

For reprint orders, please contact:
reprints@future-drugs.com



CONTENTS

- Overview
- BCI signal acquisition
- BCI signal processing
- BCI output devices
- BCI operating protocols
- Devices that are not BCIs
- Other terminology
- Moving BCI systems from the laboratory to the home
- Expert commentary
- Five-year view
- Key issues
- References
- Affiliations

[†]Author for correspondence
 Laboratory of Nervous System Disorders, Wadsworth Center, New York State Department of Health and State University of New York, PO Box 509, Albany, NY 12201-0509, USA
 Tel: +1 518 473 3631
 Fax: +1 518 486 4910
www.bciinsearch.org

KEYWORDS:
 ALS, assistive communication, BCI, BMI, brain-actuated control, brain-computer interface, brain-machine interface, EEG, ERP, locked-in syndrome, slow cortical potential, SSVEP, stroke

Brain–computer interface systems: progress and prospects

Brendan Z Allison, Elizabeth Winter Wolpaw and Jonathan R Wolpaw[†]

Brain–computer interface (BCI) systems support communication through direct measures of neural activity without muscle activity. BCIs may provide the best and sometimes the only communication option for users disabled by the most severe neuromuscular disorders and may eventually become useful to less severely disabled and/or healthy individuals across a wide range of applications. This review discusses the structure and functions of BCI systems, clarifies terminology and addresses practical applications. Progress and opportunities in the field are also identified and explicated.

Expert Rev. Med. Devices 4(4), 463–474 (2007)

Millions of people suffer from severe neuromuscular disorders, such as amyotrophic lateral sclerosis (ALS), brainstem stroke, cerebral palsy, muscular dystrophy, multiple sclerosis and Guillain–Barre syndrome [1,2]. Many of these people cannot communicate through the usual neuromuscular pathways and must rely instead on alternative means of communication that use remaining muscle function, such as eye-gaze shifting, electromyographic (EMG) activity or respiration [3–5]. Typically, these people use alternative systems because they cannot use more conventional interfaces, such as a keyboard, mouse or other interfaces that require greater muscular control.

A brain–computer interface (BCI) is a communication system by which a person can send messages or commands without any use of peripheral nerves and muscles [6–14]. BCIs record signals from the brain and translate them into useful communication. Thus, they are usable even by people who have no effective muscle control. This review describes the basic components of a BCI and the major categories of current BCIs, defines terms used in the BCI literature and considers advances that might be expected in the next few years.

Overview

Signals that might be used for BCIs can be recorded from four locations as shown schematically in FIGURE 1: from sensors that are not in

contact with the body, such as in functional MRI (fMRI) or magnetoencephalography (MEG) [15,16]; from the surface of the scalp via standard electroencephalographic (EEG) electrodes [17,18] or functional near-infrared (fNIR) spectroscopy [19,20]; from the surface of the dura or the surface of the brain using electrocorticographic (ECoG) electrodes [21,22]; or from within the brain using microelectrodes implanted in the cortex [23,24] or elsewhere in the brain. In both healthy and severely disabled people, signals from these areas can be extracted and translated for communication and control.

FIGURE 1 illustrates the basic structure of any BCI. A BCI has four essential components: the signal acquisition component, which records brain signals at one of the sites described above; the signal processing component, which includes the software that extracts the features of the brain signals that are used for the BCI and the translation algorithm that translates the extracted features into device commands; the output device component that implements the commands; and the operating protocol that governs how these components interact [7].

BCI signal acquisition

Most BCIs do not require surgery to implant electrodes [25] and are therefore termed non-invasive BCIs. At present, almost all non-invasive BCIs measure brain activity with EEG sensors placed on the surface of the scalp; this

review focuses mainly on such BCIs. BCIs that acquire signals from electrodes surgically implanted in or on the cortex or other brain areas are considered to be invasive. ECoG-based BCIs are invasive because they require surgery but are less invasive than intracortical BCIs since ECoG electrodes do not penetrate into the brain but, rather, lie on the brain's surface.

Invasive electrodes may give a more detailed view of brain activity than noninvasive systems. Since the scalp smears, dampens and filters the brain's electrical activity, invasive electrodes may allow better spatial resolution, stronger signals and a wider range of frequencies than electrodes placed on the scalp. For example, ECoG BCIs can detect movement-related activity in the 100–200-Hz range, well beyond the range of scalp electrodes [22]. Invasive BCIs can be available for use 24 h per day, require less preparation and clean-up time and are less susceptible to noise from muscle artifact and external noise [13,26–28]. However, invasive BCIs currently offer approximately the same performance as noninvasive systems [29]. Furthermore, they entail expensive surgery, scarring, risk of infection and regular medical check-ups, and their long-term stability remains unclear [8,9,30,31]. Hence, while invasive BCIs merit further study, most patients and researchers may, understandably, choose noninvasive approaches [29].

EEG-based BCIs

The μ (8–12 Hz) and β (12–30 Hz) EEG rhythms recorded over sensorimotor cortex attenuate during performed or imagined movement [32–34]. The decrease in this synchronized

activity preceding movement is called event-related desynchronization (ERD) [35]. BCI systems based on imagined movement were introduced by Wolpaw and colleagues, who demonstrated that disabled and able-bodied people could learn to use the amplitudes of μ or β rhythms to control a computer cursor in 1D [36]. Soon afterwards, Wolpaw and McFarland demonstrated that μ and β rhythms could be used for 2D control [29,37]. Five to ten 24-min training sessions are required for most users to master the skill of using μ and/or β rhythm amplitude to control 1D of movement and for the system to be optimally adapted to the rhythms of that user. Typically, users first learn to control the vertical movement of the cursor as it moves from left to right at a constant rate [38–40]. With additional training, users can learn to use μ or β rhythms over both hemispheres or at different frequencies to achieve two independent control channels and thereby obtain accurate 2D movement control [29,37,41]. A third channel might be used to make a selection in the manner of clicking on a mouse button [20]. Early in training, users typically use imagery to modulate μ and β rhythms but as they become more skilled, the task becomes more automatic and imagery is often no longer needed. In these studies, able-bodied users and users with severe disabilities learned to control the μ and β rhythms to move a computer cursor in 1D or 2D, to perform simple word-processing and to select items on a computer screen. Some subjects have achieved simple control with minimal training using μ and β rhythms associated with imagery of specific movements [42,43]. μ BCI systems have also been used to control devices, such as an orthosis or neuroprosthesis [44–47].

Birbaumer and colleagues developed a BCI system based on slow cortical potentials (SCPs) [12,48–52]. SCPs are relatively slow EEG voltage changes that can be induced by emotional or mental imagery [53]. A typical SCP BCI measures EEG activity during a 2-s resting phase and then during a 2-s active phase in which the user produces a positive or negative SCP. The SCP method requires 1–5 months of training. Able-bodied and disabled people, including people with advanced ALS, can use SCPs to perform word-processing and other tasks [48,49,52,54,55,202]. However, SCP-based communication is necessarily slow because detectable changes in SCPs take several seconds to develop [53].

