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Invited review

Brain–computer interfaces for communication and control

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Abstract

For many years people have speculated that electroencephalographic activity or other electrophysiological measures of brain function might provide a new non-muscular channel for sending messages and commands to the external world – a brain–computer interface (BCI). Over the past 15 years, productive BCI research programs have arisen. Encouraged by new understanding of brain function, by the advent of powerful low-cost computer equipment, and by growing recognition of the needs and potentials of people with disabilities, these programs concentrate on developing new augmentative communication and control technology for those with severe neuromuscular disorders, such as amyotrophic lateral sclerosis, brainstem stroke, and spinal cord injury. The immediate goal is to provide these users, who may be completely paralyzed, or 'locked in', with basic communication capabilities so that they can express their wishes to caregivers or even operate word processing programs or neuroprostheses. Present-day BCIs determine the intent of the user from a variety of different electrophysiological signals. These signals include slow cortical potentials, P300 potentials, and mu or beta rhythms recorded from the scalp, and cortical neuronal activity recorded by implanted electrodes. They 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. Current BCIs have maximum information transfer rates up to 10–25 bits/min. This limited capacity can be valuable for people whose severe disabilities prevent them from using conventional augmentative communication methods. At the same time, many possible applications of BCI technology, such as neuroprosthesis control, may require higher information transfer rates. Future progress will depend on: recognition that BCI research and development is an interdisciplinary problem, involving neurobiology, psychology, engineering, mathematics, and computer science; identification of those signals, whether evoked potentials, spontaneous rhythms, or neuronal firing rates, that users are best able to control independent of activity in conventional motor output pathways; development of training methods for helping users to gain and maintain that control; delineation of the best algorithms for translating these signals into device commands; attention to the identification and elimination of artifacts such as electromyographic and electro-oculographic activity; adoption of precise and objective procedures for evaluating BCI performance; recognition of the need for long-term as well as short-term assessment of BCI performance; identification of appropriate BCI applications and appropriate matching of applications and users; and attention to factors that affect user acceptance of augmentative technology, including ease of use, cosmesis, and provision of those communication and control capacities that are most important to the user. Development of BCI technology will also benefit from greater emphasis on peer-reviewed research publications and avoidance of the hyperbolic and often misleading media attention that tends to generate unrealistic expectations in the public and skepticism in other researchers. With adequate recognition and effective engagement of all these issues, BCI systems could eventually provide an important new communication and control option for those with motor disabilities and might also give those without disabilities a supplementary control channel or a control channel useful in special circumstances.

Keywords: Brain–computer interface; Electroencephalography; Augmentative communication; Rehabilitation; Neuroprosthesis; Brain–machine interface

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1. Introduction

1.1. Options for restoring function to those with motor disabilities

Many different disorders can disrupt the neuromuscular channels through which the brain communicates with and controls its external environment. Amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases impair the neural pathways that control muscles or impair the muscles themselves. They affect nearly two million people in the United States alone, and far more around the world (Ficke, 1991; NABMRR, 1992; Murray and Lopez, 1996; Carter, 1997). Those most severely affected may lose all voluntary muscle control, including eye movements and respiration, and may be completely locked in to their bodies, unable to communicate in any way. Modern life-support technology can allow most individuals, even those who are locked-in, to live long lives, so that the personal, social, and economic burdens of their disabilities are prolonged and severe.

In the absence of methods for repairing the damage done by these disorders, there are 3 options for restoring function. The first is to increase the capabilities of remaining pathways. Muscles that remain under voluntary control can substitute for paralyzed muscles. People largely paralyzed by massive brainstem lesions can often use eye movements to answer questions, give simple commands, or even operate a word processing program; and severely dysarthric patients can use hand movements to produce synthetic speech (e.g. Damper et al., 1987; LaCourse and Hladik, 1990; Chen et al., 1999; Kubota et al., 2000). The second option is to restore function by detouring around breaks in the neural pathways that control muscles. In patients with spinal cord injury, electromyographic (EMG) activity from muscles above the level of the lesion can control direct electrical stimulation of paralyzed muscles, and thereby restore useful movement (Hoffer et al., 1996; Kilgore et al., 1997; Ferguson et al., 1999).

The final option for restoring function to those with motor impairments is to provide the brain with a new, non-muscular communication and control channel, a direct brain–computer interface (BCI) for conveying messages and commands to the external world. A variety of methods for monitoring brain activity might serve as a BCI. These include, besides electroencephalography (EEG) and more invasive electrophysiological methods, magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging. However, MEG, PET, fMRI, and optical imaging are still technically demanding and expensive. Furthermore, PET, fMRI, and optical imaging, which depend on blood flow, have long time constants and thus are less amenable to rapid communication. At present, only EEG and related methods, which have relatively short time constants, can function in most environments, and require relatively simple and inexpensive equipment, offer the possibility of a new non-muscular communication and control channel, a practical BCI.

1.2. The fourth application of the EEG

In the 7 decades since Hans Berger's original paper (Berger, 1929), the EEG has been used mainly to evaluate neurological disorders in the clinic and to investigate brain function in the laboratory; and a few studies have explored its therapeutic possibilities (e.g. Travis et al., 1975; Kuhlman, 1978; Elbert et al., 1980; Rockstroh et al., 1989; Rice et al., 1993; Sterman, 2000). Over this time, people have also speculated that the EEG could have a fourth application, that it could be used to decipher thoughts, or intent, so that a person could communicate with others or control devices directly by means of brain activity, without using the normal channels of peripheral nerves and muscles. This idea has appeared often in popular fiction and fantasy (such as the movie 'Firefox' in which an airplane is controlled in part by the pilot's EEG (Thomas, 1977)). However, EEG-based communication attracted little serious scientific attention until recently, for at least 3 reasons.

First, while the EEG reflects brain activity, so that a person's intent could in theory be detected in it, the resolution and reliability of the information detectable in the spontaneous EEG is limited by the vast number of electrically active neuronal elements, the complex electrical and spatial geometry of the brain and head, and the disconcerting trial-to-trial variability of brain function. The possibility of recognizing a single message or command amidst this complexity, distortion, and variability appeared to be extremely remote. Second, EEG-based communication requires the capacity to analyze the EEG in real-time, and until recently the requisite technology either did not exist or was extremely expensive. Third, there was in the past little interest in the limited communication capacity that a first-generation EEG-based BCI was likely to offer.

Recent scientific, technological, and societal events have changed this situation. First, basic and clinical research has yielded detailed knowledge of the signals that comprise the EEG. For the major EEG rhythms and for a variety of evoked potentials, their sites and mechanisms of origin and their relationships with specific aspects of brain function, are no longer wholly obscure. Numerous studies have demonstrated correlations between EEG signals and actual or imagined movements and between EEG signals and mental tasks (e.g. Keirn and Aunon, 1990; Lang et al., 1996; Pfurtscheller et al., 1997; Anderson et al., 1998; Altenmüller and Gerloff, 1999; McFarland et al., 2000a). Thus, researchers are in a much better position to consider which EEG signals might be used for communication and control, and how they might best be used. Second, the extremely rapid and continuing development of inexpensive computer hardware and software supports sophisticated online analyses of multichannel EEG. This digital revolution has also led to appreciation of the fact that simple communication capacities (e.g. 'Yes' or 'No', 'On' or 'Off') can be configured to serve complex functions (e.g. word processing, prosthesis control). Third, greatly increased societal recognition of the needs and potential of people with severe neuromuscular disorders like spinal cord injury or cerebral palsy has generated clinical, scientific, and commercial interest in better augmentative communication and control technology. Development of such technology is both the impetus and the justification for current BCI research. BCI technology might serve people who cannot use conventional augmentative technologies; and these people could find even the limited capacities of first-generation BCI systems valuable.

In addition, advances in the development and use of electrophysiological recording methods employing epidural, subdural, or intracortical electrodes offer further options. Epidural and subdural electrodes can provide EEG with high topographical resolution, and intracortical electrodes can follow the activity of individual neurons (Schmidt, 1980; Ikeda and Shibbasaki, 1992; Heetderks and Schmidt, 1995; Levine et al., 1999, 2000; Wolpaw et al., 2000a). Furthermore, recent studies show that the firing rates of an appropriate selection of cortical neurons can give a detailed picture of concurrent voluntary movement (e.g. Georgopoulos et al., 1986; Schwartz, 1993; Chapin et al., 1999; Wessberg et al., 2000). Because these methods are invasive, the threshold for their clinical use would presumably be higher than for methods based on scalp-recorded EEG activity, and they would probably be used mainly by those with extremely severe disabilities. At the same time, they might support more rapid and precise communication and control than the scalp-recorded EEG.

1.3. The present review

This review summarizes the current state of BCI research with emphasis on its application to the needs of those with severe neuromuscular disabilities. In order to address all current BCI research, it includes approaches that use standard scalp-recorded EEG as well as those that use epidural, subdural, or intracortical recording. While all these present-day BCIs use electrophysiological methods, the basic principles of BCI design and operation discussed here should apply also to BCIs that use other methods to monitor brain activity (e.g. MEG, fMRI). The next sections describe the essential elements of any BCI and the several categories of electrophysiological BCIs, review current research, consider prospects for the future, and discuss the issues most important for further BCI development and application.

2. Definition and features of a BCI

2.1. Dependent and independent BCIs

A BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles. For example, in an EEG-based BCI the messages are encoded in EEG activity. A BCI provides its user with an alternative method for acting on the world. BCIs fall into two classes: dependent and independent.

A dependent BCI does not use the brain's normal output pathways to carry the message, but activity in these pathways is needed to generate the brain activity (e.g. EEG) that does carry it. For example, one dependent BCI presents the user with a matrix of letters that flash one at a time, and the user selects a specific letter by looking directly at it so that the visual evoked potential (VEP) recorded from the scalp over visual cortex when that letter flashes is much larger that the VEPs produced when other letters flash (Sutter, 1992). In this case, the brain's output channel is EEG, but the generation of the EEG signal depends on gaze direction, and therefore on extraocular muscles and the cranial nerves that activate them. A dependent BCI is essentially an alternative method for detecting messages carried in the brain's normal output pathways: in the present example, gaze direction is detected by monitoring EEG rather than by monitoring eye position directly. While a dependent BCI does not give the brain a new communication channel that is independent of conventional channels, it can still be useful (e.g. Sutter and Tran, 1992).

In contrast, an independent BCI does not depend in any way on the brain's normal output pathways. The message is not carried by peripheral nerves and muscles, and, furthermore, activity in these pathways is not needed to generate the brain activity (e.g. EEG) that does carry the message. For example, one independent BCI presents the user with a matrix of letters that flash one at a time, and the user selects a specific letter by producing a P300 evoked potential when that letter flashes (Farwell and Donchin, 1988; Donchin et al., 2000). In this case, the brain's output channel is EEG, and the generation of the EEG signal depends mainly on the user's intent, not on the precise orientation of the eyes (Sutton et al., 1965; Donchin, 1981; Fabiani et al., 1987; Polich, 1999). The normal output pathways of peripheral nerves and muscles do not have an essential role in the operation of an independent BCI. Because independent BCIs provide the brain with wholly new output pathways, they are of greater theoretical interest than dependent BCIs. Furthermore, for people with the most severe neuromuscular disabilities, who may lack all normal output channels (including extraocular muscle control), independent BCIs are likely to be more useful.

2.2. BCI use is a skill

Most popular and many scientific speculations about BCIs start from the 'mind-reading' or 'wire-tapping' analogy, the assumption that the goal is simply to listen in on brain activity as reflected in electrophysiological signals and thereby determine a person's wishes. This analogy ignores the essential and central fact of BCI development and operation. A BCI changes electrophysiological signals from mere reflections of central nervous system (CNS) activity into the intended products of that activity: messages and commands that act on the world. It changes a signal such as an EEG rhythm or a neuronal firing rate from a reflection of brain function into the end product of that function: an output that, like output in conventional neuromuscular channels, accomplishes the person's intent. A BCI replaces nerves and muscles and the movements they produce with electrophysiological signals and the hardware and software that translate those signals into actions.

The brain's normal neuromuscular output channels depend for their successful operation on feedback. Both standard outputs such as speaking or walking and more specialized outputs such as singing or dancing require for their initial acquisition and subsequent maintenance continual adjustments based on oversight of intermediate and final outcomes (Salmoni, 1984; Ghez and Krakauer, 2000). When feedback is absent from the start, motor skills do not develop properly; and when feedback is lost later on, skills deteriorate.

As a replacement for the brain's normal neuromuscular output channels, a BCI also depends on feedback and on adaptation of brain activity based on that feedback. Thus, a BCI system must provide feedback and must interact in a productive fashion with the adaptations the brain makes in response to that feedback. This means that BCI operation depends on the interaction of two adaptive controllers: the user's brain, which produces the signals measured by the BCI; and the BCI itself, which translates these signals into specific commands.

Successful BCI operation requires that the user develop and maintain a new skill, a skill that consists not of proper muscle control but rather of proper control of specific electrophysiological signals; and it also requires that the BCI translate that control into output that accomplishes the user's intent. This requirement can be expected to remain even when the skill does not require initial training. In the independent BCI described above, the P300 generated in response to the desired letter occurs without training. Nevertheless, once this P300 is engaged as a communication channel, it is likely to undergo adaptive modification (Rosenfeld, 1990; Coles and Rugg, 1995), and the recognition and productive engagement of this adaptation will be important for continued successful BCI operation.

That the brain's adaptive capacities extend to control of various electrophysiological signal features was initially suggested by studies exploring therapeutic applications of the EEG. They reported conditioning of the visual alpha rhythm, slow potentials, the mu rhythm, and other EEG features (Wyricka and Sterman, 1968; Dalton, 1969; Black et al., 1970; Nowles and Kamiya, 1970; Black, 1971, 1973; Travis et al., 1975; Kuhlman, 1978; Rockstroh et al., 1989) (reviewed in Neidermeyer (1999)). These studies usually sought to produce an increase in the amplitude of a specific EEG feature. Because they had therapeutic goals, such as reduction in seizure frequency, they did not try to demonstrate rapid bidirectional control, that is, the ability to increase and decrease a specific feature quickly and accurately, which is important for communication. Nevertheless, they suggested that bidirectional control is possible, and thus justified and encouraged efforts to develop EEG-based communication. In addition, studies in monkeys showed that the firing rates of individual cortical neurons could be operantly conditioned, and thus suggested that cortical neuronal activity provides another option for non-muscular communication and control (Fetz and Finocchio, 1975; Wyler and Burchiel, 1978; Wyler et al., 1979; Schmidt, 1980).

At the same time, these studies did not indicate to what extent the control that people or animals develop over these electrophysiological phenomena depends on activity in conventional neuromuscular output channels (e.g. Dewan, 1967). While studies indicated that conditioning of hippocampal activity did not require mediation by motor responses (Dalton, 1969; Black, 1971), the issue was not resolved for other EEG features or for cortical neuronal activity. This question of independent control of the various electrophysiological signal features used in current and contemplated BCIs is important both theoretically and practically, and arises at multiple points in this review.

2.3. The parts of a BCI

Like any communication or control system, a BCI has input (e.g. electrophysiological activity from the user), output (i.e. device commands), components that translate input into output, and a protocol that determines the onset, offset, and timing of operation. Fig. 1 shows these elements and their principal interactions.

2.3.1. Signal acquisition

In the BCIs discussed here, the input is EEG recorded from the scalp or the surface of the brain or neuronal activity recorded within the brain. Thus, in addition to the fundamental distinction between dependent and independent BCIs (Section 2.1 above), electrophysiological BCIs can be categorized by whether they use non-invasive (e.g. EEG) or invasive (e.g. intracortical) methodology. They can also be categorized by whether they use evoked or spontaneous inputs. Evoked inputs (e.g. EEG produced by flashing letters) result from stereotyped sensory stimulation provided by the BCI. Spontaneous inputs (e.g. EEG rhythms over sensorimotor cortex) do not depend for their generation on such stimulation. There is, presumably, no reason why a BCI could not combine non-invasive and invasive methods or evoked and spontaneous inputs. In the signal-acquisition part of BCI operation, the chosen input is acquired by the recording electrodes, amplified, and digitized.

