimann, B., Keinrath, C., Skliris, D., Wörtz, M., Supp, G. and Schrank, C. (2003a).

Graz-BCI: state of the art and clinical applications. *IEEE Trans Neural Sys Rehabil Eng*, **11**, 177–180.

Pfurtscheller, G., Graimann, B., Huggins, J.E., Levine, S.P. and Schuh, L.A. (2003b). Spatiotemporal patterns of beta desynchronization and gamma synchronization in corticographic data during self-paced movement. *Clin Neurophysiol*, **114**, 1226–1236.

Ramoser, H., Wolpaw, J.R. and Pfurtscheller, G. (1997). EEG-based communication: evaluation of alternative signal prediction methods. *Biomedical Technik*, 42, 226–233.

Robbins, R.A., Simmons, Z., Bremer, B.A., Walsh, S.M. and Fischer, S. (2001). Quality of life in ALS is maintained as physical function declines. *Neurology*, **56**, 442–444.

Roberts, S.J. and Penny, W.D. (2000). Real-time brain–computer interfacing: a preliminary study using Bayesian learning. *Med Biol Eng Comp*, **38**, 56–61.

Salmoni, A.R., Schmidt, R.A. and Walter, C.B. (1984). Knowledge of results and motor learning: a review and critical appraisal. *Psychol Bull*, **5**, 355–386.

Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N. and Wolpaw, J.R. (2004). BCI2000: A general-purpose brain–computer interface (BCI) system. *IEEE Trans Biomed Eng*, **51**, 1034–1043.

Serruya, M.D., Hatsopoulos, N.G., Paninski, L., Fellows, M.R. and Donoghue, J.P. (2002). Instant neural control of a movement signal. *Nature*, **416**, 141–142.

Simmons, Z., Bremer, B.A., Robbins, R.A., Walsh, S.M. and Fischer, S. (2000). Quality of life in ALS depends on factors other than strength and physical function. *Neurology*, **55**, 388–392.

Taylor, D.M., Tillery, S.I. and Schwartz, A.B. (2002). Direct cortical control of 3D neuroprosthetic devices. *Science*, **296**, 829–832.

Taylor, D.M., Helms Tillery, S.I. and Schwartz, A.B. (2003). Information conveyed through braincontrol: cursor versus robot. *IEEE Trans Neural Sys Rehabil Eng*, **11**(**2**), 195–199.

Vaughan, T.M., Heetderks, W.J., Trejo, L.J., Rymer, W.Z., Weinrich, M., Moore, M.M., Kübler, A., Dobkin, B.H., Birbaumer, N., Donchin, E., Wolpaw, E.W. and Wolpaw, J.R. (2003). Brain–computer interface technology: a review of the Second International Meeting. *IEEE Trans Neural Sys Rehabil Eng*, **11**, 94–109.

Vidal, J.J. (1973). Towards direct brain–computer communication. *Ann Rev of Biophy Bioeng*, **2**, 157–180.

Vidal, J.J. (1977). Real-time detection of brain events in EEG. *IEEE Proc Spl Issue Biol Signal Proc Anal*, **65**, 633–664.

Wolpaw, J.R. and McFarland, D.J. (1994). Multichannel EEG-based brain–computer communication. *Electroencephalogr Clinl Neurophy*, **90**, 444–449.

Wolpaw, J.R. and McFarland, D.J. (2003). Two-dimensional movement control by scalp-recorded sensorimotor rhythms in humans. Program No. 607.2. 2003 Abstract Viewer/Itinerary Planner. Society for Neuroscience, Online, Washington, DC.

Wolpaw, J.R., McFarland, D.J., Neat, G.W. and Forneris, C.A. (1991). An EEG-based braincomputer interface for cursor control. *Electroencephalogr Clin Neurophy*, **78**, 252–259.

Wolpaw, J.R., Birbaumer, N., Heetderks, W.J., McFarland, D.J., Peckham, P.H., Schalk, G., Donchin, E., Quatrano, L.A., Robinson, C.J. and Vaughan, T.M. (2000). Brain–computer interface technology: a review of the first international meeting. *IEEE Trans Rehabil Eng*, **8**, 164–173.

Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G. & Vaughan, T.M. (2002). Brain–computer interfaces for communication and control. *Clin Neurophysiol*, **113**, 767–791.

Wolpaw, J.R., McFarland, D.J., Vaughan, T.M. and Schalk, G. (2003). The Wadsworth center brain–computer interface research and development program. *IEEE Trans Neural Sys Rehabil Eng*, **11**, 204–207.