Although SCP and sensorimotor (μ/β) BCIs normally require some user training, other BCIs do not rely on operant conditioning and can be used with minimal training. For example, the P300 component of the event-related potential (ERP), which is typically elicited when stimuli are perceived and discriminated [56], can be

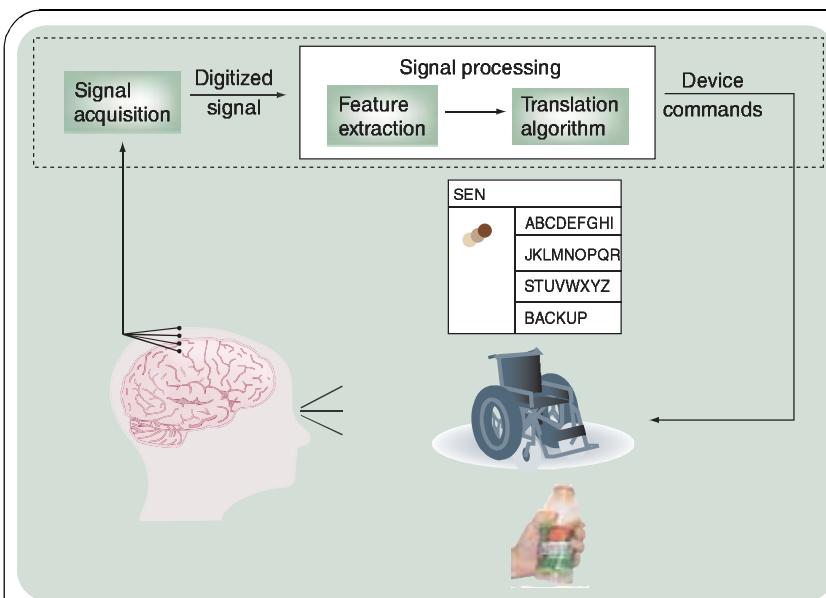


Figure 1. The basic design of any brain–computer interface (BCI) system. Signals reflecting brain activity are acquired from sensors above the scalp, on the scalp, on the cortical surface or within the brain, and are analyzed to measure signal features (such as amplitudes of evoked potentials or electroencephalogram rhythms or firing rates of single neurons) that reflect the user's intent. These features are translated into messages or commands that operate a device, such as a word-processing program, a wheelchair or a neuroprosthesis.

Modified from [7].

used for a BCI. Farwell and Donchin developed a P300-based BCI, which presents the user with a matrix of letters or other elements on a computer screen [57]. The individual rows and columns of the matrix flash rapidly in a random sequence and the user is instructed to silently count flashes that include the letter or symbol that he/she wants to select, while ignoring other flashes. The row or column containing the desired target elicits a P300 response that in most people is adequate for BCI use [56,57]. Despite initial concerns that the P300 may be weaker in ALS patients [58,59] or after sustained use [6], initial data suggest that P300 BCIs are effective for ALS patients for hours of daily use over many months [SELLERS EW ET AL, UNPUBLISHED DATA]. P300 BCIs have also been developed with auditory stimuli for users with visual impairments [60,62]. Very recent work suggests that P300 BCIs may yield better performance than SCP or sensorimotor BCIs in many subjects [12,202]. Additional research comparing different BCI approaches across various subjects is needed.

Steady-state visual evoked potentials (SSVEPs) reflect attention to a rapidly oscillating stimulus [63,64]. If users direct attention to one such stimulus, activity over occipital areas at corresponding frequencies can be used to infer user intent [65–70]. BCIs might conceivably use other steady-state phenomena, such as steady-state somatosensory evoked potentials induced by variable frequency vibrators [71] or steady-state auditory evoked potentials [62,72]. Simultaneous attention to two or more target stimuli, such as two visual stimuli or stimuli in two different modalities, might improve information throughput [64,73].

EEG spectra may change as users perform common mental tasks, such as composing a statement, mental rotation or arithmetic [74]. Some BCIs allow communication by determining which mental tasks a user is performing [15,29,75–77]. This approach offers low information throughput relative to most other BCIs, primarily because the process of identifying mental tasks via EEG activity and of switching between tasks are both slow.

ECoG-based BCIs

In humans, ECoG BCI studies have been limited to epilepsy patients who have ECoG electrode grids temporarily implanted (for up to several weeks) in preparation for epilepsy surgery [9,22,78,79]. ECoG grids are often placed over cortical areas involved in motor activity, and the BCI studies often involve imagined movements. A recent study suggests that people can learn to use the ECoG activity associated with imagery of specific movements to control cursor movement more quickly than they can learn to use EEG activity using similar movement imagery [22]. ECoG-based BCIs use methods comparable to those of EEG-based BCIs. At the same time, ECoG is substantially superior to EEG in signal strength, frequency range and topographic resolution, and is far less subject to artifacts, such as EMG activity. Furthermore, ECoG recording is less invasive and may exhibit better long-term stability than intracortical BCI recording methods. Thus, although not yet well developed, ECoG has great promise for the development of future BCI technology.

Intracortical BCIs

The possibility that signals recorded within the cortex or in other brain areas might be used for BCIs has received substantial attention over the past decade [9,23,24,79–81]. A number of different multielectrode implants have been developed for recording action potentials (spikes) of multiple single neurons or local field potentials (LFPs), which are essentially micro-EEG activity. Since cortical implants require surgery, these BCI systems have been investigated mainly in rats and monkeys [80–84]. A few human studies have been conducted [13,23,24]. Similar to ECoG BCI studies, intracortical BCI studies have focused on translating imagined movements into movement commands, usually for cursor control. These studies have demonstrated movement control. At the same time, performance is highly variable both within and across subjects, and, at present, is not substantially greater than that achievable with an EEG-based BCI [29] (compare the noninvasive EEG-based BCI movement control [203] with the invasive intracortical BCI movement control [204]). Extensive further animal and human studies are needed to try to achieve stable intracortical BCI control that is substantially better than that possible with less invasive BCI methods (e.g., through development of better algorithms and user training methods) and to develop and validate wholly implanted, safe and reliable intracortical BCI systems for long-term human use.

BCIs using nonelectrical signals

The signals that have been discussed thus far are all electrical. Some investigators have explored the use of nonelectrical signals as a possible basis for a BCI. These methods include fMRI [15,52], fNIR spectroscopy [19,20] and MEG [16,21]. While these signals are appealing because, similar to EEG, they are noninvasive and involve little risk, they face substantial methodological and/or practical problems. fMRI and fNIR both rely on changes in the brain's blood flow, which develop more slowly than electrical activity. Moreover, fMRI and MEG are extremely expensive and technically demanding, and require highly controlled environments [31].