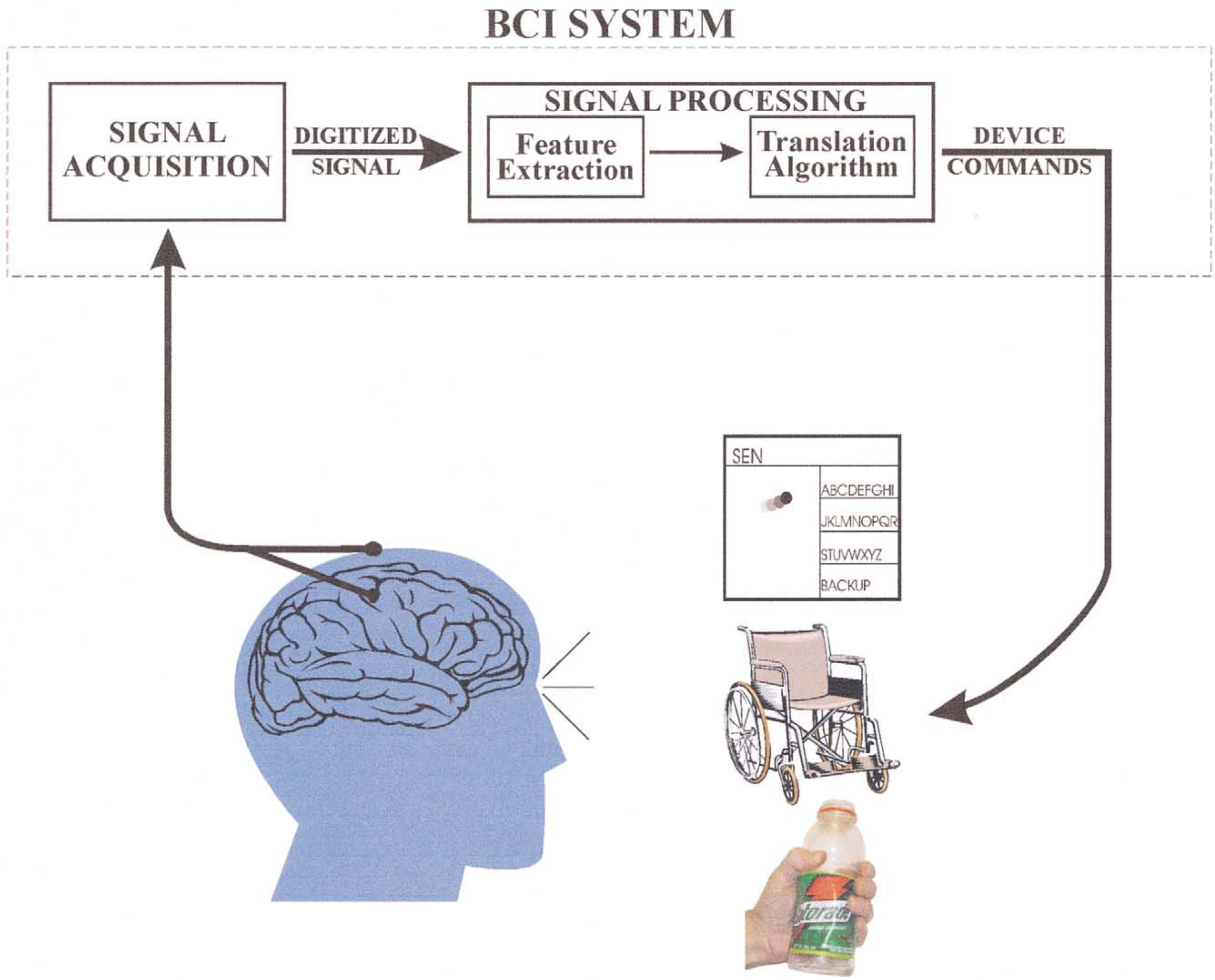

Fig. 1. Basic design and operation of any BCI system. Signals from the brain are acquired by electrodes on the scalp or in the head and processed to extract specific signal features (e.g. amplitudes of evoked potentials or sensorimotor cortex rhythms, firing rates of cortical neurons) that reflect the user's intent. These features are translated into commands that operate a device (e.g. a simple word processing program, a wheelchair, or a neuroprosthesis). Success depends on the interaction of two adaptive controllers, user and system. The user must develop and maintain good correlation between his or her intent and the signal features employed by the BCI; and the BCI must select and extract features that the user can control and must translate those features into device commands correctly and efficiently.

2.3.2. Signal processing: feature extraction

The digitized signals are then subjected to one or more of a variety of feature extraction procedures, such as spatial filtering, voltage amplitude measurements, spectral analyses, or single-neuron separation. This analysis extracts the signal features that (hopefully) encode the user's messages or commands. BCIs can use signal features that are in the time domain (e.g. evoked potential amplitudes or neuronal firing rates) or the frequency domain (e.g. mu or beta-rhythm amplitudes) (Farwell and Donchin, 1988; Lopes da Silva and Mars, 1987; Parday et al., 1996; Lopes da Silva, 1999; Donchin et al., 2000; Kennedy et al., 2000; Wolpaw et al., 2000b; Pfurtscheller et al., 2000a; Penny et al., 2000; Kostov and Polak, 2000). A BCI could conceivably use both time-domain and frequency-domain signal features, and might thereby improve performance (e.g. Schalk et al., 2000).

In general, the signal features used in present-day BCIs reflect identifiable brain events like the firing of a specific cortical neuron or the synchronized and rhythmic synaptic activation in sensorimotor cortex that produces a mu rhythm. Knowledge of these events can help guide BCI development. The location, size, and function of the cortical area generating a rhythm or an evoked potential can indicate how it should be recorded, how users might best learn to control its amplitude, and how to recognize and eliminate the effects of non-CNS artifacts. It is also possible for a BCI to use signal features, like sets of autoregressive parameters, that correlate with the user's intent but do not necessarily reflect specific brain events. In such cases, it is particularly important (and may be more difficult) to ensure that the chosen features are not contaminated by EMG, electro-oculography (EOG), or other non-CNS artifacts.

2.3.3. Signal processing: the translation algorithm

The first part of signal processing simply extracts specific signal features. The next stage, the translation algorithm, translates these signal features into device commands-orders that carry out the user's intent. This algorithm might use linear methods (e.g. classical statistical analyses (Jain et al., 2000) or nonlinear methods (e.g. neural networks). Whatever its nature, each algorithm changes independent variables (i.e. signal features) into dependent variables (i.e. device control commands).

Effective algorithms adapt to each user on 3 levels. First, when a new user first accesses the BCI the algorithm adapts to that user's signal features. If the signal feature is mu-rhythm amplitude, the algorithm adjusts to the user's range of mu-rhythm amplitudes; if the feature is P300 amplitude, it adjusts to the user's characteristic P300 amplitude; and if the feature is the firing rate of a single cortical neuron, it adjusts to the neuron's characteristic range of firing rates. A BCI that possesses only this first level of adaptation, i.e. that adjusts to the user initially and never again, will continue to be effective only if the user's performance is very stable. However, EEG and other electrophysiological signals typically display short- and long-term variations linked to time of day, hormonal levels, immediate environment, recent events, fatigue, illness, and other factors. Thus, effective BCIs need a second level of adaptation: periodic online adjustments to reduce the impact of such spontaneous variations. A good translation algorithm will adjust to these variations so as to match as closely as possible the user's current range of signal feature values to the available range of device command values.

While they are clearly important, neither of these first two levels of adaptation addresses the central fact of effective BCI operation: its dependence on the effective interaction of two adaptive controllers, the BCI and the user's brain. The third level of adaptation accommodates and engages the adaptive capacities of the brain. As discussed in Section 2.2, when an electrophysiological signal feature that is normally merely a reflection of brain function becomes the end product of that function, that is, when it becomes an output that carries the user's intent to the outside world, it engages the adaptive capacities of the brain. Like activity in the brain's conventional neuromuscular communication and control channels, BCI signal features will be affected by the device commands they are translated into: the results of BCI operation will affect future BCI input. In the most desirable (and hopefully typical) case, the brain will modify signal features so as to improve BCI operation. If, for example, the feature is mu-rhythm amplitude, the correlation between that amplitude and the user's intent will hopefully increase over time. An algorithm that incorporates the third level of adaptation could respond to this increase by rewarding the user with faster communication. It would thereby recognize and encourage the user's development of greater skill in this new form of communication. On the other hand, excessive or inappropriate adaptation could impair performance or discourage further skill development. Proper design of this third level of adaptation is likely to prove crucial for BCI development. Because this level involves the interaction of two adaptive controllers, the user's brain and the BCI system, its design is among the most difficult problems confronting BCI research.

2.3.4. The output device

For most current BCIs, the output device is a computer screen and the output is the selection of targets, letters, or icons presented on it (e.g. Farwell and Donchin, 1988; Wolpaw et al., 1991; Perelmouter et al., 1999; Pfurtscheller et al., 2000a). Selection is indicated in various ways (e.g. the letter flashes). Some BCIs also provide additional, interim output, such as cursor movement toward the item prior to its selection (e.g. Wolpaw et al., 1991; Pfurtscheller et al., 2000a). In addition to being the intended product of BCI operation, this output is the feedback that the brain uses to maintain and improve the accuracy and speed of communication. Initial studies are also exploring BCI control of a neuroprosthesis or orthesis that provides hand closure to people with cervical spinal cord injuries (Lauer et al., 2000; Pfurtscheller et al., 2000b). In this prospective BCI application, the output device is the user's own hand.

2.3.5. The operating protocol

Each BCI has a protocol that guides its operation. This protocol defines how the system is turned on and off, whether communication is continuous or discontinuous, whether message transmission is triggered by the system (e.g. by the stimulus that evokes a P300) or by the user, the sequence and speed of interactions between user and system, and what feedback is provided to the user.

Most protocols used in BCI research are not completely suitable for BCI applications that serve the needs of people with disabilities. Most laboratory BCIs do not give the user on/off control: the investigator turns the system on and off. Because they need to measure communication speed and accuracy, laboratory BCIs usually tell their users what messages or commands to send. In real life the user picks the message. Such differences in protocol can complicate the transition from research to application.

3. Present-day BCIs

While many studies have described electrophysiological or other measures of brain function that correlate with concurrent neuromuscular outputs or with intent and might therefore function in a BCI system, relatively few peer-reviewed articles have described human use of systems that satisfy the BCI definition given in Section 2.1 and illustrated in Fig. 1, systems that give the user control over a device and concurrent feedback from the device. These studies are reviewed here. Studies from the vast group describing phenomena that might serve as the basis for a

BCI are mentioned only when they relate directly to actual BCI systems.

Present-day BCIs fall into 5 groups based on the electrophysiological signals they use. The first group, those using VEPs, are dependent BCIs, i.e. they depend on muscular control of gaze direction. The other 4 groups, those using slow cortical potentials, P300 evoked potentials, mu and beta rhythms, and cortical neuronal action potentials, are believed to be independent BCIs (Section 2.1), though this belief remains to some extent an assumption still in need of complete confirmation.

3.1. Visual evoked potentials

In the 1970s, Jacques Vidal used the term ‘brain–computer interface’ to describe any computer-based system that produced detailed information on brain function. This early usage was broader than current usage, which applies the term BCI only to those systems that support communication and control by the user. Nevertheless, in the course of his work, Vidal developed a system that satisfied the current definition of a dependent BCI (Vidal, 1973, 1977). This system used the VEP recorded from the scalp over visual cortex to determine the direction of eye gaze (i.e. the visual fixation point), and thus to determine the direction in which the user wished to move a cursor.

Sutter (1992) described a similar BCI system called the brain response interface (BRI). It uses the VEPs produced by brief visual stimuli and recorded from the scalp over visual cortex. The user faces a video screen displaying 64 symbols (e.g. letters) in an 8×8 grid and looks at the symbol he or she wants to select. Subgroups of these 64 symbols undergo an equiluminant red/green alternation or a fine red/green check pattern alternation 40–70 times/s. Each symbol is included in several subgroups, and the entire set of subgroups is presented several times. Each subgroup’s VEP amplitude about 100 ms after the stimulus is computed and compared to a VEP template already established for the user. From these comparisons, the system determines with high accuracy the symbol that the user is looking at. A keyboard interface gives access to output devices. Normal volunteers can use it to operate a word processing program at 10–12 words/min. In users whose disabilities cause uncontrollable head and neck muscle activity, scalp EMG can impede reliable VEP measurement and reduce performance. For one such user, a man with ALS, this problem was solved by placing a strip of 4 epidural electrodes over visual cortex. With this implant, he could communicate 10–12 words/min (Sutter, 1984, 1992).

Middendorf et al. (2000) reported another method for using VEPs to determine gaze direction. Several virtual buttons appear on a screen and flash at different rates. The user looks at a button and the system determines the frequency of the photic driving response over visual cortex. When this frequency matches that of a button, the system concludes that the user wants to select it.

These VEP-based communication systems depend on the user’s ability to control gaze direction. Thus, they perform the same function as systems that determine gaze direction from the eyes themselves, and can be categorized as dependent BCI systems. They show that the EEG can yield precise information about concurrent motor output, and might prove superior to other methods for assessing gaze direction. It is possible that VEP amplitude in these systems reflects attention as well as gaze direction (e.g. Teder-Sälejärvi et al., 1999), and thus that they may be to some extent independent of neuromuscular function.

3.2. Slow cortical potentials

Among the lowest frequency features of the scalp-recorded EEG are slow voltage changes generated in cortex. These potential shifts occur over 0.5–10.0 s and are called slow cortical potentials (SCPs). Negative SCPs are typically associated with movement and other functions involving cortical activation, while positive SCPs are usually associated with reduced cortical activation (Rockstroh et al., 1989; Birbaumer, 1997). In studies over more than 30 years, Birbaumer and his colleagues have shown that people can learn to control SCPs and thereby control movement of an object on a computer screen (Elbert et al., 1980, Birbaumer et al., 1999, 2000). This demonstration is the basis for a BCI referred to as a ‘thought translation device’ (TTD). The principal emphasis has been on developing clinical application of this BCI system. It has been tested extensively in people with late-stage ALS and has proved able to supply basic communication capability (Kübler, 2000).

In the standard format (Fig. 2A), EEG is recorded from electrodes at the vertex referred to linked mastoids. SCPs are extracted by appropriate filtering, corrected for EOG activity, and fed back to the user via visual feedback from a computer screen that shows one choice at the top and one at the bottom. Selection takes 4 s. During a 2 s baseline period, the system measures the user’s initial voltage level. In the next 2 s, the user selects the top or bottom choice by decreasing or increasing the voltage level by a criterion amount. The voltage is displayed as vertical movement of a cursor and final selection is indicated in a variety of ways. The BCI can also operate in a mode that gives auditory or tactile feedback (Birbaumer et al., 2000). Users train in several 1–2 h sessions/week over weeks or months. When they consistently achieve accuracies $\geq 75\%$, they are switched to a language support program (LSP).

The LSP (Perelmouter et al., 1999; Perelmouter and Birbaumer, 2000) enables the user to choose a letter or letter combination by a series of two-choice selections. In each selection, the choice is between selecting or not selecting a set of one or more letters. The first two selections choose between the two halves of the alphabet, the next two between the two quarters of the selected half, and so on until a single letter is chosen. A backup or erase option is provided. With this program, users who have two-choice

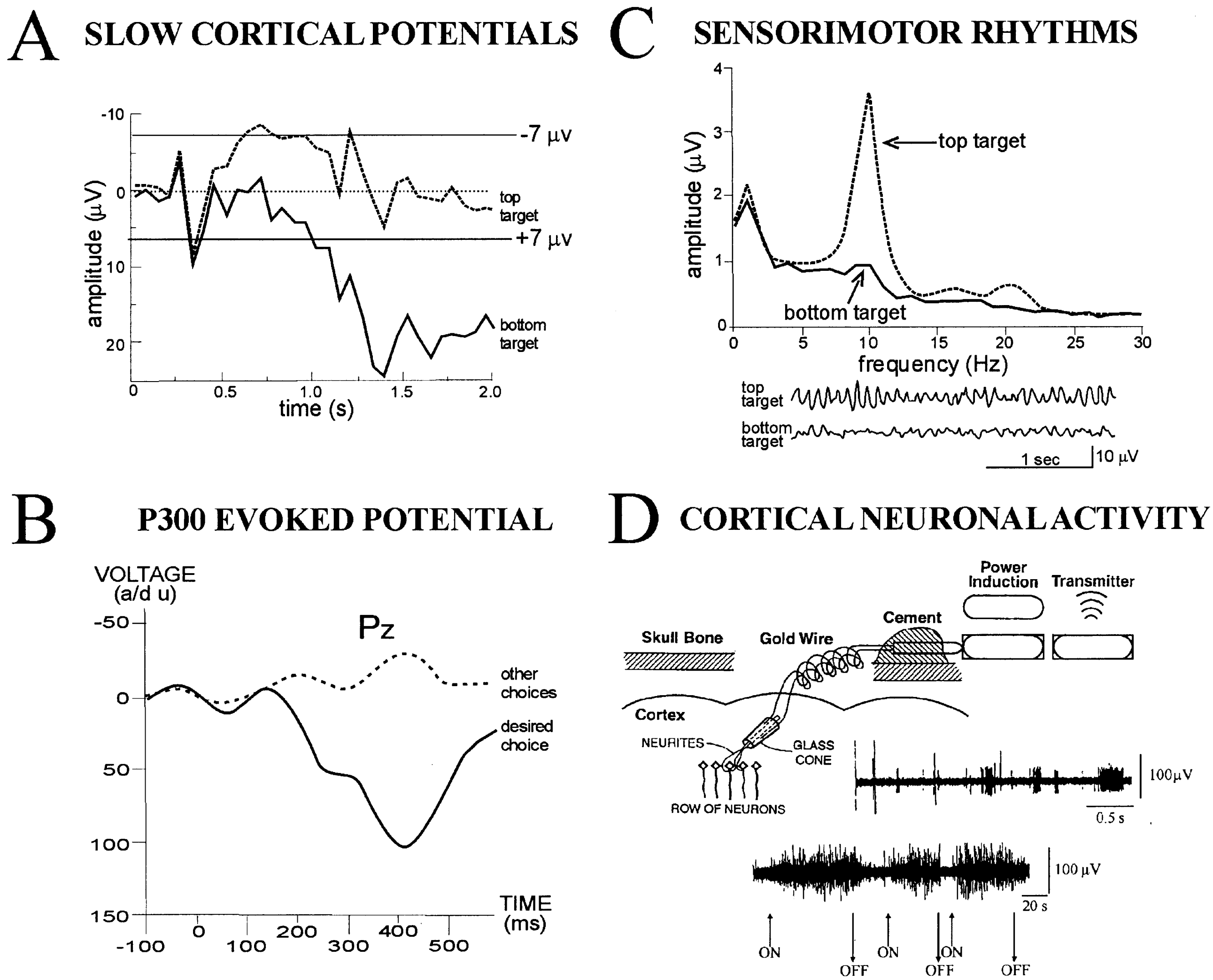

Fig. 2. Present-day human BCI system types. (Modified from Kübler et al. (2001).) A–C are non-invasive methods, D is invasive. (A) SCP BCI. Scalp EEG is recorded from the vertex. Users learn to control SCPs to move a cursor toward a target (e.g. a desired letter or icon) at the bottom (more positive SCP) or top (more negative SCP) of a computer screen (Kübler et al., 2001;Birbaumer et al., 1999, 2000). (B) P300 BCI. A matrix of possible choices is presented on a screen and scalp EEG is recorded over the centroparietal area while these choices flash in succession. Only the choice desired by the user evokes a large P300 potential (i.e. a positive potential about 300 ms after the flash) (Farwell and Donchin, 1988; Donchin et al., 2000). (C) Sensorimotor rhythm BCI. Scalp EEG is recorded over sensorimotor cortex. Users control the amplitude of a 8–12 Hz 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 show that control is clearly focused in the mu-rhythm frequency band. Sample EEG traces (bottom) also indicate that the mu rhythm is prominent when the target is at the top and minimal when it is at the bottom (Wolpaw et al., 1991, 2000b; McFarland et al., 1997a). (D) Cortical neuronal BCI. Cone electrodes implanted in motor cortex detect action potentials of single cortical neurons (traces). Users learn to control neuronal firing rate(s) to move a cursor to select letters or icons on a screen (Kennedy and Bakay, 1998; Kennedy et al., 2000).

accuracies of 65–90% can write 0.15–3.0 letters/min, or 2–36 words/h. While these rates are low, the LSP has proved useful to and highly valued by people who cannot use conventional augmentative communication technologies. Furthermore, a predictive algorithm that uses the first two letters of a word to select the word from a lexicon that encompasses the user's vocabulary can markedly increase the communication rate. A new protocol provides Internet access to one disabled user (Birbaumer et al., 2000). A stand-by mode allows users wearing collodium-fixed electrodes to access the system 24 h/day by producing a specific sequence of positive and negative SCPs (Kaiser et al., 2001). This sequence is essentially a key for turning the BCI on and off.

3.3. P300 evoked potentials

Infrequent or particularly significant auditory, visual, or somatosensory stimuli, when interspersed with frequent or routine stimuli, typically evoke in the EEG over parietal cortex a positive peak at about 300 ms (Walter et al., 1964; Sutton et al., 1965; Donchin and Smith, 1970). Donchin and his colleagues have used this 'P300', or 'oddball' response in a BCI (Farwell and Donchin, 1988; Donchin et al., 2000).

The user faces a 6×6 matrix of letters, numbers, and/or other symbols or commands. Every 125 ms, a single row or column flashes; and, in a complete trial of 12 flashes, each row or column flashes twice. The user makes a selection by counting how many times the row or column containing the desired choice flashes. EEG over parietal cortex is digitized, the average response to each row and column is computed, and P300 amplitude for each possible choice is computed. As Fig. 2B shows, P300 is prominent only in the responses elicited by the desired choice, and the BCI uses this effect to determine the user's intent. In online experiments and offline simulations, a variety of different algorithms (e.g. stepwise discriminant analysis, discrete wavelet transform) for recognizing the desired choice have been evaluated, and the relationship between the number of trials per selection and BCI accuracy has been described. These analyses suggest that the current P300-based BCI could yield a communication rate of one word (i.e. 5 letters) per minute and also suggest that considerable further improvement in speed should be possible. In people with visual impairments, auditory or tactile stimuli might be used (Glover et al., 1986; Roder et al., 1996). In related work, Bayliss and Ballard (2000) recorded P300s in a virtual environment. Offline analyses suggested that single-trial P300 amplitudes might be used for environmental control.

A P300-based BCI has an apparent advantage in that it requires no initial user training: P300 is a typical, or naive, response to a desired choice. At the same time, P300 and related potentials change in response to conditioning protocols (Glover et al., 1986; Miltner et al., 1988; Sommer and Schweinberger, 1992; Roder et al., 1996). A P300 used in a BCI is also likely to change over time. Studies up to the present have been short-term. In the long term, P300 might habituate (Ravden and Polich, 1999) so that BCI performance deteriorates, or it might get larger so that performance improves. Thus, appropriate adaptation by the translation algorithm is likely to be important for this BCI, as it is for others.

3.4. Mu and beta rhythms and other activity from sensorimotor cortex

In awake people, primary sensory or motor cortical areas often display 8–12 Hz EEG activity when they are not engaged in processing sensory input or producing motor output (Gastaut, 1952; Kozelka and Pedley, 1990; Fisch, 1999) (reviewed in Neidermeyer, 1999). This idling activity, called mu rhythm when focused over somatosensory or motor cortex and visual alpha rhythm when focused over visual cortex, is thought to be produced by thalamocortical circuits (Lopes da Silva, 1991; Neidermeyer, 1999). Unlike the visual alpha rhythm, which is obvious in most normal people, the mu rhythm was until quite recently found only in a minority (Chatrian, 1976). However, computer-based analyses reveal the mu rhythm in most adults (Pfurtscheller, 1989). Such analyses also show that mu-rhythm activity comprises a variety of different 8–12 Hz rhythms, distinguished from each other by location, frequency, and/or relationship to concurrent sensory input or motor output. These mu rhythms are usually associated with 18–26 Hz beta rhythms. While some beta rhythms are harmonics of mu rhythms, some are separable from them by topography and/or timing, and thus are independent EEG features (Pfurtscheller and Berghold, 1989; Pfurtscheller, 1999; McFarland et al., 2000a).

Several factors suggest that mu and/or beta rhythms could be good signal features for EEG-based communication. They are associated with those cortical areas most directly connected to the brain's normal motor output channels. Movement or preparation for movement is typically accompanied by a decrease in mu and beta rhythms, particularly contralateral to the movement. This decrease has been labeled 'event-related desynchronization' or ERD (Pfurtscheller and Lopes da Silva, 1999b; Pfurtscheller, 1999). Its opposite, rhythm increase, or 'event-related synchronization' (ERS) occurs after movement and with relaxation (Pfurtscheller, 1999). Furthermore, and most relevant for BCI use, ERD and ERS do not require actual movement, they occur also with motor imagery (i.e. imagined movement) (Pfurtscheller and Neuper, 1997; McFarland et al., 2000a). Thus, they might support an independent BCI. Since the mid-1980s, several mu/beta rhythm-based BCIs have been developed.

3.4.1. The Wadsworth BCI

With the BCI system of Wolpaw, McFarland, and their colleagues (Wolpaw et al., 1991, 2000b; McFarland et al., 1997a), people with or without motor disabilities learn to control mu- or beta-rhythm amplitude and use that control to move a cursor in one or two dimensions to targets on a computer screen. Fig. 2C shows the basic phenomenon. In this example, the user increases the amplitude of a 8–12 Hz mu rhythm to move a cursor to a target at the top of the screen or decreases it to move to a target at the bottom. Frequency spectra (top) for top and bottom targets show that 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.

For each dimension of cursor control, a linear equation translates mu- or beta-rhythm amplitude from one or several scalp locations into cursor 10 times/s. Users learn over a series of 40 min sessions to control cursor movement. They participate in 2–3 sessions per week, and most (i.e. about 80%) acquire significant control within 2–3 weeks. In the initial sessions, most employ motor imagery (e.g. imagination of hand movements, whole body activities, relaxation, etc.) to control the cursor. As training proceeds, imagery usually becomes less important, and users move the cursor like they perform conventional motor acts, that is, without thinking about the details of performance.

While EEG from only one or two scalp locations controls cursor movement online, data from 64 locations covering the entire scalp are gathered for later offline analysis that defines the full topography of EEG changes associated with target position and helps guide improvements in online operation. This analysis relies largely on the measure r^2, which is the proportion of the total variance in mu- or beta-rhythm amplitude that is accounted for by target position and thus reflects the user's level of EEG control. The r^2 topographical analyses (e.g. Fig. 3C) show that control is sharply focused over sensorimotor cortex and in the mu- and/or beta-rhythm frequency bands. With this control, users can move the cursor to answer spoken yes/no questions with accuracies >95% (Miner et al., 1998; Wolpaw et al., 1998). They can also achieve independent control of two different mu- or beta-rhythm channels and use that control to move a cursor in two dimensions (Wolpaw and McFarland, 1994). Recent work has concentrated on developing precise one-dimensional control, and on applying it to choosing among up to 8 different targets. Users have achieved information transfer rates up to 20–25 bits/min (McFarland et al., 2000b).

Research with this BCI has focused on defining the topographical, spectral, and temporal features of mu- and beta-rhythm control and on optimizing the mutually adaptive interactions between the user and the BCI system. Improvements include: spatial filters that match the spatial frequencies of the user's mu or beta rhythms (Fig. 3), autoregressive frequency analysis which gives higher resolution for short time segments and thus permits more rapid device control, and better selection of the constants in the equations that translate EEG control into device control (e.g. McFarland et al., 1997a,b; Ramoser et al., 1997). Recent studies have also explored incorporation of other EEG features into this BCI. In well-trained users, errors in target selection are associated with a positive potential centered at the vertex (Schalk et al., 2000). This potential might be used to recognize and cancel mistakes. While work to date has used cursor control as a prototype BCI application and has concentrated on improving it, effort is also being devoted to applications like answering simple questions or basic word processing (Miner et al., 1998; Wolpaw et al., 1998; Vaughan et al., 2001).

3.4.2. The Graz BCI

This BCI system is also based on ERD and ERS of mu and beta rhythms. Research up to the present has focused on distinguishing between the EEG associated with imagination of different simple motor actions, such as right or left hand or foot movement, and thereby enabling the user to control a cursor or an orthotic device that opens and closes a paralyzed hand (Pfurtscheller et al., 1993, 2000a,b; Neuper et al., 1999). In the standard protocol, the user first participates in an initial session to select a motor imagery paradigm. In each of a series (e.g. 160) of 5.25 s trials, the user imagines one of several actions (e.g. right or left hand or foot movement, tongue movement) while EEG from electrodes over sensorimotor cortex is submitted to frequency analysis to derive signal features (e.g. the powers in the frequency bands from 5 to 30 Hz). For each imagined action, an n-dimensional feature vector is defined. These vectors establish a user-specific linear or non-linear classifier (e.g. linear discriminant analysis, distinction sensitive learning vector quantization (DSLVQ), or a neural network) that determines from the EEG which action the user is imagining (Pregenzer et al., 1996; Pfurtscheller et al., 1996; Pregenzer and Pfurtscheller, 1999; Müller-Gerking et al., 1999). In subsequent sessions, the system uses the classifier to translate the user's motor imagery into a continuous output (e.g. extension of a lighted bar or cursor movement) or a discrete output (e.g. selection of a letter or other symbol), which is presented to the user as online feedback on a computer screen. Normally, the classification algorithm is adjusted between daily sessions. Over 6–7 sessions with two-choice trials (i.e. left hand vs. right hand imagery) users can reach accuracies over 90%. About 90% of people can use this system successfully. The signal features that reflect motor imagery and are used by the classifier are concentrated in the mu- and beta-rhythm bands in EEG over sensorimotor cortex (Pfurtscheller and Neuper, 1997).

Current studies seek modifications that improve classification. These include use of parameters derived by autoregressive frequency analysis (instead of the values for power in specific frequency bands) and use of alternative spatial filters. Additional effort has been devoted to developing remote control capabilities that allow the BCI to function in users' homes while the classification algorithm is updated in the laboratory. With this remote control system, a user paralyzed by a mid-cervical spinal cord injury uses hand and foot motor imagery to control an orthosis that provides hand grasp. EEG over sensorimotor cortex is translated into hand opening and closing by autoregressive parameter estimation and linear discriminative classification (Obermaier et al., 2001; Guger et al., 1999; Pfurtscheller et al., 2000b; Pfurtscheller and Neuper, 2001).

3.4.3. Other systems

Kostov and Polak (2000) report BCI control of one- and two-dimensional cursor movement. EEG is recorded with a 28-electrode array and a linked-ear reference, digitized at 200 Hz, and analyzed. Autoregressive parameters from 2 to 4 locations are translated into cursor movements by an adaptive logic network (Armstrong and Thomas, 1996). User training is important (Polak, 2000).