BCI signal processing

Once signals are acquired by one of the methods described above, the second component of a BCI, the signal processing unit (FIGURE 1), extracts signal features and translates them into messages or commands. The signal processing unit first analyzes the raw signal and isolates those features to be used by the BCI. Feature extraction may use relatively simple approaches, such as autoregressive frequency analysis [29], or more complex techniques, such as independent component analysis (ICA) [59,85,86]. The translation algorithm then translates these extracted features into an output command. For a BCI to be a practical method for communication, the system must perform this and all other tasks rapidly and online. Translation algorithms vary widely in complexity, from linear methods, such as stepwise discriminant analysis or weighted frequency summation, to nonlinear neural and adaptive logic networks [18,41,57,60,83,87–90].

Signal processing parameters need to adapt to each user. Ideally, a BCI first identifies the most appropriate signal features for each user and continues to adapt to changes in these features that occur spontaneously (e.g., due to time of day, fatigue, medication or hunger) or that occur as the user adapts to the BCI [7].

BCI output devices

After the features of the brain signal are extracted and translated, the third component of the BCI, the output device, implements the messages or commands conveyed by the translation algorithm. To date, the most commonly used BCI output device is a computer monitor. Monitor-based BCIs have been developed in which users move a cursor to chosen targets in one [39,48] or more dimensions [15,29,59,81,91], select one item from two or more choices [60,68], select items from a scrolling [92] or iterative [66,93] menu, browse the internet [51,61,94,95,205] or navigate a virtual environment [85,96–98]. Some BCIs use speakers or headphones to provide auditory stimulation or feedback [50,60,62,99,100]. BCIs have also been used to control switches [101,102], common appliances, such as an air conditioner, television or music player [66,68,130], medical devices [6,61,66,68,93,103], robotic arms [80,81,84], mobile robots [77], functional electrical stimulators or orthoses [18,24,44,45,67,104] and a full-motion flight simulator [67].

BCI operating protocols

The operating protocol defines the real-time interactions between the user's brain and the BCI system. It provides a front end for the user and operator, governs how the other three modules interact with each other and the operating system, and mediates details of user–system interaction, such as what selections are available to the user, when and how user activity may effect control, and the nature and timing of feedback [7,38,105].

Similar to other BCI components, operating protocols have advanced significantly in the last several years. Many papers have addressed timing, feedback and usability [18,38–40,46,106–110]. Error correction based on EEG activity, such as the error-related negativity, P300 or other measures, may improve performance in some users [111–114]. Some operating protocols allow a much larger vocabulary than most early BCIs, either by presenting many options [68,110,115] or by letting the user select from among different palettes of options, sometimes via a menu [51,66,93,116].

The most widely used BCI operating system is BCI2000 [117], which is currently being used by over 150 laboratories worldwide [SCHALK, PERS. COMM.]. BCI2000 has many features that make it appealing to researchers. It is highly flexible and interchangeable, and has been validated with a wide variety of signal acquisition, signal processing and output systems. It offers a variety of real-time and offline analyses and is available free of charge for research use [206].

Devices that are not BCIs

Some devices record brain signals but are not BCIs. For example, devices that evaluate cognitive and neural activity associated with alertness or workload [ALLISON & POLICH UNPUBLISHED

DATA] [118,119], sleep stage [120], sleep apnea [121], depth of anesthesia [72,122,123], deception [124,125], error detection [111,113] or image recognition [126] may seem similar to BCIs but do not provide the user with real-time communication or control. Systems that send signals to the brain are not BCIs, though they might be called computer–brain interfaces (CBIs) [127–129]. Finally, it is essential to distinguish actual BCIs from systems that use non-CNS signals recorded from the head, such as EMG or electrooculographic activity.

Other terminology

Readers of BCI literature frequently encounter a number of important terms and distinctions [25,130,131]. The most prominent ones are briefly defined here.

BCI versus BMI

While the term BCI now predominates in both the scientific and popular literature, other terms are sometimes used to describe a BCI system. These include: brain–machine interface (BMI) [9,28], direct brain interface (DBI) [78], brain interface [25,131], cognitive neural prosthetic [8,79], neural interface system [13] and brain actuated control [77,132,133]. Although efforts are sometimes made to give these terms different meanings, they all mean essentially the same thing: a communication and control system that uses signals generated in the CNS and does not depend on peripheral nerves or muscles.

Dependent versus independent BCIs

BCIs can be either dependent or independent. Dependent BCI systems require some muscle control to produce the neural activity used for communication or control. Independent or 'pure' BCIs do not require any muscle control. For example, some SSVEP BCIs are dependent on gaze control and, thus, on muscle activity [207]. By contrast, typical P300-based or sensorimotor rhythm-based BCIs appear to be independent of muscle activity [7,29,134]. While dependent BCIs may be of use for a variety of applications, they may not be considered pure BCIs since individuals without motor control may not be able to use them.

Synchronous versus asynchronous BCIs

In synchronous BCI systems, the timing of operation is determined by the BCI, not by the user. For example, most P300 BCIs require the user to observe flashes that are presented at a fixed pace controlled by the system [57,59,60]. Most μ and SCP BCIs require users to produce activity when so instructed by the BCI. By contrast, in asynchronous BCI systems, the user controls the timing of communication [71,131]. For example, some BCI systems allow users to voluntarily imagine or perform mental tasks or movements at their own pace [18,77,92,135]. Asynchronous BCIs may be more vulnerable to the phenomenon of unrelated activity being interpreted as a message or command [108]. This problem has fostered exploration of methods for turning a BCI on or off with brain activity [101,136].

Automaticity

In the context of BCI technology, the term automaticity refers to the degree to which a person can, with practice, learn to use a BCI without paying exclusive attention to doing so [137,138]. Learning to use some BCIs appears to be similar to learning to play the piano, to type, to drive or to perform another motor task [6,7,49,52,55]. Anecdotal experience with some sensorimotor rhythm- and SCP-based BCI methods suggests that novices devote their full attention to the mental imagery needed for BCI operation, whereas experienced users find BCI use much less demanding. They often dispense with motor imagery and are able to perform other tasks simultaneously [116]. As with many other skills, improvements in BCI performance tend to be most rapid early in skill acquisition [29,97].

Other BCI systems do not rely overtly on operant conditioning. While long-term use of P300, SSVEP, mental task and some sensorimotor-rhythm BCI approaches have not been extensively studied, learning to use these BCIs may be more like learning facts, events or other declarative memories [42,57,92,98]. Users typically perform effectively once given initial instructions and rarely develop new strategies or improve performance with practice [59,60,67,109,112].

Terminology relating to the degree of a patient's disability

Some patients described in the BCI literature as having 'locked-in syndrome' or having 'complete motor paralysis' do retain minimal motor function, such as limited eye-movement control, which may or may not be sufficient to provide a simple communication channel [54]. By contrast, people with complete locked-in syndrome retain absolutely no useful motor control and, thus, cannot operate any conventional assistive communication device. For these individuals, only a BCI or perhaps a system that uses autonomic function, might provide a means of communication [139].