Penny et al. (2000) describe a BCI that also uses EEG over sensorimotor cortex to control cursor movement. They concentrate on detecting the EEG associated with imagery of actions like right or left hand movements, and/or tasks like simple calculations. Their translation algorithm uses autoregressive parameters and a logistic regression model

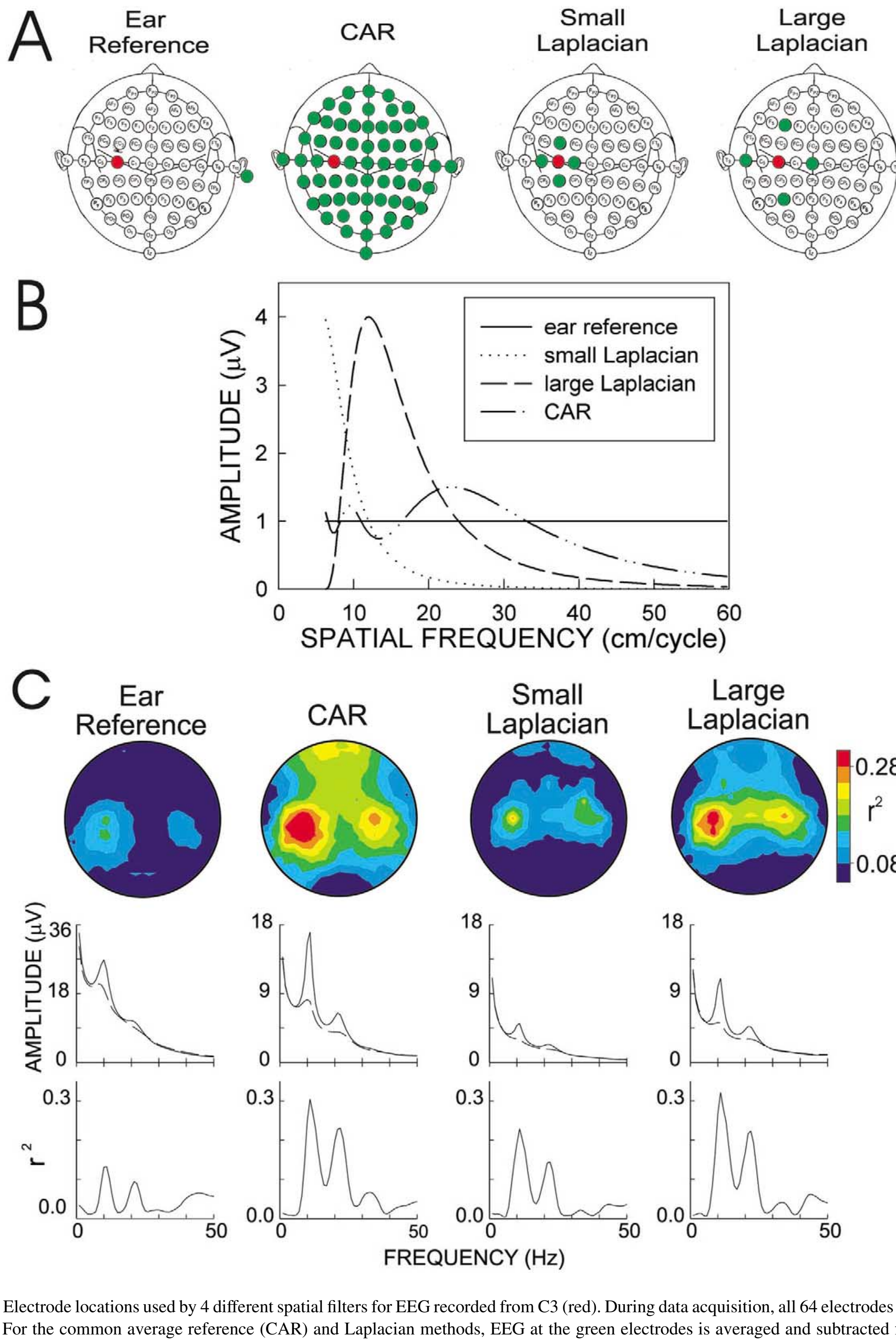

Fig. 3. (A) Electrode locations used by 4 different spatial filters for EEG recorded from C3 (red). During data acquisition, all 64 electrodes are referred to the ear reference. For the common average reference (CAR) and Laplacian methods, EEG at the green electrodes is averaged and subtracted from EEG at C3. (B) Spatial band-pass. For each method, the trace shows the square root of the root-mean-square values (amplitude in μV) of a signal that varies sinusoidally in amplitude across the scalp as its spatial frequency varies from 6 cm, twice the inter-electrode distance (i.e. the highest spatial frequency that would not cause spatial aliasing), to 60 cm (i.e. approximate head circumference). (C) Average r^2 topography, and amplitude and r^2 spectra for each spatial filter method for trained BCI users at the frequency and electrode location, respectively, used online. Each method is applied to the same body of data. With each method, EEG control (measured as r^2, the proportion of the variance of the signal feature that is accounted for by the user's intent) is focused over sensorimotor cortices and in the mu- and beta-rhythm frequency bands. The value of r^2 is highest for the CAR and large Laplacian spatial filters and lowest for the ear reference. (Modified from McFarland et al. 1997b.)

trained with a Bayesian evidence framework. They report user success in controlling one-dimensional cursor movement (Roberts and Penny, 2000).

Other groups have explored offline a variety of approaches not yet tested online. Birch and Mason (Birch et al., 1993; Birch and Mason, 2000; Mason and Birch, 2000) describe methods for recognizing potentials related to voluntary movement (VMRPs) in EEG over sensorimotor and supplementary motor cortices, and for using that recognition to control cursor movement. Their translation algorithm uses features extracted from the 1–4 Hz band in bipolar EEG channels. They have focused on recognizing VMRPs in ongoing EEG rather than in the EEG associated with externally paced trials. Thus, they are addressing a problem important for practical applications: detection of user commands without the timing cues provided by structured trials. Levine et al. (2000) recorded electrocorticogram (EcoG) activity from 17 patients temporarily implanted with 16–126 subdural electrodes prior to epilepsy surgery. They found topographically focused potentials associated with specific movements and vocalizations. These potentials might provide the basis for a BCI with multiple control channels. Pineda and Allison (Pineda et al., 2000, Allison et al., 2000) explored the relationship between single and combined movements as seen in the mu rhythm and the readiness potential. Babiloni et al. (2000) are developing a Laplacian EEG analysis and a signal-space projection algorithm to detect imagined movements in EEG over sensorimotor cortex.

3.5. Cortical neurons

Since the 1960s, metal microelectrodes have been used to record action potentials of single neurons in the cerebral cortices of awake animals during movements (e.g. Evarts, 1966; Humphrey, 1986). While most studies focused on the relationships between this neuronal activity and simple or complex sensorimotor performances, a few have explored the capacity of animals to learn to control neuronal firing rates. With operant conditioning methods, several studies showed that monkeys could learn to control the discharge of single neurons in motor cortex (Fetz and Finocchio, 1975; Wyler and Burchiel, 1978; Wyler et al., 1979; Schmidt, 1980). From such work came the expectation that humans, including many with motor disabilities, could develop similar control and use it to communicate or to operate neuroprostheses.

Evaluation of this possibility was delayed by lack of intracortical electrodes suitable for human use and capable of stable long-term recording from single neurons. Conventional implanted electrodes induce scar tissue and/or move in relation to individual neurons, so that over time recording deteriorates or neurons come and go. In 1989, Kennedy described an intracortical electrode consisting of a hollow glass cone containing recording wires (Kennedy, 1989). Neural tissue or neurotrophic factors placed inside the cone induced cortical neurons to send processes into the cone so that their action potentials could be recorded (Fig. 2D). These electrodes, implanted in motor cortices of monkeys and several humans nearly locked-in by ALS or brainstem stroke, have provided stable neuronal recordings for more than a year (Kennedy and Bakay, 1998; Kennedy et al., 2000).

Up to now, one user has learned to control neuronal firing rates and uses this control to move a cursor to select icons or letters on a computer screen. By using neuronal activity to control one dimension of cursor movement and residual EMG control to control the other dimension and final selection, communication rates up to about 3 letters/min (i.e. about 15 bits/min) have been achieved. While training has been limited by recurring illness and medication effects, the results have been encouraging and suggest that more rapid and accurate control should be possible in the future. Furthermore, by demonstrating this control in people who are almost totally paralyzed, these initial data suggest that cortical neurons can support an independent BCI system.

Several laboratories have used multielectrode arrays to record from single neurons in motor cortex of monkeys or rats during learned movements (Georgopoulos et al., 1986; Schmidt et al., 1988; Schwartz, 1993; Donoghue and Sanes, 1994; Heetderks and Schmidt, 1995; Nicolelis et al., 1998; Liu et al., 1999; Williams et al., 1999; Chapin et al., 1999; Isaacs et al., 2000; Wessberg et al., 2000). The results show that the firing rates of a set of cortical neurons can reveal the direction and nature of movement. At the same time, almost all of this work has studied neuronal activity associated with actual movement. It is not clear whether the same patterns of neuronal activity, or other stable patterns, will be present when the movements are not made, and, most important, when the animal is no longer capable of making the movements (due, for example, to a spinal cord injury). Limited data suggest that the patterns persist for at least a time in the absence of movement (Craggs, 1975; Chapin et al., 1999; Taylor and Schwartz, 2001).

4. The future of BCI-based communication and control: key issues

Non-muscular communication and control is no longer merely speculation. The studies reviewed in the previous section show that direct communication from the brain to the external world is possible and can serve useful purposes. At the same time, the reality does not yet match the fantasy (e.g. Thomas, 1977): BCIs are not yet able to fly airplanes and are not likely to be doing so anytime soon. Present independent BCIs in their best moments reach 25 bits/min. For those who have no voluntary muscle control whatsoever or in whom remaining control (e.g. eye movement) is weak, easily fatigued, or unreliable, this modest capacity may be valuable. For people who are totally paralyzed (e.g. by ALS, brainstem stroke, or severe polyneuropathy) or lack any useful muscle control (e.g. due to severe cerebral palsy), a BCI might give the ability to answer simple questions quickly (i.e. 20 bits/min is 20 'yes/no' questions/min, or one/3 s), control the environment (e.g. lights, temperature, television, etc.), perform slow word processing (i.e. with a predictive program, 25 bits/min could produce 2 words/min), or even operate a neuroprosthesis (reviewed in Wolpaw et al., 2000a; Kübler et al., 2001). Nevertheless, the future value of BCI technology will depend substantially on how much information transfer rate can be increased.

BCI development is still in its earliest stages. It is not yet clear how far the field can or will go. What is clear is that how far it does go will depend on a number of crucial issues. These include: BCI independence from normal neuromuscular communication channels and dependence on internal aspects of normal brain function; selection of signal acquisition methods, signal features, feature extraction methods, translation algorithms, output devices, and operational protocols; development of user training strategies; attention to psychological and behavioral factors that affect user motivation and success; adoption of standard research methods and evaluation criteria; choice of applications and user groups; and the largely unknown capacities and limitations of non-muscular communication channels.

4.1. Independence from neuromuscular output channels

While a dependent BCI, which simply reflects activity in conventional neuromuscular output channels, can be useful (e.g. Sutter, 1984, 1992), the future importance of BCI technology will hinge on the extent to which its function can be independent of conventional neuromuscular output channels. The BCIs in Fig. 2 are thought to be independent, but this issue is yet to be completely settled.

The generally successful application of an SCP-based BCI to people with late-stage ALS who lack almost all voluntary movement is persuasive evidence that SCPs can support independent BCIs (Birbaumer et al., 1999, 2000). The P300-based BCI is also likely to be independent (Donchin et al., 2000). P300s are believed to reflect the significance of the stimulus, that is, in the case of the P300- based BCI, whether it is the choice that the user wants to select. At the same time, however, the visual stimuli needed to elicit P300 may depend to some degree on control of eye gaze (Michalski, 1999; Teder-Sälejärvi et al., 1999; Nobre et al., 2000). Available data suggest that mu and beta rhythms from sensorimotor cortex can support independent BCIs. These rhythms are affected by motor imagery in the absence of movement (e.g. McFarland et al., 2000a). Furthermore, mu- or beta-rhythm based cursor control does not depend on activity in cranial or limb muscles (Vaughan et al., 1998). Finally, mu rhythm-based BCI operation was achieved by a user almost totally locked in by ALS (Miner et al., 1996).

The cortical and subcortical neuronal activity that accompanies voluntary movement is in part a function of the proprioceptive and other sensory feedback that occurs during that movement (e.g. Houk and Rymer, 1981). It is not yet clear to what extent users can produce this activity or comparably controlled activity without actual movement, nor to what extent other sensory modalities, e.g. vision or audition, can substitute effectively for the somatosensory feedback associated with normal voluntary motor function. Initial studies (Craggs, 1975; Kennedy and Bakay, 1998; Chapin et al., 1999; Kennedy et al., 2000; Taylor and Schwartz, 2001; Serruya et al., 2002) suggest that neuronal activity can function without movement, but the long-term stability of this function is not yet established.

4.2. Degree of dependence on normal brain function

While BCIs based on SCPs, P300s, mu and beta rhythms, or cortical neuronal activity may not require voluntary muscle control, they certainly depend to some degree on normal brain function. Each of these electrophysiological phenomena reflects the combined function of cortical and subcortical areas. Impairments of cortex (e.g. with ALS or stroke), basal ganglia or other subcortical areas that interact with cortex (e.g. with cerebral palsy) or loss of ascending sensory input (e.g. with brainstem stroke or spinal cord injury) could affect the user's ability to achieve control of cortical potentials, mu or beta rhythms, or cortical neurons. Thus, the ability to use BCIs and the best choice among the different BCIs, are likely to differ among users. Studies that evaluate specific BCIs in specific user groups are needed, and should include long-term assessments of performance.

4.3. Non-CNS artifacts

Muscle activation and eye movement can contribute to the electrical activity recorded from the scalp (Anderer et al., 1999; Croft and Barry, 2000). At frontal, temporal, and occipital locations particularly, EMG and/or EOG can exceed EEG, even in the characteristic EEG frequency bands (McFarland et al., 1997a; Goncharova et al., 2000). While EMG and EOG may serve in their own rights in augmentative communication systems (ten Kate and Hepp, 1989; Tecce et al., 1998; Barreto et al., 2000), in the context of BCI research they are simply artifacts that must be recognized and addressed. They can mislead investigators by mimicking actual EEG-based control and/or can impede measurement of the EEG features used for control. For example, frontalis muscle EMG can dominate the beta- or mu-rhythm frequency range at frontal locations, and eyeblinks can affect the theta- or even mu-rhythm range at frontal or central locations (e.g. McFarland et al., 1997a; Goncharova et al., 2000). Thus, a user might control BCI output by raising his eyebrows or blinking her eyes; or such activity might obscure the user's actual EEG control.

Spectral and topographic analyses can usually detect non-CNS artifacts. However, studies that look only at one frequency band or scalp location, or rely completely on signal features, such as autoregressive parameters, that may be complex functions of EEG and non-CNS activity, risk contamination by non-CNS artifacts. These artifacts can produce misleading results that lead to erroneous conclusions about the characteristics, capacities, and limitations of EEG-based BCIs, and can thereby impede research and development. A recent preliminary study (Lauer et al., 1999) that purported to show control of a neuroprosthesis by EEG over frontal cortex illustrates this danger. Subsequent work showed that frontalis EMG was largely or wholly responsible for the control (Lauer et al., 2000). The spectral and topographical analyses that can detect such artifacts and the procedures that can prevent them from affecting BCI operation or misleading investigators are extremely important in BCI research (Wolpaw et al., 2000a).

4.4. Signal features

Most current BCIs use electrophysiological signal features that represent brain events that are reasonably well-defined anatomically and physiologically. These include rhythms reflecting oscillations in particular neuronal circuits (e.g. mu or beta rhythms from sensorimotor cortex), potentials evoked from particular brain regions by particular stimuli (e.g. VEPs or P300s), or action potentials produced by particular cortical neurons (Kennedy et al., 2000). A few are exploring signal features, such as autoregressive parameters, that bear complex and uncertain relationships to underlying brain events (Lopes da Silva and Mars, 1987; Parday et al., 1996; Lopes da Silva, 1999).

The special characteristics and capacities of each signal feature will largely determine the extent and nature of its usefulness. SCPs are, as their name suggests, slow. They develop over 300 ms to several seconds. Thus, if an SCP-based BCI is to exceed a bit rate of one every 1–2 s, users will need to produce more than two SCP levels at one location, and/or control SCPs at several locations independently. Initial studies suggest that such control may be possible (Kotchoubey et al., 1996, 1997; Hardman et al., 1997). While mu and beta rhythms have characteristic frequencies of 8–12 and 18–26 Hz, respectively, change in mu- or beta-rhythm amplitude appears to have a latency of about 0.5 s (Wolpaw et al., 1997; Pfurtscheller, 1999; Pfurtscheller and Lopes da Silva, 1999a). On the other hand, users are certainly able to provide more than two amplitude levels, and can achieve independent control of different rhythms (Wolpaw and McFarland, 1994; Vaughan et al., 1999). Projecting from results to date, a mu/beta rhythm BCI might select among 4 or more choices every 2–3 s (McFarland et al., 2000b). While the possibility for distinguishing more than two amplitude ranges from VEPs or P300 potentials has not been explored, these potentials can be evoked in partially overlapping series of trials, so that selection rate can be increased (Donchin et al., 2000). Alternatively or in addition, selection rate might be increased if users could learn to control shorter-latency evoked potentials (e.g. Finley, 1984). The firing rates of individual cortical neurons, if they prove to be independently controllable in the absence of the concurrent motor outputs and sensory inputs that normally accompany and reflect their activity, might support quite high information transfer rates.

The key determinant of a signal feature's value is its correlation with the user's intent, that is, the level of voluntary control the user achieves over it. Users are likely to differ in the signal features they can best control. In 3 users nearly locked in by ALS, Kübler (2000) found that one used a positive SCP, another a relatively fast negative-positive SCP shift, and a third a P300. Once developed, these strategies were extremely resistant to change. Particularly early in training, BCI systems should be able to identify, accommodate, and encourage the signal features best suited to each user.

User training may be the most important and least understood factor affecting the BCI capabilities of different signal features. Up to now, researchers have usually assumed that basic learning principles apply. However, BCI signal features are not normal or natural brain output channels. They are artificial output channels created by BCI systems. It is not yet clear to what extent these new artificial outputs will observe known conditioning principles. For example, mu rhythms and other features generated in sensorimotor cortex, which is directly involved in motor output, may prove more useful than alpha rhythms generated in visual or auditory cortex, which is strongly influenced by sensory input. The success of neuronally based BCI methods will presumably also vary from area to area. Initial efforts have focused on neurons in motor cortex (Kennedy, 1989; Kennedy and Bakay, 1998). While this focus is logical, other cortical areas and even subcortical areas warrant exploration (e.g. Chapin et al., 1999). For example, in a user paralyzed by a peripheral nerve or muscle disorder, the activity of spinal cord motoneurons controlling specific muscles, detected by implanted electrodes (e.g. Nuwer, 1999; Mushahwar et al., 2000), might prove most useful for communication and control.

4.5. Signal processing: feature extraction

The performance of a BCI, like that of other communication systems, depends on its signal-to-noise ratio. The goal is to recognize and execute the user's intent, and the signals are those aspects of the recorded electrophysiological activity that correlate with and thereby reveal that intent. The user's task is to maximize this correlation; and the system's first task is to measure the signal features accurately, i.e. to maximize the signal-to-noise ratio. When the features are mu rhythms from sensorimotor cortex, noise includes visual alpha rhythms, and when the features are the firing rates of specific neurons, noise includes activity of other neurons. Of particular importance for EEG-based BCIs is the detection and/or elimination of non-CNS activity, such as EMG from cranial or facial muscles and EOG (Section 4.3).

Feature extraction methods can greatly affect signal-to-noise ratio. Good methods enhance the signal and reduce CNS and non-CNS noise. This is most important and difficult when the noise is similar to the signal. For example, EOG is of more concern than EMG for a BCI that uses SCPs as signal features (Birbaumer et al., 1990), because EOG and SCPs have overlapping frequency ranges; and for the same reason EMG is of more concern than EOG for BCIs that use beta rhythms (Goncharova et al., 2000).

A variety of options for improving BCI signal-to-noise ratios are under study. These include spatial and temporal filtering techniques, signal averaging, and single-trial recognition methods. Much work up to now has focused on showing by offline data analyses that a given method will work. Careful comparisons of alternative methods are also essential. A statistical measure useful in such comparisons is r^2, the proportion of the total variance in the signal feature that is accounted for by the user's intent. Alternative feature extraction methods can be compared in terms of r^2. (At the same time, of course, it is essential to insure that a high r^2 is not being achieved by non-CNS activity such as EMG.) Finally, any method must ultimately be shown to be useful for actual online operation.

Spatial filters derive signal features by combining data from two or more locations so as to focus on activity with a particular spatial distribution. The simplest spatial filter is the bipolar derivation, which derives the first spatial derivative and thereby enhances differences in the voltage gradient in one direction. The Laplacian derivation is the second derivative of the instantaneous spatial voltage distribution, and thereby emphasizes activity in radial sources immediately below the recording location (Zhou, 1993; Nunez et al., 1997). It can be computed by combining the voltage at the location with the voltages of surrounding electrodes (e.g. Hjorth, 1991; Nunez et al., 1994). As the distance to the surrounding electrodes decreases, the Laplacian becomes more sensitive to voltage sources with higher spatial frequencies (i.e. more localized sources) and less sensitive to those with lower spatial frequencies (i.e. more broadly distributed sources).

The choice of a spatial filter can markedly affect the signal-to-noise ratio of a BCI that uses mu and beta rhythms (McFarland et al., 1997b). Fig. 3 displays the results for 4 different spatial filters applied to the same data from trained users. It shows that a Laplacian with an inter-electrode distance of 6 cm (or a common average reference method) provides a much higher signal-to-noise ratio (measured as r^2) than does either a Laplacian with a distance of 3 cm or a monopolar derivation. On the other hand, a spatial filter best suited for mu and beta rhythms, which are relatively localized, would probably not be the best choice for measurement of SCPs or P300s, which are more broadly distributed over the scalp.

Laplacian and common average reference spatial filters apply a fixed set of weights to a linear combination of channels (i.e. electrode locations). Both use weights that sum to zero so that the result is a difference and the spatial filter has high-pass characteristics. Other spatial filters are available. Principal components, independent components, and common spatial patterns analyses are alternative methods for deriving weights for a linear combination of channels (e.g. Müller-Gerking et al., 1999; Jung et al., 2000). In these methods, the weights are determined by the data. Principal components analysis, which produces orthogonal components, may not be appropriate for separation of signal features from overlapping sources. Independent components analysis can, in principle, distinguish between mu rhythms from such sources (Makeig et al., 2000). These methods have yet to be compared to simpler spatial filters like the Laplacian, in which the channel weights are data-independent.

Appropriate temporal filtering can also enhance signal-to-noise ratios (e.g. McFarland et al., 1997a). Oscillatory signals like the mu rhythm can be measured by the integrated output of a band-pass filter (Pfurtscheller and Aranibar, 1979) or by the amplitude in specific spectral bands of Fourier or autoregressive analysis (Marple, 1987). Because BCIs must provide relatively rapid user feedback and because signals may change rapidly, frequency analysis methods (e.g. band-pass filters or autoregressive methods) that need only relatively short time segments may be superior to methods like Fourier analysis that need longer segments. The choice of temporal filtering method, particularly for research studies, should also consider the need to detect non-CNS artifacts. A single band-pass filter cannot identify a broad-band artifact like EMG; a representative set of such filters is needed. Similarly, when autoregressive parameters are used as signal features (e.g. Pfurtscheller et al., 1998), additional spectral-band analyses are needed to detect artifacts like EMG. For SCP recording, the focus on extremely-low frequency activity (e.g. high-pass filter cutoff $\leq$0.1 Hz) requires attention to eye-movement (Gratton et al., 1983) and other low-frequency artifacts like those due to amplifier drift or changes in skin resistance (e.g. with sweating).

The signal-to-noise ratios of evoked time-domain signals like P300 can be enhanced by averaging. The accompanying loss in communication rate may be minimized by overlapping the trials (e.g. Donchin et al., 2000). A variety of methods have been proposed for detecting signals in single trials (Arpaia et al., 1989; Hufschmidt et al., 1990; Birch et al., 1993; Lange et al., 1995; Mineva and Popivanov, 1996; Schlögl et al., 1997; Samar et al., 1999; Birch and Mason, 2000). These methods have yet to be extensively applied in BCI research. Thus, their potential usefulness is unclear.

Invasive methods using epidural, subdural, or intracortical electrodes might give better signal-to-noise ratios than noninvasive methods using scalp electrodes. At the same time, the threshold for their use will presumably be higher. They will be used only when they can provide communication clearly superior to that provided by noninvasive methods, or when they are needed to avoid artifacts or other problems that can impede noninvasive methods (e.g. uncontrollable head and neck EMG in a user with cerebral palsy).

4.6. Signal processing: translation algorithms

BCI translation algorithms convert independent variables, that is, signal features such as rhythm amplitudes or neuronal firing rates, into dependent variables (i.e. device control commands). Commands may be continuous (e.g. vertical cursor movements) or discrete (e.g. letter selection). They should be as independent of each other (i.e. orthogonal) as possible, so that, for example, vertical cursor movement and horizontal cursor movement do not depend on each other. The success of a translation algorithm is determined by the appropriateness of its selection of signal features, by how well it encourages and facilitates the user's control of these features, and by how effectively it translates this control into device commands. If the user has no control (i.e. if the user's intent is not correlated with the signal features), the algorithm can do nothing, and the BCI will not work. If the user has some control, the algorithm can do a good or bad job of translating that control into device control.

Initial selection of signal features for the translation algorithm can be based on standard guidelines (e.g. the known locations and temporal and spatial frequencies of mu and beta rhythms) supplemented by operator inspection of initial topographical and spectral data from each user (Rockstroh et al., 1984; McFarland et al., 1997a). These methods may be supplemented or even wholly replaced by automated procedures. For example, Pregenzer et al. (1996), used the learning vector quantizer (LVQ) to select optimal electrode positions and frequency bands for each user.

Extant BCIs use a variety of translation algorithms, ranging from linear equations, to discriminant analysis, to neural networks (e.g. Wolpaw et al., 2000b; Pfurtscheller et al., 2000a; Kostov and Polak, 2000). In the simplest case, in which only a single signal feature is used, the output of the translation algorithm can be a simple linear function of the feature value (e.g. a linear function of mu-rhythm amplitude). The algorithm needs to use appropriate values for the intercept and the slope of this function (McFarland et al., 1997a). If the command is vertical cursor movement, the intercept should ensure that upward and downward movement are equally possible for the user. Ramoser et al. (1997) found that the mean value of the signal feature over some interval of immediately preceding performance provides a good estimate of the proper intercept. The slope determines the scale of the command (e.g. the speed of cursor movement). When a single signal feature is used to select among more than two choices, the slope also affects the relative accessibility of the choices (e.g. McFarland et al., 1999, 2000b). A wide variety of more complex translation algorithms are possible. These include supervised learning approaches such as linear discriminate analysis (e.g. Jain et al., 2000) and non-linear discriminate analysis (e.g. an adaptive logic network (Kostov and Polak, 2000).

The evaluation of a translation algorithm reduces to determining how well it accomplishes the 3 levels of adaptation described in Section 2.3.3: initial adaptation to the individual user; continuing adaptation to spontaneous changes in the user's performance (e.g. fatigue, level of attention); and continuing adaptation that encourages and guides the user's adaptation to the BCI (i.e. user training). Up to the present, most evaluations have concentrated on the first and simplest level of adaptation. In these evaluations, alternative algorithms are applied offline to a body of data gathered from one or more users. Typically, portions of the data are used to set the parameters of the algorithm (e.g. to train the neural network), which is then applied to the rest of the data (i.e. the test data) (Pregenzer et al., 1996; Müller-Gerking et al., 1999). The algorithm is rated according to the accuracy with which it derives the user's intent from the test data. While such evaluations are convenient and certainly valuable in making gross distinctions between algorithms, they do not take into account spontaneous changes in the signal features, nor can they assess user adaptation to the algorithm.

The second level of adaptation – continual adjustments for spontaneous changes in signal features – can be addressed by offline analysis that mimics the online situation, that is, if adaptation is based on earlier data and applied to later data (e.g. Ramoser et al., 1997). This analysis needs substantial bodies of data gathered over substantial periods of time, so that all major kinds of spontaneous variation can be assessed. The need for this second level of adaptation tends to favor simpler algorithms. Parameter adaptation is likely to be more difficult and more vulnerable to instabilities for complex algorithms like those using neural networks or non-linear equations, than it is for simple algorithms like those using linear equations with relatively few variables.

The third level of adaptation – adaptation to the user's adaptation to the BCI system – is not accessible to offline evaluation. Because this level responds to and affects the continual interactions between the user and the BCI, it can only be assessed online. The goal of this adaptation is to induce the user to develop and maintain the highest possible level of correlation between his or her intent and the signal features that the BCI employs to decipher that intent. The algorithm can presumably accomplish these aims by rewarding better performance – by moving the cursor or selecting the letter more quickly when the signal feature has a stronger correlation with intent. At the same time, such efforts at shaping user performance risk making the task too difficult. As with acquisition of conventional skills, anxiety, frustration, or fatigue can degrade performance (e.g. Dibartolo et al., 1997). Particularly in the first stages of training, the user is easily overwhelmed by the difficulty of the task. User success may correlate with self-perception of brain states, and may be promoted by procedures that increase this perception (Lang and Kotchoubey, 2000). Because the translation algorithm's adaptations are likely to shape the user's adaptations, and because users are likely to differ from one another, the selection of methods for this third level of adaptation inevitably requires prolonged online studies in large numbers of representative users.

This level of adaptation might also help address the problem of artifacts, such as EMG or EOG for scalp EEG or extraneous neuronal activity for neuronal recording. It may be possible to induce the user to reduce or eliminate such artifacts by making them impediments to performance. Thus, a specific measure of EMG activity, like amplitude in a high frequency band at a suitable location, could be monitored, and, by exceeding a criterion value, could halt BCI operation.

The mutual adaptation of user and BCI is likely to be important even for BCIs that use signal features (e.g. P300 evoked potentials, or mu- or beta-rhythm amplitude changes accompanying specific motor imagery) that are already present in users at the very beginning of training. Once these features are used for communication and control, they can be expected to change. Like the activity responsible for the brain's neuromuscular outputs, these electrophysiological phenomena are likely to be continuously adjusted on the basis of feedback. The process of mutual adaptation of the user to the system and the system to the user is likely to be a fundamental feature of the operation of any BCI system (McFarland et al., 1998; Siniatchkin et al., 2000). Thus, the value of starting from signal features that are already correlated with specific intents in the naive user (e.g. P300) is an empirical issue. That is, does BCI training that begins with such features ultimately lead to faster and more accurate communication and control than does training that begins with other features?

These adaptations by the translation algorithm may be more difficult in actual BCI applications than in the laboratory. In the usual laboratory situation, user intent is defined by the research protocol (i.e. the user is told what to select), so that the translation algorithm knows whether the user's selections are correct and can use this knowledge in its adaptations. In real life, the user decides what to select, so that the translation algorithm does not have this knowledge and adaptation is therefore more difficult. Possible solutions are to configure applications so as to insure fairly predictable sets of past intents, to incorporate calibration routines that consist of series of trials with defined intents, and/or to include methods for error correction (e.g. a backspace key) that permit the translation algorithm to assume that all or most final selections are correct. Unsupervised learning approaches, like cluster or principal components analysis, which can be trained without knowledge of correct results, might also be effective (Müller-Gerking et al., 1999; Jung et al., 2000).

4.7. Operating protocols

Ideally, a BCI would be available at all times. Such availability might be provided either by always translating input into output, or by a BCI-based on/off switch. Continuous translation could produce much unintended, meaningless, or random output. One research group is now evaluating this option (Birch and Mason, 2000; Mason and Birch, 2000). Another possibility is a BCI-based on/off key, such as a distinctive pattern of signal features that is extremely unlikely to occur spontaneously (e.g. a specific pattern of SCP shifts (Birbaumer et al., 2000; Kaiser et al., 2001).

In voice communication, the speaker controls when words are said and the rate at which they are said. In contrast, present-day BCIs usually control timing and rate and indicate them to the user by visual or auditory means. To some extent, the system control of timing and rate results from the requirements of research: to assess BCI performance it is necessary to know user intent, and the simplest way to do this is to have the system tell the user what to communicate and when. In actual BCI applications, control of timing and rate might be vested wholly or partially in the user (e.g. McFarland et al., 1999).

4.8. Applications and users

Practical applications depend first on speed and accuracy. Current BCIs are suitable for basic environmental control (e.g. temperature, lights, television), for answering yes/no questions, and for word processing at slow rates (e.g. 1–2 words/min). They might also operate devices like a wheelchair. In this application, in which errors are dangerous, the system could be configured to ensure very high accuracy at the expense of speed. These BCIs might also operate simple neuroprostheses or orthoses, like those providing hand grasp to people with cervical spinal cord injuries (Lauer et al., 2000; Pfurtscheller et al., 2000b).

At the same time, while current BCIs might provide such functions, most potential users have better conventional options. Those who retain control of only a single muscle (e.g. eyebrow, finger flexor, diaphragm) can often use it for communication and control that is faster and more accurate than that provided by current BCIs. Thus, immediate users will be mainly those who lack all muscle control or whose remaining control is easily fatigued or otherwise unreliable. They include those who are totally paralyzed (e.g. by ALS or brainstem stroke) or have movement disorders (e.g. severe cerebral palsy) that abolish muscle control. Conventional augmentative communication methods may have little to offer them, so that even the simplest BCI-based communication, like the ability to say 'yes' or 'no', could be valuable. Recent data indicate that their incidence of depression is not necessarily higher than that of the general population (e.g. Robbins et al., 2002). This suggests that, if their communication and control needs can be satisfied, they can lead enjoyable and productive lives.