Moving BCI systems from the laboratory to the home

The central goal of BCI research is to develop BCIs that provide disabled people with communication and control in their homes on a daily basis to improve their quality of life. Although many groups have reported successful BCI use with severely disabled people, including some in their home environments [24,59–61,140,141], BCIs have not yet been available for use by substantial numbers of disabled users in their homes for important purposes every day. Such deployment is just beginning [61,208].

Several significant obstacles currently impede the widespread adoption of BCIs. Few healthcare providers and rehabilitation experts are familiar with the capabilities that BCIs can offer their patients. Although healthcare providers and family members often assume that people with chronic and severe motor impairment are depressed and do not want to go on living, studies have shown that these individuals are little more likely to be depressed than healthy individuals and that, given a good support system and a means to communicate, they can lead lives that they consider to be enjoyable and productive [12,49,142,143].

Long-term use of a BCI in a patient's home requires ongoing support by the user's family and caretakers, as well as some basic degree of technical support. One of the greatest challenges in BCI research and development is to make the systems sufficiently user-friendly and robust so that caretakers and patient users can operate them on a daily basis with minimal technical support [135,144,145].

Reimbursement by insurers is another important issue. Currently, Medicare guidelines allow reimbursement for communication devices only if they provide speech. Thus, under current guidelines, BCIs that only allow word-processing, internet browsing, device control and environmental control are not covered. However, auditory output, including speech, could be added to most systems with little difficulty. Many patients may have no access to reimbursement. Moreover, since ongoing technical support of a BCI may be more expensive than the purchase of the BCI system itself, it is essential to develop BCIs that are easy to use, reliable and adaptive to the needs of the user and caregiver.

The preferences of people with severe disabilities may sometimes be difficult to anticipate. For example, Kübler and colleagues describe a patient who had been unable to communicate for months, whose first requests via her BCI pertained to her clothing and her desire for a manicure [6]. This may seem surprising to able-bodied people trying to imagine life unable to move or communicate and underscores the need for further research and continuing efforts to customize BCIs to patients' abilities, needs and desires.

At the present time, no commercial entities supply clinically practical BCIs for the general patient population. Thus, current BCI users typically work with the BCI system and protocol of a particular BCI research group rather than a system best suited to their needs, desires and abilities. Since some people exhibit much better performance with certain BCI approaches than others [12,202] and often have different preferences and goals [6,108,145], it will be important to ensure that each potential user has access to a range of BCI options.

Although BCI systems are sometimes evaluated and compared based on their information throughput or information transfer rate (ITR), it is important to note that factors other than speed and accuracy may be important. For example, some users prefer interfaces with a slower ITR because they are easier to use, less fatiguing, easier to customize, more reliable or otherwise more suitable. A BCI that allows rapid spelling may be less desirable than a much slower BCI that instead allows control of a thermostat, television, wheelchair, prosthesis or other personal medical device. Availability, invasiveness, cost, portability, training time, online and personal support, cosmesis, and the time and skill needed to prepare for BCI usage are also important considerations.

Expert commentary

People with severe motor disabilities need BCIs more than any other group. Systems must be reliable, easy to use, widely available at a reasonable cost and operable by disabled people in their homes without the need for extensive ongoing technical support. They should entail little or no additional health risk to people who are already heavily burdened with health concerns. Users,

healthcare and rehabilitation professionals, families and caretakers must be educated about the opportunities and limitations offered by the various BCI alternatives.

BCIs are becoming useful to a wider audience. As BCIs become more powerful and better integrated with existing hardware and software, BCIs may out-perform or complement other assistive communication systems. For example, the patient described in [61,208] has an eye-tracking system that he could use but instead chooses to communicate via a BCI because he considers it easier to use. BCI systems have been used in combination with other assistive interfaces, such as a switch controlled by mouth or foot movement [101,103], and might even be used in combination with a conventional interface, such as a keyboard or mouse. People without severe disabilities, including healthy users, might use a BCI despite the availability of faster interfaces for many reasons, such as novelty, confidentiality, access to otherwise unavailable information or because the user's hands are busy with other tasks [130,209]. BCI research might also inspire systems to treat disorders that do not directly impair communication, such as epilepsy, anxiety, attentional disorders, psychopathy and stroke [12,53,145,163–166,210].

BCI research can capitalize on advances in basic science and technology. Cognitive neuroscience can inform and inspire research concerning training, feedback, display parameters, control strategies, usability, distraction, fatigue, motivation and discomfort [6,39,40,46,49,102,109,115,146]. Questionnaires, interviews, performance and neuroimaging data can assess subjective and objective factors across subjects with different backgrounds, pathologies, needs, abilities and interests.

Conversely, BCI progress has created opportunity for basic science research. Implanted BCI research has elucidated the firing patterns of individual and small groups of neurons [9,22,147]. Studies using μ and SCP BCI systems have clarified mechanisms underlying the generation and regulation of these signals [32,35,49,146,148,149]. BCI studies have improved understanding of disease pathology and patient psychology [6,12,59,60,143,149–151] and addressed EMG and EEG interactions [134,152].

Five-year view

Signal acquisition methods for invasive and noninvasive BCIs are likely to advance in different ways. Invasive electrodes may soon exhibit better signal quality and long-term reliability with less tissue damage [26,147]. Scalp electrodes will become easier to apply, use and integrate with existing headgear. Newer electrodes have been described that require little or no gel and/or do not require contact with the scalp [153,154]. While EEG-based BCIs are likely to remain most widely used over the next several years owing to their ease of use and success to date, some other methods (e.g., ECoG, fNIR) hold considerable promise for the future [20,22,31]. fMRI and MEG-based methods are likely to remain too expensive and cumbersome for long-term practical patient use within the next 5 years. As noted above, the future use of intracortical BCI methods depends on demonstrating that they can provide better control than less invasive methods and are safe and practical for long-term use.

Signal processing will continue to be a very active area in BCI research and development. Data analysis competitions have already provided an international venue for comparing signal processing methods and will probably continue to do so [155,156]. Pattern recognition is a very active area of research for other purposes and, thus, many researchers have the experience and tools necessary to contribute to this aspect of BCI research. Improved approaches to pattern recognition may identify additional useful components of existing signals. For example, spectral activity might change reliably with selective attention and, thus, might be used to improve classification in a P300 or SSVEP BCI [17,69,89,157,158].

The next 5 years will also probably see several new output devices for BCIs. Current versions of mobile robots are not yet useful to the BCI user population but may be stepping stones to more practical output devices, such as BCI-controlled wheelchairs [77,159]. Highly immersive virtual environments, which often require a head-mounted display or several large displays, may produce a more absorbing experience for BCI users and accelerate learning [46,85,97,112,132,210]. BCI systems may also be adapted to work with headgear, clothing or alternative displays [106,160].

Operating protocols are likely to develop in many different ways. Improved feedback approaches, perhaps including new modalities, such as auditory or somatosensory feedback, may facilitate training and usability [26,90]. Error correction, response verification, improved letter selection and word completion algorithms are likely to improve performance and reduce frustration [116,161]. Goal-oriented operating protocols, which do not burden the subject with unnecessary details of the process that must be followed to attain a goal, could also substantially improve usability and effective information throughput [14]. Efforts to integrate BCIs with other output devices, as well as other interfaces, such as eye-trackers, EMG detectors and even keyboards and mice, will also require new operating protocols [5,106,130,160,162]. Hybrid BCI systems may allow a user to combine different BCI approaches, such as different signal features, imaging approaches or mental activities, to improve information throughput, reliability and ease of use [7,85,130,154].