Efforts to provide BCI-based communication to users who are locked-in may encounter several difficult issues. First, a user's lack of conventional communication ability can make it hard to assess his or her cognition or even consciousness, and may impede the operator/user interactions important in initial BCI training. Kotchoubey et al. (2002) describe a set of event-related potential-based tests designed to assess cortical sensory and cognitive processing in such users and evaluate their capacity for mastering BCI use. Second, the deficits that abolish all voluntary muscle control may also impair user control of the signal features used by a BCI. The loss of cortical neurons that can occur with ALS or the extensive cortical and/or subcortical damage typically associated with severe cerebral palsy may affect generation or control of the rhythms, evoked potentials, or neuronal activity used for BCI-based communication. Damage to prefrontal cortex (e.g. with multiple sclerosis, Parkinson's disease, or ALS) can impair attention and thereby adversely affect BCI use (Rockstroh et al., 1989; Müller et al., 1997). Third, motivational factors can be critically important (Birbaumer et al., 2000). Changes in an individual's physical environment or social interactions can greatly affect the extent of BCI use. Effective BCI application in clinical situations requires careful and continual assessment of quality of life. Standard quality of life measures may not be appropriate for people who are severely paralyzed. Their emotional and psychological well being does not necessarily worsen as motor function declines (e.g. Robbins et al., 2001). In sum, BCI applications require expertise in and attention to a complex set of human factors.

People who retain minimal voluntary movement might use hybrid systems that combine BCI-based control with conventional control (e.g. Kennedy et al., 2000). BCIs might also serve those whose communication and control capacities are impaired by aphasias, apraxias, or autism (Birbaumer, 1999).

If BCI speed and accuracy can be substantially improved, the range of applications and the number of potential users would greatly increase. At the same time, speed and accuracy are not the only important factors. The extent to which BCI use can be integrated with other activities is crucial. Up to now, most BCIs have been tested in the laboratory with the users totally involved in their operation. A few studies have explored BCI integration into normal life. The Wadsworth BCI can be used to answer spoken questions, and the Tuebingen TTD to communicate user-chosen messages (Miner et al., 1998; Birbaumer et al., 1999). Much more information concerning such integration with other brain functions is needed.

BCI success will hinge also on the extent to which operation is standardized. Most present BCIs operate in the laboratory with expert oversight. Even the Tuebingen TTD, which has been taken out of the laboratory, still requires frequent adjustment by skilled personnel (Kübler et al., 2001; Kaiser et al., 2001). If BCIs are to function in homes or long-term care facilities, this dependence must be greatly reduced.

Especially important in determining the practical value of BCI systems will be their success in satisfying the user (e.g. De Foa and Loeb, 1991; Scherer and Lane, 1997; Stroh Wuolle et al., 1999). Satisfaction will not depend only, or perhaps even mainly, on speed and accuracy. The level of user acceptance of a new technology depends on more than the theoretical value of the technology, and is often unpredictable or even inexplicable. Kübler et al. (1999) found that several users preferred slow selection of single letters to faster computer-aided word completion because letter-by-letter selection, which was completely under their control, made them feel more independent. Ease of use is also important. Factors such as the need for constantly wearing an electrode cap or constantly confronting a particular visual display can have tremendous influence. Cosmesis is often crucial; that is, how the system looks and how the user looks while employing it. Users are likely to differ considerably in their needs and desires, and BCI success will depend in large part on recognition and accommodation of this reality. The primary emphasis should be on identifying and providing those BCI applications most desired by the user.

4.9. Research methods and standards

BCI research is an interdisciplinary endeavor. The phenomena that comprise BCI signal features arise in the brain and reflect its anatomy, chemistry, and physiology. BCIs perform signal processing, and depend on computer hardware and software. They incorporate adaptation routines that depend on learning principles and on other human factors like attention, motivation, and fatigue. BCI outputs control devices that have specific electronic and/or mechanical characteristics and provide feedback that engages the user's perceptive and reactive capacities. Finally, BCI operating protocols orchestrate operation in accord with the characteristics of the inputs, feature extraction methods, translation algorithms, and outputs. Thus, BCI research involves neurobiology, psychology, engineering, applied mathematics, and computer science. Success depends on expertise in all these disciplines and on effective interactions between them.

While all BCI research programs share the same goal – rapid and accurate communication and control – they differ widely not only in their inputs, feature extraction methods, translation algorithms, outputs, and operating protocols, but also in their immediate objectives. Some focus on specific applications like word processing or neuroprosthesis control, while others concentrate on establishing general features of BCI design and operation and use a prototype application like cursor control to do so. Whatever their objectives, all need hardware and software that can acquire electrophysiological input with sufficient rate and precision, translate it into output quickly enough to control devices with acceptable delays, and manage adaptive interactions between user and system. Because their purpose is research, they also need to store complete data for later evaluation.

Furthermore, if their efforts are to be productive and their results credible, BCI research programs must adhere to certain principles in experimental design, data evaluation, and documentation and dissemination of results.

4.9.1. Assessment of inter- and intra-user variations

Users are likely to differ greatly in the prominence and stability of specific signal features, and in their capacities for initially demonstrating or acquiring and subsequently maintaining control over these features. Users with disabilities are likely to display even more variation. Thus, BCI methods should be tested in more than one or a few users, and the test populations should include users with relevant disabilities. Intra-individual variation is an equally important issue. Those few research programs that have acquired long-term data have found that marked variations in performance typically occur over minutes, hours, days, weeks, and months. Thus, data should be gathered from each user many times over substantial periods. Furthermore, appropriate and comprehensive statistical tests should be applied. Simply describing the single best result or the performance for a few sessions is not enough.

4.9.2. Online validation of offline analyses

Offline analyses of data stored during BCI operation are not by themselves sufficient for assessing and comparing alternative signal features, feature extraction routines, translation algorithms, etc. While they can suggest which methods are likely to work best online, they cannot predict the short- or long-term effects of differences among methods in the user feedback. Methods that appear promising in offline analyses must ultimately be validated by extensive online testing over prolonged periods in adequate numbers of users, and this testing should incorporate to the greatest extent possible appropriate internal (i.e. intra-individual) and/or external (i.e. inter-individual) controls.

4.9.3. Assessment of both user performance and system performance

Effective assessment of BCI performance requires two levels of evaluation: the user and the system. The user must control the signal features, and the system must recognize that control and translate it into device control effectively and consistently. User performance can be defined as the level of correlation between user intent and the signal feature(s) the BCI employs to recognize that intent. One useful measure of this correlation is r^2 (Section 4.5). Perfect correlation produces an r^2 value of 1.00. As illustrated in Fig. 3, this measure proved very useful in choosing the best spatial filter method for extracting mu- or beta-rhythm signal features (McFarland et al., 1997b). It is also valuable for selecting the electrode location and frequency band used to determine mu- or beta-rhythm amplitude (e.g. Wolpaw et al., 2000b).

Evaluation of system performance has two parts: performance in a specific application, assessed as speed and/or accuracy, and theoretical performance, measured as information transfer rate. Up to now, most studies have simply reported the accuracy and/or speed for specific applications. These data are certainly important. At the same time, they are affected by the characteristics of the application and the success with which the system interfaces the user's control of the signal features with that application. Thus, they make comparisons between different studies difficult, and they do not reveal what might theoretically be done with the degree of control that the user has.

The standard method for measuring communication and control systems is information transfer rate, or bit rate. It is the amount of information communicated per unit time. Derived from Shannon and Weaver (1964) (summarized in Pierce, 1980), this measure incorporates both speed and accuracy in a single value. Fig. 4 shows the relationship between accuracy and bit rate for different numbers of choices. Bit rate is shown both as bits/trial (i.e. bits/selection), and as bits/min when 12 selections are made per min (a rate comparable to that of several current BCIs (e.g. Birbaumer et al., 2000; Donchin et al., 2000; Pfurtscheller et al., 2000a; Wolpaw et al., 2000b)). For example, the bit rate of a BCI that selects between two choices with 90% accuracy is equal to that of a BCI that selects among 4 choices with 65% accuracy. The great importance of accuracy, shown in Fig. 4, has often not received proper recognition in BCI research. With two choices, 90% accuracy is

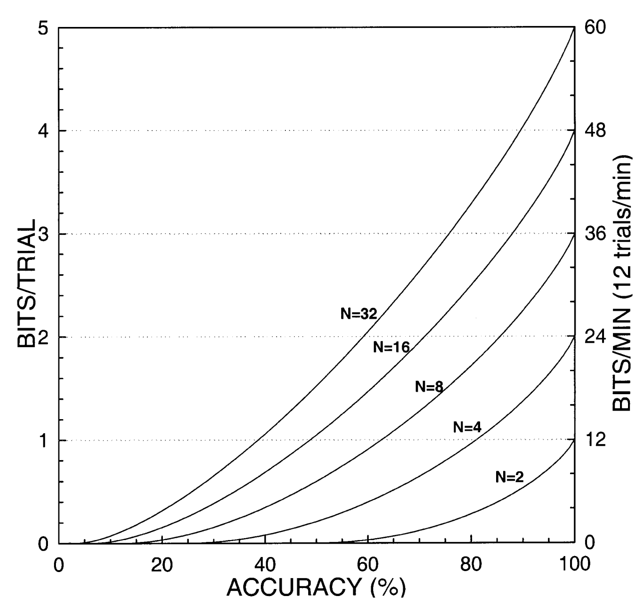

Fig. 4. Information transfer rate in bits/trial (i.e. bits/selection) and in bits/min (for 12 trials/min) when the number of possible choices (i.e. N) is 2, 4, 8, 16, or 32. As derived from Pierce (1980) (and originally from Shannon and Weaver, 1964), if a trial has N possible choices, if each choice has the same probability of being the one that the user desires, if the probability (P) that the desired choice will actually be selected is always the same, and if each of the other (i.e. undesired) choices has the same probability of selection (i.e. $(1-P)/(N-1)$), then bit rate, or bits/trial (B), is: $B = \log_2 N + P \log_2 P + (1-P)\log_2[(1-P)/(N-1)]$. For each N, bit rate is shown only for accuracy $\geq 100/N$ (i.e. $\geq$chance) (from Wolpaw et al., 2000a).

literally twice as good as 80%, and only half as good as 100%. Bit rate is an objective measure for measuring improvement in a BCI and for comparing different BCIs. It can also help select applications (Wolpaw et al., 2000a).

4.9.4. Evaluation in relevant situations

BCI evaluation should also include testing in circumstances like those of real-life applications. As noted above, assessment of online performance is essential. In addition, BCIs should be tested under conditions in which the user chooses the message or command. This testing can reveal how well the BCI adapts to spontaneous variation in the signal features when it does not have the advantage of knowing what the output is supposed to be. It is also important to evaluate how well BCI operation combines with other brain functions. A BCI that requires total user attention might not support a conversation or other interaction in which the user must continually choose the messages to send and evaluate the responses they elicit from the other person or from an external device.

4.9.5. A general purpose BCI system for research and development

In order to facilitate and encourage accommodation to these important principles across BCI research efforts, several groups are currently collaborating on development of a general purpose BCI system, called BCI2000 (Wolpaw et al., 2000c; Schalk et al., 2001). The rationale for this effort is that, while different BCI systems differ widely in their signal features, feature extraction methods, translation algorithms, output devices, and operating protocols, they all need these basic components (Fig. 1). BCI2000 is a documented, distributed, and open general purpose BCI system, with 4 interacting processes: signal acquisition and storage; feature extraction and translation; device control; and operating protocol. Each process is independently executable in Windows NT/2000 on the same machine or on several networked machines. The processes interact through a predefined interface, so that different versions of each are interchangeable, and so that different languages can be used. The plan is to make BCI2000, with associated data storage and analysis tools, available to those engaged in BCI research and development. The goal is to facilitate progress and promote use of standard methods for evaluating performance.

4.9.6. Documentation and dissemination of results

Finally, if the recent interest and progress in BCI research is to develop into a stable and successful research endeavor, the focus must be on production of peer-reviewed primary articles in high-quality scientific and engineering journals. Furthermore, researchers should recognize that the intense and often distorted media attention that the idea of direct brain-computer communication attracts, while an advantage in some respects, is also a problem, because it engenders unrealistic expectations in the public and skepticism in scientists. Thus, it is important for researchers to be conservative in their interactions with the media, and to adhere as closely as possible to 'the Ingelfinger rule', the principle that peer-reviewed publication should precede any other detailed dissemination of research results. While studies are often first reported in meeting presentations and abstracts, and may reach the popular media in that way, their first complete description and documentation should be in a peer-reviewed format (Relman, 1981).

5. Conclusions

A BCI allows a person to communicate with or control the external world without using the brain's normal output pathways of peripheral nerves and muscles. Messages and commands are expressed not by muscle contractions but rather by electrophysiological phenomena such as evoked or spontaneous EEG features (e.g. SCPs, P300, mu/beta rhythms) or cortical neuronal activity. BCI operation depends on the interaction of two adaptive controllers, the user, who must maintain close correlation between his or her intent and these phenomena, and the BCI, which must translate the phenomena into device commands that accomplish the user's intent.

Present-day BCIs have maximum information transfer rates $\leq$25 bits/min. With this capacity, they can provide basic communication and control functions (e.g. environmental controls, simple word processing) to those with the most severe neuromuscular disabilities, such as those locked in by late-stage ALS or brainstem stroke. They might also control a neuroprosthesis that provides hand grasp to those with mid-level cervical spinal cord injuries. More complex applications useful to a larger population of users depend on achievement of greater speed and accuracy, that is, higher information transfer rates.

Future progress hinges on attention to a number of crucial factors. These include: recognition that BCI development is an interdisciplinary problem, involving neurobiology, psychology, engineering, mathematics, computer science, and clinical rehabilitation; identification of the signal features, whether evoked potentials, spontaneous rhythms, or neuronal firing rates, that users are best able to control; the extent to which this control can be independent of activity in conventional motor output and sensory input channels; the extent to which this control depends on normal brain function; identification of the best feature extraction methods and the best algorithms for translating these features into device control commands; development of methods for maximizing each user's control of these signal features; attention to the identification and elimination of artifacts such as EMG and EOG activity; adoption of precise and objective procedures for evaluating BCI performance; recognition of the need for long-term as well as short-term assessment of performance; identification of appropriate applications; proper matching of BCI applications and users; close attention to factors that determine user acceptance of augmentative technology; and emphasis on peer-reviewed publications and appropriately conservative response to media attention. With adequate recognition and effective engagement of these issues, BCI systems could provide an important new communication and control option for those with disabilities that impair normal communication and control channels. They might also provide to those without disabilities a supplementary control channel or a control channel useful in special circumstances.

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References

Allison BZ, Vankov A, Obayashi J, Pineda JA. ERPs in response to different display parameters and implications for brain–computer interface systems. Soc Neurosci Abstr 2000;26:2232.

Altenmüller EO, Gerloff C. Psychophysiology and the EEG. In: Niedermeyer E, Lopes da Silva FH, editors. Electroencephalography: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, 1999. pp. 637–655.

Anderer P, Roberts S, Schlögl A, Gruber G, Klösch G, Herrmann W, Rappelsberger P, Filz O, Barbanoj MJ, Dorffner G, Saletu B. Artifact processing in computerized analysis of sleep EEG – a review. Neuropsychobiology 1999;40:150–157.

Anderson CW, Stolz EA, Shamsunder S. Multivariate autoregressive models for classification of spontaneous electroencephalographic signals during mental tasks. IEEE Trans Biomed Eng 1998;45:277–286.

Armstrong WW, Thomas M. Adaptive logic networks. Handbook of neural computation, New York, NY: Oxford University Press, 1996.

Arpaia JP, Isenhart R, Sandman CA. A characterization of a single-trial adaptive filter and its implementation in the frequency domain. Electroenceph clin Neurophysiol 1989;73(4):362–368.

Babiloni F, Cincotti F, Lazzarini L, Millán J, Mouriño J, Varsta M, Heikkonen J, Bianchi B, Marciani MG. Linear classification of low-resolution EEG patterns produced by imagined hand movements. IEEE Trans Rehabil Eng 2000;8:186–188.

Barreto AB, Scargle SD, Adjouadi M. A practical EMG-based human–computer interface for users with motor disabilities. J Rehabil Res Dev 2000;37:53–63.

Bayliss JD, Ballard DH. A virtual reality testbed for brain–computer interface research. IEEE Trans Rehabil Eng 2000;8:188–190.

Berger H. Uber das electrenkephalogramm des menchen. Arch Psychiatr Nervenkr 1929;87:527–570.

Birbaumer N, Elbert T, Canavan AGM, Roch B. Slow potentials of the cerebral cortex and behavior. Physiol Rev 1990;70:1–41.

Birbaumer N. Slow cortical potentials: their origin, meaning, and clinical use. In: van Boxtel GJM, Böcker KBE, editors. Brain and behavior past, present, and future, Tilburg: Tilburg University Press, 1997. pp. 25–39.