BCI systems have just begun to provide significant assistive communication technology to people without other effective means of communication in their home environments. As BCI research and development advances, and more people become aware of available options, BCIs may soon provide more customized assistance to a larger and more eclectic group of users. Given the pace of BCI development and the progress it has spurred in related disciplines, the next few years should see the deployment and adoption of a variety of such devices and their ongoing development to help improve the lives of many different people.

Acknowledgements

The authors' BCI research has been supported by NIH grants HD30146 (NCMRR/NICHD) and EB00856 (NIBIB & NINDS), The James S McDonnell Foundation, The Altran Foundation and The ALS Hope Foundation.

Key issues

- Brain–computer interfaces (BCIs) are provided for people with severe disabilities to use in their homes.
- Effective information throughput is being improved by developing or improving sensor and hardware technology; signal processing and translation approaches; error correction and response verification; word and/or sentence selection and/or completion algorithms; additional signals, including hybrid BCIs; sequential menus; and goal-oriented protocols.
- The right BCI for a given user can be found by considering factors including performance, fatigue, training time, invasiveness, reliability, cost, flexibility, environment, cosmesis, comfort, ease of set-up and use, the user's needs, desires, motivation and abilities, and access to assistance with preparing, using, repairing, cleaning or updating the BCI.
- BCIs can be integrated with conventional computers, medical equipment, headwear, software, accessories and interfaces, allowing more flexible, usable mainstream BCIs.
- BCI-related clinical and research infrastructure should continue to be improved to provide information to and among researchers, medical personnel, patients and other users, support staff, students, potential and actual funding sources, the media and the public.

References

Papers of special note have been highlighted as:

- of interest
- of considerable interest

- 1 Kennedy PR, Adams KD. A decision tree for brain–computer interface devices. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 148–150 (2003).
- 2 Dobkin BH, Havton LA. Basic advances and new avenues in therapy of spinal cord injury. *Ann. Rev. Med.* 55, 255–282 (2004).
- 3 Tecce JJ, Gips J, Olivieri CP, Pok LJ, Consiglio MR. Eye movement control of computer functions. *Int. J. Psychophysiol.* 29, 319–325 (1998).
- 4 Cook A, Hussey S. *Assistive Technologies: Principles and Practice* (2nd Edition). Elsevier, NY, USA (2002).
- 5 Ward DJ, MacKay DJC. Fast hands-free writing by gaze direction. *Nature* 418, 838 (2002).
- 6 Kübler A, Kotchoubey B, Kaiser J, Wolpaw JR, Birbaumer N. Brain–computer communication: unlocking the locked in. *Psychol. Bull.* 127, 358–375 (2001).
- Important early review that highlights issues in psychological principles crucial for effective brain–computer interface (BCI) use.
- 7 Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain–computer interfaces for communication and control. *Clin. Neurophysiol.* 113, 767–791 (2002).
- The most heavily cited BCI review, which presents BCI components, categories, evaluation criteria and future challenges.
- 8 Andersen RA, Burdick JW, Musallam S, Pesaran B, Cham JG. Cognitive neural prosthetics. *Trends Cog. Sci.* 8, 486–493 (2004).

- 9 Fries G, Penn RD, Park MC et al. Initial surgical experience with an intracortical microelectrode array for brain–computer interface applications. *Neurosurgery* 59, 481 (2006).
- 10 Santana D, Ramirez M, Ostrosky-Solis F. Recent advances in rehabilitation technology, a review of the brain–computer interface. *Rev. Neurol.* 39, 447–450 (2004).
- 11 Yang BH, Yan GZ, Yan RG. A review of brain–computer interfaces (BCIs). *Zhongguo Yi Liao Qi Xie Za Zhi* 29, 353–357 (2005).
- 12 Birbaumer N, Cohen LG. Brain–computer interfaces: communication and restoration of movement in paralysis. *J. Physiol.* 579(Pt 3), 621–636 (2007).
- Includes an overview of BCIs for communication and other medical applications, including implications for non-BCI systems.
- 13 Donoghue JP, Nurmikko A, Black M, Hochberg LR. Assistive technology and robotic control using motor cortex ensemble-based neural interface systems in humans with tetraplegia. *J. Physiol.* 579, 603–611 (2007).
- 14 Wolpaw JR. Brain–computer interface systems as new output pathways. *J. Physiol.* 579(Pt 3), 613–619 (2007).
- 15 Yoo SS, Fairnery T, Chen NK et al. Brain–computer interface using fMRI: spatial navigation by thoughts. *NeuroReport* 15, 1591–1595 (2004).
- 16 Kauhanen L, Nykopp T, Lehtonen J et al. EEG and MEG brain–computer interface for tetraplegic patients. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 190–193 (2006).
- 17 Donchin E, Spencer KM, Wijesinghe R. The mental prosthesis: assessing the speed of a P300-based brain–computer interface. *IEEE Trans. Rehabil. Eng.* 8, 174–179 (2000).
- 18 Pfurtscheller G, Leeb R, Keinrath C et al. Walking from thought. *Ergon Res.* 1071, 145–152 (2006).
- 19 Coyle S, Ward T, Markham C, McDarby G. On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. *J. Physiol. Meas.* 25, 815–822 (2004).
- 20 Sitaran R, Zhang HH, Guan CT et al. Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain–computer interface. *Neuroimage* 34, 1416–1427 (2007).
- 21 Hill NJ, Lal TN, Schroder M et al. Classifying EEG and ECoG signals without subject training for fast BCI implementation, comparison of nonparalyzed and completely paralyzed subjects. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 183–186 (2006).
- 22 Leuthardt EC, Miller KJ, Schalk G, Rao RPN, Ciemann JG. Electrocorticography-based brain computer interface – the Seattle experience. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 194–198 (2006).
- 23 Kennedy PR, Bakay RA, Moore MM, Adams K, Goldwainthe J. Direct control of a computer from the human central nervous system. *IEEE Trans. Rehabil. Eng.* 8, 198–202 (2000).
- 24 Hochberg LR, Serruya MD, Fries GM et al. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature* 442, 164–171 (2006).
- 25 Mason SG, Bashashati A, Fatourechi M, Navarro KF, Birch GE. A comprehensive survey of brain interface technology designs. *Ann. Biomed. Eng.* 35, 137–169 (2007).
- 26 Schwartz AB, Cui XT, Weber DJ, Moran DW. Brain-controlled interfaces: movement restoration with neural prosthetics. *Neuron* 52, 205–220 (2006).