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

Birbaumer N. Rain Man's revelations. Nature 1999;399:211–212.

Birbaumer N, Kübler A, Ghanayim N, Hinterberger T, Perelmouter J, Kaiser J, Iversen I, Kotchoubey B, Neumann N, Flor H. The thought translation device (TTD) for completely paralyzed patients. IEEE Trans Rehabil Eng 2000;8:190–192.

Birch GE, Lawrence PD, Hare RD. Single-trial processing of event-related potentials using outlier information. IEEE Trans Biomed Eng 1993;40:59–73.

Birch GE, Mason SG. Brain–computer interface research at the Neil Squire Foundation. IEEE Trans Rehabil Eng 2000;8:193–195.

Black AH, Young GA, Batenchuk C. Avoidance training of hippocampal theta waves in flaxedilized dogs and its relation to skeletal movement. J Comp Physiol Psychol 1970;70:15–24.

Black AH. The direct control of neural processes by reward and punishment. Am Sci 1971;59:236–245.

Black AH. The operant conditioning of the electrical activity in the brain as a method for controlling neural and mental processes. In: McGuigan FJ, Schoonover RA, editors. The psychology of thinking, New York, NY: Academic Press, 1973. pp. 35–68.

Carter GT. Rehabilitation management in neuromuscular disease. J Neurol Rehabil 1997;11:69–80.

Chapin JK, Moxon KA, Markowitz RS, Nicolelis MA. Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. Nat Neurosci 1999;2:664–670.

Chatrian GE. The mu rhythm. In: Rémond A, editor. Handbook of electroencephalography and clinical neurophysiology: the EEG of the waking adult, Amsterdam: Elsevier, 1976. pp. 46–69.

Chen YL, Tang FT, Chang WH, Wong MK, Shih YY, Kuo TS. The new design of an infrared-controlled human–computer interface for the disabled. IEEE Trans Rehabil Eng 1999;7:474–481.

Coles MGH, Rugg MD. Event-related potentials: an introduction. In: Rugg MD, Coles MGH, editors. Electrophysiology of the mind: event-related brain potentials and cognition, New York, NY: Oxford University Press, 1995.

Craggs MD. Cortical control of motor prostheses: using the cord-transected baboon as the primate model for human paraplegia. Adv Neurol 1975;10:91–101.

Croft RJ, Barry RJ. Removal of ocular artifact from the EEG: a review. Neurophysiol Clin 2000;30:5–19.

Dalton AJ. Discriminative conditioning of hippocampal electrical activity in curarized dogs. Comm Behav Bio 1969;3:283–287.

Damper RI, Burnett JW, Gray PW, Straus LP, Symes RA. Hand-held text-to-speech device for the non-vocal disabled. J Biomed Eng 1987;9:332–340.

De Foa JL, Loeb GE. Issues in cochlear prosthetics from an international survey of opinions. Int J Technol Assess Health Care 1991;7:403–410.

Dewan AJ. Occipital alpha rhythm, eye position and lens accommodation. Nature 1967;214:975–977.

Dibartolo PM, Brown TA, Barlow DH. Effects of anxiety on attentional allocation and task performance: an information processing analysis. Behav Res Ther 1997;35:1101–1111.

Donoghue JP, Sanes JN. Motor areas of the cerebral cortex. J Clin Neurophysiol 1994;11:382–396.

Donchin E, Smith DB. The contingent negative variation and the late positive wave of the average evoked potential. Electroenceph clin Neurophysiol 1970;29:201–203.

Donchin E. Presidential address, 1980. Surprise!…Surprise? Psychophysiology 1981;18:493–513.

Donchin E, Spencer KM, Wijesinghe R. The mental prosthesis: assessing the speed of a P300-based brain–computer interface. IEEE Trans Rehabil Eng 2000;8:174–179.

Elbert T, Rockstroh B, Lutzenberger W, Birbaumer N. Biofeedback of slow cortical potentials. Electroenceph clin Neurophysiol 1980;48:293–301.

Evarts EV. Pyramidal tract activity associated with a conditioned hand movement in the monkey. J Neurophysiol 1966;29:1011–1027.

Fabiani M, Gratton G, Karis D, Donchin E. Definition, identification and reliability of the P300 component of the event-related brain potential.

Ackles PK, Jennings JR, Coles MGH, editors. Advances in psychophysiology, vol. 2. New York, NY: JAI Press, 1987. pp. 1–78.

Farwell LA, Donchin E. Talking off the top of your head: toward a mental prothesis utilizing event-related brain potentials. Electroenceph clin Neurophysiol 1988;70:510–523.

Ferguson KA, Polando G, Kobetic R, Triolo RJ, Marsolais EB. Walking with a hybrid orthosis system. Spinal Cord 1999;37:800–804.

Fetz EE, Finocchio DV. Correlations between activity of motor cortex cells and arm muscles during operantly conditioned response patterns. Exp Brain Res 1975;23:217–240.

Ficke RC. Digest of data on persons with disabilities, Washington, DC: US Department of Education, National Institute on Disability and Rehabilitation Research, 1991.

Finley WW. Biofeedback of very early potentials from the brain stem. In: Elbert T, Rockstroh B, Lutzenberger W, Birbaumer N, editors. Self-regulation of the brain and behavior, Berlin: Springer, 1984. pp. 143–163.

Fisch BJ. Fisch and Spehlmann's third revised and enlarged EEG Primer, Amsterdam: Elsevier, 1999.

Gastaut H. Etude electrocorticographique de la reactivite des rythmes rolandiques. Rev Neurol 1952;87:176–182.

Georgopoulos AP, Schwartz AB, Kettner RE. Neuronal population coding of movement direction. Science 1986;233:1416–1419.

Ghez C, Krakauer J. Voluntary movement. In: Kandel ER, Schwartz JH, Jessell TM, editors. Principles of neural science, 4th ed. New York, NY: McGraw-Hill, 2000. pp. 653–674.

Glover AA, Onofrj MC, Ghilardi MF, Bodis-Wollner I. P300-like potentials in the normal monkey using classical conditioning and the auditory 'oddball' paradigm. Electroenceph clin Neurophysiol 1986;65:231–235.

Goncharova II, McFarland DJ, Vaughan TM, Wolpaw JR. EEG-based brain–computer interface (BCI) communication: scalp topography of EMG contamination. Soc Neurosci Abstr 2000;26:1229.

Gratton G, Coles MG, Donchin E. A new method for off-line removal of ocular artifact. Electroenceph clin Neurophysiol 1983;55:468–484.

Guger C, Schlögl A, Walterspacher D, Pfurtscheller G. Design of an EEG-based brain–computer interface (BCI) from standard components running in real-time under Windows. Biomed Tech 1999;44:12–16.

Hardman E, Gruzelier J, Cheesman K, Jones C, Liddiard D, Schleichert H, Birbaumer N. Frontal interhemispheric asymmetry: self regulation and individual differences in humans. Neurosci Lett 1997;221:117–120.

Heetderks WJ, Schmidt EM. Chronic multiple unit recording of neural activity with micromachined silicon electrodes. In: Lang A, editor. Proceedings of RESNA 95 Annual Conference, Arlington, TX: RESNA Press, 1995. pp. 649–653.

Hjorth B. Principles for transformation of scalp EEG from potential field into source distribution. J Clin Neurophysiol 1991;8:391–396.

Hoffer JA, Stein RB, Haugland MK, Sinkjaer T, Durfee WK, Schwartz AB, Loeb GE, Kantor C. Neural signals for command control and feedback in functional neuromuscular stimulation: a review. J Rehabil Res Dev 1996;33:145–157.

Houk JC, Rymer WZ. Neural control of muscle length and tension. In: Brookhart JM, Mountcastle VB, Brooks VB, Geiger SR, editors. The nervous system. Motor control, The handbook of physiology. Part 1, vol. II. Bethesda, MD: American Physiological Society, 1981. pp. 257–325.

Hufschmidt A, Winker T, Lucking CH. Statistical evaluation of slow brain potentials on the basis of single trials. Electroenceph clin Neurophysiol 1990;76:413–418.

Humphrey DR. Representation of movements and muscles within the primate pre-central motor cortex: historical and current perspectives. Fed Proc 1986;45:2687–2699.

Ikeda A, Shibbasaki H. Invasive recording of movement-related cortical potentials in humans. J Clin Neurophysiol 1992;9:409–520.

Isaacs RE, Weber DJ, Schwartz AB. Work towards a real-time control of a cortical neural prothesis. IEEE Trans Rehabil Eng 2000;8:196–198.

Jain AK, Duin PW, Mao J. Statistical pattern recognition: a review. IEEE Trans Pattern Anal Machine Intell 2000;22:4–37.

Jung TP, Makeig S, Humphries C, Lee TW, McKeown MJ, Iragui V, Sejnowski TJ. Removing electroencephalographic artifacts by blind source separation. Psychophysiology 2000;37:163–178.

Kaiser J, Perelmouter J, Iversen I, Neumann N, Ghanayim N, Hinterberger T, Kübler A, Kotchoubey B, Birbaumer N. Self-initiation of EEG-based communication in paralyzed patients. Clin Neurophysiol 2001;112:551–554.

Kennedy PR. The cone electrode: a long-term electrode that records from neurites grown onto its recording surface. J Neurosci Methods 1989;29:181–193.

Kennedy PR, Bakay RA. Restoration of neural output from a paralyzed patient by a direct brain connection. NeuroReport 1998;9:1707–1711.

Kennedy PR, Bakay RAE, Moore MM, Adams K, Goldwaithe J. Direct control of a computer from the human central nervous system. IEEE Trans Rehabil Eng 2000;8:198–202.

Keirn ZA, Aunon JI. A new mode of communication between man and his surroundings. IEEE Trans Biomed Eng 1990;37:1209–1214.

Kilgore KL, Peckham PH, Keith MW, Thrope GB, Wuolle KS, Bryden AM, Hart RL. An implantable upper-extremity neuroprothesis. J Bone Joint Surg 1997;79A:533–541.

Kostov A, Polak M. Parallel man-machine training in development of EEG-based cursor control. IEEE Trans Rehabil Eng 2000;8:203–204.

Kotchoubey B, Schleichert H, Lutzenberger W, Anokhin AP, Birbaumer N. Self-regulation of interhemispheric asymmetry in humans. Neurosci Lett 1996;214:91–94.

Kotchoubey B, Schleichert H, Lutzenberger W, Birbaumer N. A new method for self-regulation of slow cortical potentials in a timed paradigm. Appl Psychophysiol Biofeedback 1997;22:77–93.

Kotchoubey B, Lang S, Bostanov V, Birbaumer N. Is there a mind? Electrophysiology of unconscious patients. News Physiol Sci 2002;17:38–42.

Kozelka JW, Pedley TA. Beta and mu rhythms. J Clin Neurophysiol 1990;7:191–207.

Kübler A. Brain–computer communication – development of a brain–computer interface for locked-in patients on the basis of the psychophysiological self-regulation training of slow cortical potentials (SCP), Tübingen: Schwäbische Verlagsgesellschaft, 2000.

Kübler A, Kotchoubey B, Hinterberger T, Ghanayim N, Perelmouter J, Schauer M, Fritsch C, Taub E, Birbaumer N. The thought translation device: a neurophysiological approach to communication in total motor paralysis. Exp Brain Res 1999;124:223–232.

Kübler A, Kotchoubey B, Kaiser J, Wolpaw JR, Birbaumer N. Brain–computer communication: unlock the locked-in. Psychol Bull 2001;127:358–375.

Kubota M, Sakakihara Y, Uchiyama Y, Nara A, Nagata T, Nitta H, Ishimoto K, Oka A, Horio K, Yanagisawa M. New ocular movement detector system as a communication tool in ventilator-assisted Werdnig–Hoffmann disease. Dev Med Child Neurol 2000;42:61–64.

Kuhlman WN. EEG feedback training of epileptic patients: clinical and electroencephalographic analysis. Electroenceph clin Neurophysiol 1978;45:699–710.

LaCourse JR, Hladik FC. An eye movement communication-control system for the disabled. IEEE Trans Biomed Eng 1990;37:1215–1220.

Lang W, Cheyne D, Hollinger P, Gerschlager W, Lindinger G. Electric and magnetic fields of the brain accompanying internal simulation of movement. Cogn Brain Res 1996;3:125–129.

Lang S, Kotchoubey B. Learning effects on event-related brain potentials. NeuroReport 2000;11:3327–3331.

Lange DH, Pratt H, Inbar GF. Segmented matched filtering of single event related evoked potentials. IEEE Trans Biomed Eng 1995;42:317–321.

Lauer RT, Peckham PH, Kilgore KL. EEG-based control of a hand grasp neuroprothesis. NeuroReport 1999;10:1767–1771.

Lauer RT, Peckham PH, Kilgore KL, Heetderks WJ. Applications of cortical signals to neuroprosthetic control: a critical review. IEEE Trans Rehabil Eng 2000;8:205–208.

Levine SP, Huggins JE, BeMent SL, Kushwaha RK, Schuh LA, Passaro EA, Rohde MM, Ross DA. Identification of electrocorticogram patterns as a basis for a direct brain interface. J Clin Neurophysiol 1999;16:439–447.

Levine SP, Huggins JE, BeMent SL, Kushwaha RK, Schuh LA, Rohde MM, Passaro EA, Ross DA, Elisevich KV, Smith BJ. A direct brain interface based on event-related potentials. IEEE Trans Rehabil Eng 2000;8:180–185.

Liu X, McCreery DB, Carter RR, Bullara LA, Yuen THE, Agnew WF. Stability of the interface between neural tissue and chronically implanted intracortical microelectrodes. IEEE Trans Rehabil Eng 1999;7:315–326.

Lopes da Silva F, Mars NJI. Parametric methods in EEG analysis. In: Gevins AS, Rémond A, editors. Methods and analysis of brain electrical and magnetic signals, 4th ed. Amsterdam: Elsevier, 1987. pp. 243–260.

Lopes da Silva FH. Neural mechanisms underlying brain waves: from neural membranes to networks. Electroenceph clin Neurophysiol 1991;79:81–93.

Lopes da Silva F. Event-related potentials: methodology and quantification. In: Niedermeyer E, Lopez da Silva F, editors. Electroencephalogaphy: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, 1999. pp. 947–957.

Makeig S, Enghoff S, Jung T-P, Sejnowski TJ. A natural basis for efficient brain-actuated control. IEEE Trans Rehabil Eng 2000;8:208–211.

Marple SL. Digital spectral analysis with applications, Englewood Cliffs, NJ: Prentice-Hall, 1987.

Mason SG, Birch GE. A brain-controlled switch for asynchonous control applications. IEEE Trans Biomed Eng 2000;47:1297–1307.

McFarland DJ, Lefkowicz AT, Wolpaw JR. Design and operation of an EEG-based brain–computer interface (BCI) with digital signal processing technology. Behav Res Methods Instrum Comput 1997a;29:337–345.

McFarland DJ, McCane LM, David SV, Wolpaw JR. Spatial filter selection for EEG-based communication. Electroenceph clin Neurophysiol 1997b;103:386–394.

McFarland DJ, McCane LM, Wolpaw JR. EEG-based communication: short-term role of feedback. IEEE Trans Rehabil Eng 1998;6:7–11.

McFarland DJ, Vaughan TM, Sarnacki WA, Wolpaw JR. EEG-based brain–computer interface (BCI): user-paced versus fixed-paced trials. Soc Neurosci Abstr 1999;25:1413.

McFarland DJ, Miner LA, Vaughan TM, Wolpaw JR. Mu and beta rhythm topographies during motor imagery and actual movement. Brain Topogr 2000a;3:177–186.

McFarland DJ, Sarnacki WA, Vaughan TM, Wolpaw JR. EEG-based brain–computer interface communication effect of target number and trial length on information transfer rate. Soc Neurosci Abstr 2000b;26:1228.

Michalski A. Feedback processing as parallel task in P300 conditioning. Acta Neurobiol Exp 1999;59:123–139.

Middendorf M, McMillan G, Calhoun G, Jones KS. Brain–computer interfaces based on steady-state visual evoked response. IEEE Trans Rehabil Eng 2000;8:211–213.

Miltner W, Larbig W, Braun C. Biofeedback of somatosensory event-related potentials: can individual pain sensations be modified by biofeedback-induced self-control of event-related potentials. Pain 1988;35:205–213.

Miner LA, McCane LM, McFarland DJ, Vaughan TM, Wolpaw JR. EEG-based brain–computer interface (BCI) training in a man with advanced amyotrophic lateral sclerosis (ALS). Soc Neurosci Abstr 1996;22:891.