- Excellent up-to-date BCI review with in-depth coverage of some important technical issues.
- 27 Kennedy PR, Bakay RA. Restoration of neural output from a paralyzed patient by a direct brain connection. *NeuroReport* 9, 1707–1711 (1998).
- 28 Musallam S, Corneil BD, Greger B, Scherberger H, Andersen RA. Cognitive control signals for neural prosthetics. *Science* 305, 258–262 (2005).
- 29 Wolpaw JR, McFarland DJ. Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. *Proc. Natl Acad. Sci. USA* 101, 17849–17854 (2004).
- Presents substantial improvements to 2D μ BCI systems and dispels the previously widespread assumption that noninvasive systems cannot attain performance comparable to invasive systems.
- 30 Shain W, Spataro L, Dilgen J et al. Controlling cellular reactive responses around neural prosthetic devices using peripheral and local intervention strategies. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 186–188 (2003).
- 31 Wolpaw JR, Loeb GE, Allison BZ et al. BCI Meeting 2005 – workshop on signals and recording methods. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 138–141 (2006).
- 32 McFarland DJ, Miner LA, Vaughan TM, Wolpaw JR. μ and β rhythm topographies during motor imagery and actual movements. *Brain Topogr.* 12, 177–186 (2000).
- 33 Pineda JA, Allison BZ, Vankov A. The effects of self-movement, observation, and imagination on μ rhythms and readiness potentials (RPs): toward a brain-computer interface (BCI). *IEEE Trans. Rehabil. Eng.* 8, 219–222 (2000).
- 34 Pineda JA. The functional significance of μ rhythms: translating “seeing” and “hearing” into “doing”. *Brain Res. Rev.* 50, 57–68 (2005).
- 35 Neuper C, Pfurtscheller G. ERD/ERS basic principles: evidence for resonance-like frequencies in sensorimotor areas. *Int. J. Psychophysiol.* 45, 23–24 (2002).
- 36 Wolpaw JR, McFarland DJ, Neat GW, Forneris CA. An EEG-based brain-computer interface for cursor control. *Electroencephalogr. Clin. Neurophysiol.* 78, 252–259 (1991).
- 37 Wolpaw JR, McFarland DJ. Multichannel EEG-based brain-computer communication. *Electroencephalogr. Clin. Neurophysiol.* 90, 444–449 (1994).
- 38 McFarland DJ, McCane LM, Wolpaw JR. EEG-based communication and control: short-term role of feedback. *IEEE Trans. Rehabil. Eng.* 6(1), 7–11 (1998).
- 39 McFarland DJ, Sarnacki WA, Wolpaw JR. Brain-computer interface (BCI) operation: optimizing information transfer rates. *Biol. Psychol.* 63, 237–251 (2003).
- 40 McFarland DJ, Wolpaw JR. EEG-based communication and control: speed-accuracy relationships. *Appl. Psychophysiol. Biofeedback* 28, 217–231 (2003).
- 41 Kostov A, Polak M. Parallel man-machine training in development of EEG-based cursor control. *IEEE Trans. Rehabil. Eng.* 8, 203–205 (2000).
- 42 Guger C, Edlinger G, Harkam W, Niedermayer I, Pfurtscheller G. How many people are able to operate an EEG-based brain-computer interface (BCI)? *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 145–147 (2003).
- Evaluates BCI utility across a very large number of subjects who were not prescreened or trained; should be replicated with other BCI approaches.
- 43 Blankertz B, Dornhege G, Krauledat M et al. The Berlin brain-computer interface: EEG-based communication without subject training. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 147–152 (2006).
- 44 Pfurtscheller G, Müller G, Korisek G. Mental activity hand orthosis control using the EEG: a case study. *Rehabil. (Stuttg.)* 41, 48–52 (2002).
- 45 Pfurtscheller G, Müller GR, Pfurtscheller J, Gerner HJ, Rupp R. ‘Thought’ – control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. *Neurosci. Lett.* 351, 33–36 (2003).
- 46 Pfurtscheller G, Müller-Putz GR, Schlogl A et al. 15 years of BCI research at Graz University of Technology: current projects. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 205–210 (2006).
- Good overview of the many BCI projects from the Graz research team.
- 47 Müller-Putz GR, Scherer R, Neuper C, Pfurtscheller G. Steady-state somatosensory evoked potentials: suitable brain signals for brain-computer interfaces? *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 30–37 (2006).
- 48 Birbaumer N, Ghanayim N, Hinterberger T et al. A spelling device for the paralysed. *Nature* 398, 297–298 (1999).
- 49 Birbaumer N, Hinterberger T, Kübler A, Neumann N. The thought-translation device (TTD): neurobehavioral mechanisms and clinical outcome. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 120–123 (2003).
- 50 Hinterberger T, Schmidt S, Neumann N et al. Brain-computer communication and slow cortical potentials. *IEEE Trans. Biomed. Eng.* 51, 1011–1018 (2004).
- 51 Hinterberger T, Neumann N, Pham M et al. A multimodal brain-based feedback and communication system. *Exp. Brain Res.* 154, 521–526 (2004).
- 52 Hinterberger T, Weiskopf N, Veit R, Wilhelm B, Betta E, Birbaumer N. An EEG-driven brain-computer interface combined with functional magnetic resonance imaging (fMRI). *IEEE Trans. Biomed. Eng.* 51, 971–974 (2004).
- 53 Rockstroh B, Elbert T, Birbaumer N, Lutzenberger W. *Slow Brain Potentials and Behavior*. Urban and Schwarzenberg, MD, USA (1989).
- 54 Neumann N, Kübler A. Training locked-in patients: a challenge for the use of brain-computer interfaces. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 169–172 (2003).
- 55 Neumann N, Hinterberger T, Kaiser J, Leins U, Birbaumer N, Kübler A. Automatic processing of self-regulation of slow cortical potentials: evidence from brain-computer communication in paralysed patients. *Clin. Neurophysiol.* 115, 628–635 (2004).
- 56 Polich J. P3A and P3B: towards an integrative theory. *Int. J. Psychophysiol.* 61, 295–295 (2006).
- 57 Farwell LA, Donchin E. Talking off the top of your head – toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr. Clin. Neurophysiol.* 70, 510–523 (1988).
- Introduces P300 BCIs. Includes several important analyses and suggestions for future research that have not been addressed, such as presenting flashes in sequence instead of at random to generate a contingent negative variation.
- 58 Hanagasi HA, Gurvit IH, Ermuthlu N et al. Cognitive impairment in amyotrophic lateral sclerosis: evidence from neuropsychological investigation and event-related potentials. *Brain Res. Cog. Brain Res.* 14, 234–244 (2002).
- 59 Piccione F, Giorgi F, Tonin P et al. P300-based brain computer interface: reliability and performance in healthy and paralysed participants. *Clin. Neurophysiol.* 117, 531–537 (2006).

- 60 Sellers EW, Donchin E. A P300-based brain-computer interface: initial tests by ALS patients. *Clin. Neurophysiol.* 117, 538–548 (2006).
- 61 Vaughan TM, McFarland DJ, Schalk G *et al.* The Wadsworth BCI research and development program: at home with BCI. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 229–233 (2006).
- 62 Allison BZ, Kadner A, Moore MM. A sequential P3 BCI for visually impaired users. *Cog. Neurosci. Soc.* Poster presented at: 12th Annual Cognitive Neuroscience Society Society Conference, April 9, NY, USA 2005.
- 63 Regan D. *Human Brain Electrophysiology*. Elsevier, NY, USA (1989).
- 64 Müller MM, Malinowski P, Gruber T, Hillyard SA. Sustained division of the attentional spotlight. *Nature* 424, 309–312 (2003).
- 65 Vidal JJ. Real-time detection of brain events in EEG. *Proc. IEEE* 65, 633–641 (1977).
- 66 Sutter E. The brain response interface: communication through visually-induced electrical brain responses. *J. Microcomp. Appl.* 15, 31–45 (1992).
- Early paper describing a BCI dependent on gaze direction that provides excellent information throughput and includes several innovations, including a menuing system that users can customize, wireless infrared control, μ -sequence encoding in BCIs, an epidurally implanted electrode and amyotrophic lateral sclerosis patient validation.
- 67 Middendorf M, McMillan G, Calhoun G, Jones KS. Brain-computer interfaces based on the steady-state visual-evoked response. *IEEE Trans. Rehabil. Eng.* 8, 211–214 (2000).
- 68 Gao X, Xu D, Cheng M, Gao S. A BCI-based environmental controller for the motion-disabled. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 137–140 (2003).
- 69 Kelly SP, Lalor EC, Reilly RB, Foxe JJ. Visual spatial attention tracking using high-density SSVEP data for independent brain-computer communication. *IEEE Trans. Neural Syst. Rehabil. Eng.* 13, 172–178 (2005).
- 70 Müller-Putz GR, Scherer R, Brauneis C, Pfurtscheller G. Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components. *J. Neural Eng.* 2, 123–130 (2005).
- 71 Müller-Putz GR, Scherer R, Pfurtscheller G, Rupp R. Brain-computer interfaces for control of neuroprostheses: from synchronous to asynchronous mode of operation. *Biomedizinische Technik* 51, 57–63 (2006).
- 72 Picton TW, John MS, Dimitrijevic A, Purcell D. Human auditory steady-state responses. *Int. J. Audiol.* 42, 177–219 (2003).
- 73 Talsma D, Doty TJ, Stroud R, Woldorff MG. Attentional capacity for processing concurrent stimuli is larger across sensory modalities than within a modality. *Psychophysiology* 43, 541–549 (2006).
- 74 Keirn ZA, Aunon JI. A new mode of communication between man and his surroundings. *IEEE Trans. Biomed. Eng.* 37, 1209–1214 (1990).
- 75 Obermaier B, Neuper C, Guger C, Pfurtscheller G. Information transfer rate in a five-classes brain-computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.* 9, 283–288 (2001).
- 76 Curran E, Sykacek P, Stokes M *et al.* Cognitive tasks for driving a brain-computer interfacing system: a pilot study. *IEEE Trans. Neural Syst. Rehabil. Eng.* 12, 48–54 (2004).
- 77 Millan JD, Renkens F, Mourino J, Gerstner W. Noninvasive brain-actuated control of a mobile robot by human EEG. *IEEE Trans. Biomed. Eng.* 51, 1026–1033 (2004).
- 78 Levine SP, Huggins JE, BeMent SL *et al.* A direct brain interface based on event-related potentials. *IEEE Trans. Neural Syst. Rehabil. Eng.* 8, 180–185 (2000).
- 79 Pesaran B, Musallam S, Andersen RA. Cognitive neural prosthetics. *Curr. Biol.* 16, R77–R80 (2006).
- 80 Chapin JK, Moxon KA, Markowitz RS, Nicolelis MAL. Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. *Nature Neurosci.* 2, 664–670 (1999).
- 81 Taylor DM, Tillery SI, Schwartz AB. Direct cortical control of 3D neuroprosthetic devices. *Science* 296, 1829–1832 (2002).
- 82 Wessberg J, Stambaugh CR, Kralik JD *et al.* Real-time prediction of hand trajectory by ensembles of cortical neurons in primates. *Nature* 408, 361–365 (2000).
- 83 Serruya MD, Hatsopoulos NG, Paninski L, Fellows MR, Donoghue JP. Instant neural control of a movement signal. *Nature* 416, 141–142 (2002).
- 84 Carmena JM, Lebedev MA, Crist RE *et al.* Learning to control a brain-machine interface for reaching and grasping by primates. *PLoS Biol.* 1, E42 (2003).
- 85 Bayliss JD, Ballard DH. A virtual reality testbed for brain-computer interface research. *IEEE Trans. Rehabil. Eng.* 8, 188–190 (2000).
- 86 Serby H, Yom-Tov E, Inbar GF. An improved P300-based brain-computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.* 13, 89–98 (2005).
- 87 Garrett D, Peterson DA, Anderson CW, Thaut MH. Comparison of linear, nonlinear, and feature selection methods for EEG signal classification. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 141–144 (2003).
- 88 Müller KR, Anderson CW, Birch GE. Linear and nonlinear methods for brain-computer interfaces. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 165–169 (2003).
- 89 Kaper M, Meinicke P, Grossekathofer U, Lingner T, Ritter H. BCI competition 2003 – data set IIb, support vector machines for the P300 speller paradigm. *IEEE Trans. Biomed. Eng.* 51, 1073–1076 (2004).
- 90 McFarland DJ, Anderson CW, Müller KR, Schlogl A, Krusienski DJ. BCI meeting 2005 – workshop on BCI signal processing, feature extraction and translation. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 135–138 (2006).
- 91 Trejo LJ, Rosipal R, Matthews B. Brain-computer interfaces for 1-D and 2-D cursor control: designs using volitional control of the EEG spectrum or steady-state visual evoked potentials. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 225–229 (2006).
- 92 Scherer R, Müller GR, Neuper C, Graimann B, Pfurtscheller G. An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate. *IEEE Trans. Biomed. Eng.* 51, 979–984 (2004).
- 93 Kaiser J, Kübler A, Hinterberger T, Neumann N, Birbaumer N. A non-invasive communication device for the paralyzed. *Min. Invasive Neurosurg.* 45, 19–23 (2002).
- 94 Karim AA, Hinterberger T, Richter J *et al.* Neural internet: web surfing with brain potentials for the completely paralyzed. *Neurorehabil. Neural Repair* 20, 508–515 (2006).