Miner LA, McFarland DJ, Wolpaw JR. Answering questions with an EEG-based brain–computer interface (BCI). Arch Phys Med Rehabil 1998;79:1029–1033.

Mineva A, Popivanov D. Method for single-trial readiness potential identification, based on singular spectrum analysis. J Neurosci Methods 1996;68:91–99.

Müller V, Mohr B, Rosin R, Pulvermuller F, Müller F, Birbaumer N. Short-term effects of behavioral treatment on movement initiation and postural control in Parkinson's disease: a controlled clinical study. Mov Disord 1997;12:306–314.

Müller-Gerking J, Pfurtscheller G, Flyvbjerg H. Designing optimal spatial filters for single-trial EEG classification in a movement task. Clin Neurophysiol 1999;110:787–798.

Murray CJL, Lopez AD, editors. The global burden of disease: a comprehensive assessment of mortality and disability from diseases, injuries, and risk factors in 1990 projected to 2020 [summary] Global burden of disease and injury series, Boston, MA: Harvard University Press, 1996.

Mushahwar VK, Collins DF, Prochazka A. Spinal cord microstimulation generates functional limb movements in chronically implanted cats. Exp Neurol 2000;163:422–429.

National Advisory Board on Medical Rehabilitation Research. Report and Research Plan for the National Center for Medical Rehabilitation Research. National Institute of Child Health and Human Development, National Institute of Health. 1992.

Neidermeyer E. The normal EEG of the waking adult. In: Niedermeyer E, Lopes da Silva FH, editors. Electroencephalography: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, 1999. pp. 149–173.

Neuper C, Schlögl A, Pfurtscheller G. Enhancement of left–right sensorimotor EEG differences during feedback-regulated motor imagery. J Clin Neurophysiol 1999;16:373–382.

Nicolelis MA, Ghazanfar AA, Stambaugh CR, Oliveira LM, Lambach M, Chapin JK, Nelson RJ, Kaas JH. Simultanious encoding of tactile information by three primate cortical areas. Nat Neurosci 1998;7:621–630.

Nobre AC, Sebestyen GN, Miniussi C. The dynamics of shifting visuospacial attention revealed by event-related potentials. Neuropsychologia 2000;38:964–974.

Nowles DP, Kamiya J. The control of electroencephalographic alpha rhythms through auditory feedback and the associated mental activity. Psychophysiology 1970;6:75–84.

Nunez PL, Silberstein RB, Cadusch PJ, Wijesinghe RS, Westdorp AS, Srinivasan RA. A theoretical and experimental study of high resolution EEG based on surface Laplacians and cortical imaging. Electroenceph clin Neurophysiol 1994;90:40–57.

Nunez PL, Srinivasan R, Westdorp AF, Wijesinghe RS, Tucker DM, Silberstein RB, Cadusch PJ. EEG coherency. I: Statistics, reference electrode, volume conduction, Laplacians, cortical imaging, and interpretation at miltiple scales. Electroenceph clin Neurophysiol 1997;103:499–515.

Nuwer MR. Spinal cord recording. In: Niedermeyer E, Lopes da Silva FH, editors. Electroencephalography: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, 1999. pp. 823–835.

Obermaier B, Guger C, Neuper C, Pfurtscheller G. Hidden Markov models used for online classification of single trial EEG. Pattern Recognition Letters 2001;22:1299–1309.

Parday J, Roberts S, Tarassenko L. A review of parametric techniques for EEG analysis. Med Eng Phys 1996;18:2–11.

Penny WD, Roberts SJ, Curran EA, Stokes MJ. EEG-based communication: a pattern recognition approach. IEEE Trans Rehabil Eng 2000;8:214–215.

Perelmouter J, Kotchouby B, Kübler A, Taub E, Birbaumer N. Language support program for thought-translation devices. Automedica 1999;18:67–84.

Perelmouter J, Birbaumer N. A binary spelling interface with random errors. IEEE Trans Rehabil Eng 2000;8:227–232.

Pfurtscheller G, Aranibar A. Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movement. Electroenceph clin Neurophysiol 1979;46:138–146.

Pfurtscheller G. Functional topography during sensorimotor activation studied with event-related desynchronization mapping. J Clin Neurophysiol 1989;6:75–84.

Pfurtscheller G, Berghold A. Patterns of cortical activation during planning of voluntary movement. Electroenceph clin Neurophysiol 1989;72:250–258.

Pfurtscheller G, Flotzinger D, Kalcher J. Brain-computer interface – a new communication device for handicapped persons. J Microcomput Appl 1993;16:293–299.

Pfurtscheller G, Flotzinger D, Pregenzer W, Wolpaw JR, McFarland DJ. EEG-based brain–computer interface (BCI): search for optimal electrode positions and frequency components. Med Prog Technol 1996;21:111–121.

Pfurtscheller G, Neuper C. Motor imagery activates primary sensorimotor area in man. Neurosci Lett 1997;239:65–68.

Pfurtscheller G, Neuper C, Flotzinger D, Pregenzer M. EEG-based discrimination between imagination of right and left hand movement. Electroenceph clin Neurophysiol 1997;103:642–651.

Pfurtscheller G, Neuper C, Schlögl A, Lugger K. Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. IEEE Trans Rehabil Eng 1998;6:316–325.

Pfurtscheller G. EEG event-related desynchronization (ERD) and event-related synchronization (ERS). In: Niedermeyer E, Lopes da Silva FH, editors. Electroencephalography: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, 1999. pp. 958–967.

Pfurtscheller G, Lopes da Silva FH. Event-related EEG/MEG synchronization and desynchronization: basic principles. Clin Neurophysiol 1999a;110:1842–1857.

Pfurtscheller G, Lopes da Silva FH, editors. Event-related desynchronization. Handbook of electroencephalography and clinical neurophysiology, vol. 6. Amsterdam: Elsevier, 1999b [revised edition].

Pfurtscheller G, Neuper N, Guger C, Harkam W, Ramoser H, Schlögl A, Obermaier B, Pregenzer M. Current trends in Graz Brain-Computer Interface (BCI) research. IEEE Trans Rehabil Eng 2000a;8:216–219.

Pfurtscheller G, Guger C, Müller G, Krausz G, Neuper C. Brain oscillations control hand orthosis in a tetraplegic. Neurosci Lett 2000b;292:211–214.

Pfurtscheller G, Neuper C. Motor imagery and direct brain-computer communication. Proc IEEE 2001;89:1123–1134.

Pierce JR. An introduction to information theory, New York, NY: Dover Press, 1980.

Pineda JA, Allison BZ, Vankov A. The effects of self-movement, observation, imagination on Mu rhythms and readiness potentials (RPs): toward a brain–computer interface (BCI). IEEE Trans Rehabil Eng 2000;8:219–222.

Polak MJ. Adaptive logic networks in a brain–computer interface system. Graduate thesis. Faculty of Graduate Studies and Research, Department of Computer Science, University of Alberta. September 2000.

Polich J. P300 in clinical applications. In: Niedermeyer E, Lopes da Silva FH, editors. Electroencephalography: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, 1999. pp. 1073–1091.

Pregenzer M, Pfurtscheller G, Flotzinger D. Automated feature selection with a distinction sensitive learning vector quantizier. Neurocomp 1996;11:19–29.

Pregenzer M, Pfurtscheller G. Frequency component selection for and EEG-based brain computer interface. IEEE Trans Rehabil Eng 1999;7:413–419.

Ramoser H, Wolpaw JR, Pfurtscheller G. EEG-based communication: evaluation of alternative signal prediction methods. Biomed Tech 1997;42:226–233.

Ravden D, Polich J. On P300 measurement stability, habituation, intra-trial block variation, and ultadian rhythms. Biol Psychol 1999;51:59–76.

Relman AS. The Ingelfinger rule. N Engl J Med 1981;305:824–826.

Rice KM, Blanchard EB, Purcell M. Biofeedback treatments of generalized anxiety disorder: preliminary results. Biofeedback Self Regul 1993;18:93–105.

Robbins RA, Simmons Z, Bremer BA, Walsh SM, Fischer S. Quality of life in ALS is maintained as physical function declines. Neurology 2001;56:442–444.

Roberts SJ, Penny WD. Real-time brain–computer interfacing: a preliminary study using Bayesian learning. Med Biol Eng Comput 2000;38:56–61.

Rockstroh B, Elbert T, Canavan A, Lutzenberger W, Birbaumer N. Slow cortical potentials and behavior, 2nd ed. Baltimore, MD: Urban and Schwarzenberg, 1989.

Rockstroh B, Birbaumer N, Elbert T, Lutzenberger W. Operant control of EEG and event-related and slow brain potentials. Biofeedback Self Regul 1984;9:139–160.

Roder B, Rosler F, Hennighausen E, Nacker F. Event-related potentials during auditory and somatosensory discrimination in sighted and blind human subjects. Brain Res Cogn Brain Res 1996;4:77–93.

Rosenfeld JP. Applied psychophysiology and biofeedback of event-related potentials (brain waves): historical perspective, review, future directions. Biofeedback Self Regul 1990;15:99–119.

Salmoni AR, Schmidt RA, Walter CB. Knowledge of results and motor learning: a review and critical appraisal. Psychol Bull 1984;5:355–386.

Samar VJ, Bopardikar A, Rao R, Swartz K. Wavelet analysis of neuroelectric waveforms: a conceptual tutorial. Brain Lang 1999;66:7–60.

Schalk G, Wolpaw JR, McFarland DJ, Pfurtscheller G. EEG-based communication and control: presence of error potentials. Clin Neurophysiol 2000;111:2138–2144.

Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. BCI2000: development of a general purpose brain–computer interface (BCI) system. Soc Neurosci Abstr 2001;27:168.

Scherer MJ, Lane JP. Assessing consumer profiles of 'ideal' assistive technologies in ten categories: an integration of quantitative and qualitative methods. Disabil Rehabil 1997;19:528–535.

Schlögl A, Flotzinger D, Pfurtscheller G. Adaptive autoregressive modeling used for single-trial EEG classification. Biomed Tech 1997;42:162–167.

Schmidt EM. Single neuron recording from motor cortex as a possible source of signals for control of external devices. Ann Biomed Eng 1980;8:339–349.

Schmidt EM, McIntosh JS, Bak MJ. Long-term implants of Parylene-C coated microelectrodes. Med Biol Eng Comput 1988;26:96–101.

Schwartz AB. Motor cortical activity during drawing movement: population representation during sinusoid tracing. J Neurophysiol 1993;70:28–36.

Serruya MD, Hatsopoulos NG, Paninski L, Fellows MR, Donoghue JP. Brain-machine interface: Instant neural control of a movement signal. Nature 2002;416:141–142.

Shannon CE, Weaver W. The mathematical theory of communication, Urbana, IL: University of Illinois Press, 1964.

Siniatchkin M, Kropp P, Gerber W-D. Neurofeedback – the significance of reinforcement and the search for an appropriate strategy and the success of self-regulation. Appl Psychophys Biofeedback 2000;25:167–175.

Sommer W, Schweinberger S. Operant conditioning of P300. Biol Psychol 1992;33:37–49.

Sterman MB. Basic concepts and clinical findings in the treatment of seizure disorders with EEG operant conditioning. Clin Neurophysiol 2000;31:45–55.

Stroh Wuolle K, Van Doren CL, Bryden AM, Peckham PH, Keith MW, Kilgore KL, Grill JH. Satisfaction with and usage of a hand neuroprothesis. Arch Phys Med Rehabil 1999;80:206–213.

Sutter EE. The visual evoked response as a communication channel. Proceedings of the IEEE Symposium on Biosensors, 1984. p. 95–100.

Sutter EE. The brain response interface: communication through visually-induced electrical brain responses. J Microcomput Appl 1992;15:31–45.

Sutter EE, Tran D. The field topography of ERG components in man. Vision Res 1992;32:433–446.

Sutton S, Braren M, Zubin J, John ER. Evoked correlates of stimulus uncertainty. Science 1965;150:1187–1188.

Taylor DM, Schwartz AB. Direct 3D control of an upper limb neural prosthesis using motor cortex cells trained in a brain-controlled virtual movement task. Soc Neurosci Abstr 2001;27:335.

Tecce JJ, Gips J, Olivieri CP, Pok LJ, Consiglio MR. Eye movement control of computer functions. Int J Psychophysiol 1998;29:319–325.

Teder-Sälejärvi WA, Münte TF, Sperlich F-J, Hillyard SA. Intra-modal and cross-modal spatial attention to auditory and visual stimuli. An event-related brain potential study. Cogn Brain Res 1999;8:327–343.

ten Kate JH, Hepp B. Optical and eye-controlled communication aids. J Med Eng Technol 1989;13:63–67.

Thomas C. Firefox, New York, NY: Holt, Rinehart and Winston, 1977.

Travis TA, Kondo CY, Knott JR. Alpha enhancement research: a review. Biol Psychiatry 1975;10:69–89.

Vaughan TM, McFarland DJ, Schalk G, Sarnacki WA, Robinson L, Wolpaw JR. EEG-based brain–computer interface: development of a speller. Soc Neurosci Abstr 2001;27:167.

Vaughan TM, Miner LA, McFarland DJ, Wolpaw JR. EEG-based communication: analysis of concurrent EMG activity. Electroenceph clin Neurophysiol 1998;107:428–433.

Vaughan TM, Sarnacki WA, McFarland DJ, Wolpaw JR. EEG-based communication with topographically differentiated mu and beta rhythms. Soc Neurosci Abstr 1999;25:1412.

Vidal JJ. Towards direct brain–computer communication. Annu Rev Biophys Bioeng 1973;2:157–180.

Vidal JJ. Real-time detection of brain events in EEG. IEEE Proc 1977;65:633–664 [Special issue on Biological Signal Processing and Analysis].

Walter WG, Cooper R, Aldridge VJ, McCallum WC, Winter AL. Contingent negative variation: an electric sign of sensorimotor association and expectancy in the human brain. Nature 1964;203:380–384.

Wessberg J, Stambaugh CR, Kralik JD, Beck PD, Laubach M, Chapin JK, Kim J, Biggs J, Srinivasan MA, Nicolelis MA. Real-time prediction of hand trajectory by ensemble of cortical neurons in primates. Nature 2000;408:361–365.

Williams JC, Rennaker RL, Kipke DR. Long-term neural recording characteristics of wire microelectrode arrays implanted in cerebral cortex. Brain Res Brain Res Protocol 1999;4:303–313.

Wolpaw JR, McFarland DJ, Neat GW, Forneris CA. An EEG-based brain–computer interface for cursor control. Electroenceph clin Neurophysiol 1991;78:252–259.

Wolpaw JR, McFarland DJ. Multichannel EEG-based brain–computer communication. Electroenceph clin Neurophysiol 1994;90:444–449.

Wolpaw JR, Flotzinger D, Pfurtscheller G, McFarland DJ. Timing of EEG-based cursor control. J Clin Neurophysiol 1997;16:529–538.

Wolpaw JR, Ramoser H, McFarland DJ, Pfurtscheller G. EEG-based communication: improved accuracy by response verification. IEEE Trans Rehabil Eng 1998;6:326–333.

Wolpaw JR, Birbaumer N, Heetderks WJ, McFarland DJ, Peckham PH, Schalk G, Donchin E, Quatrano LA, Robinson CJ, Vaughan TM. Brain–computer interface technology: a review of the first international meeting. IEEE Trans Rehabil Eng 2000a;8:161–163.

Wolpaw JR, McFarland DJ, Vaughan TM. Brain–computer interface research at the Wadsworth Center. IEEE Trans Rehabil Eng 2000b;8:222–225.

Wolpaw JR, Schalk G, McFarland DJ, Hinterberger T, Perelmouter J, Godde B, Birbaumer N, Pfurtscheller G. BCI2000: a general purpose brain–computer interface system. Soc Neurosci Abstr 2000c;26:1229.

Wyler AR, Burchiel KJ. Factors influencing accuracy of operant conditioning of tract neurons in monkey. Brain Res 1978;152:418–421.

Wyler AR, Burchiel KJ, Robbins SA. Operant control of precentral neurons in monkeys: evidence against open loop control. Brain Res 1979;171:29–39.

Wyricka W, Sterman MB. Instrumental conditioning of sensorimotor cortex EEG spindles in the waking cat. Psychol Behav 1968;3:703–707.

Zhou P. Numerical analysis of electromagnetic fields, Berlin: Springer, 1993.