- 95 Surdilovic T, Zhang YQ. Convenient intelligent cursor control web systems for Internet users with severe motor-impairments. *Int. J. Med. Informat.* 75, 86–100 (2006).
- 96 Birch GE, Mason SG, Borisoff JF. Current trends in brain-computer interface research at the Neil Squire Foundation. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 123–126 (2003).
- 97 Pineda JA, Silverman DS, Vankov A, Hestenes J. Learning to control brain rhythms: making a brain-computer interface possible. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 181–184 (2003).
- 98 Lalor EC, Kelly SP, Finucane C *et al.* Steady-state VEP-based brain-computer interface control in an immersive 3D gaming environment. *Eur. J. Appl. Signal Proc.* 19, 3156–3164 (2005).
- 99 Pham M, Hinterberger T, Neumann N *et al.* An auditory brain-computer interface based on the self-regulation of slow cortical potentials. *Neurorehabil. Neural Repair* 19, 206–218 (2005).
- 100 Nijboer F, Furdea A, Guntz I *et al.* An auditory brain-computer interface (BCI). *J. Neurosci. Meth.* DOI: 10.1016/j.jneumeth.2007.02.009 (2007) (Epub ahead of print).
- 101 Borisoff JF, Mason SG, Birch GE. Brain interface research for asynchronous control applications. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 160–164 (2006).
- 102 Müller-Putz GR, Scherer R, Pfurtscheller G, Rupp R. EEG-based neuroprosthetic control: a step towards clinical practice. *Neurosci. Lett.* 382, 169–174 (2005).
- 103 Kennedy P, Andreasen D, Ehirim P *et al.* Using human extra-cortical local field potentials to control a switch. *J. Neural Eng.* 1, 72–77 (2004).
- 104 Popovic MB. Control of neural prostheses for grasping and reaching. *Med. Eng. Phys.* 25, 41–50 (2003).
- 105 Cincotti F, Bianchi L, Birch G *et al.* BCI meeting 2005 – workshop on technology: hardware and software. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 128–131 (2006).
- 106 Bianchi L, Babiloni F, Cincotti F, Arrivas M, Bollero P, Marciani MG. Developing wearable bio-feedback systems: a general-purpose platform. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 117–119 (2003).
- 107 Krausz G, Scherer R, Korisek G, Pfurtscheller G. Critical decision-speed and information transfer in the "Graz
- brain-computer interface". *Appl. Psychophysiol. Biofeedback* 28, 233–240 (2003).
- 108 Moore MM. Real-world applications for brain-computer interface technology. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 162–165 (2003).
- 109 Allison BZ, Pineda JA. Effects of SOA and flash pattern manipulations on ERPs, performance, and preference, implications for a BCI system. *Int. J. Psychophysiol.* 59, 127–140 (2006).
- 110 Sellers EW, Krusienski DJ, McFarland DJ, Vaughan TM, Wolpaw JR. A P300 event-related potential brain-computer interface (BCI): the effects of matrix size and inter stimulus interval on performance. *Biol. Psychol.* 73, 242–252 (2006).
- 111 Parra LC, Spence CD, Gerson AD, Sajda P. Response error correction – a demonstration of improved human-machine performance using real-time EEG monitoring. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 173–177 (2003).
- 112 Bayliss JD. Use of the evoked potential P3 component for control in a virtual apartment. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 113–116 (2003).
- 113 Butfield A, Ferrez PW, Millan JD. Towards a robust BCI: error potentials and online learning. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 164–168 (2006).
- 114 Schalk G, Wolpaw JR, McFarland DJ, Pfurtscheller G. EEG-based communication: presence of an error potential. *Clin. Neurophysiol.* 111, 2138–2144 (2000).
- 115 Allison BZ, Pineda JA. ERPs evoked by different matrix sizes: implications for a brain computer interface (BCI) system. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 110–113 (2003).
- 116 Miner LA, McFarland DJ, Wolpaw JR. Answering questions with an electroencephalogram-based brain-computer interface. *Arch. Phys. Med. Rehabil.* 79, 1029–1033 (1998).
- 117 Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Trans. Biomed. Eng.* 51, 1034–1043 (2004).
- Presents BCI2000, the most widespread platform for BCI research.
- 118 Prinzel LJ, Freeman FG, Scerbo MW, Mikulka PJ, Pope AT. Effects of a psychophysiological system for adaptive automation on performance, workload, and the event-related potential P300 component. *Hum. Factors* 45, 601–613 (2003).
- 119 St John M, Kobus DA, Morrison JG, Schmorror D. Overview of the DARPA augmented cognition technical integration experiment. *Int. J. Human-Comp. Interact.* 17, 131–149 (2004).
- 120 Bibbs MB, Hirshkowitz M. Sleep stage scoring in the adult population. *Respir. Care Clin. N. Am.* 11, 691–707 (2005).
- 121 Westbrook PR, Levendowski DJ, Cvetinovic M *et al.* Description and validation of the apnea risk evaluation system: a novel method to diagnose sleep apnea-hypopnea in the home. *Chest* 128, 2166–2175 (2005).
- 122 Lehmann A, Thaler E, Boldt J. Is measuring the depth of anesthesia sensible? An overview on the currently available monitoring systems. *Anesthesiol. Intensivmedizin Notfallmedizin Schmerztherapie* 36, 683–692 (2001).
- 123 John ER. From synchronous neuronal discharges to subjective awareness? *Frog. Brain Res.* 150, 143–171 (2005).
- 124 Farwell LA, Smith SS. Using brain MERMER testing to detect knowledge despite efforts to conceal. *J. Foren. Sci.* 46, 135–143 (2001).
- 125 Langleben DD, Loughead JW, Bilker WB *et al.* Telling truth from lie in individual subjects with fast event-related fMRI. *Hum. Brain Mapp.* 26, 262–272 (2005).
- 126 Gerson AD, Parra LC, Sajda P. Cortically coupled computer vision for rapid image search. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 174–179 (2006).
- 127 Talwar SK, Xu SH, Hawley ES, Weiss SA, Moxon KA, Chapin JK. Behavioural neuroscience: rat navigation guided by remote control – free animals can be 'virtually' trained by microstimulating key areas of their brains. *Nature* 417, 37–38 (2002).
- 128 Danilov Y, Tyler M. Brainport: an alternative input to the brain. *J. Integr. Neurosci.* 4, 537–550 (2005).
- 129 Dowling J. Artificial human vision. *Exp. Rev. Med. Devices* 2, 73–85 (2005).
- 130 Allison BZ. *P3 or not P3: Toward a Better P300 BCI*. PhD Thesis. University of California, CA, USA (2003).
- Includes a thorough review, with extensive commentary based on cognitive science topics and future directions.
- 131 Mason SG, Jackson MM, Birch GE. A general framework for characterizing studies of brain interface technology. *Ann. Biomed. Eng.* 33, 1653–1670 (2005).

- 132 Nasman VT, Calhoun GL, McMillan GR. Brain-actuated control and HMD's. In: *Head Mounted Displays: Designing For the User*. Melzer JE, Moffitt K (Eds). McGraw Hill, NY, USA 285–312 (1997).
- 133 Makeig S, Enghoff S, Jung TP, Sejnowski TJ. A natural basis for efficient brain-actuated control. *IEEE Trans. Rehabil. Eng.* 8, 208–211 (2000).
- 134 McFarland DJ, Sarnacki WA, Vaughan TM, Wolpaw JR. Brain–computer interface (BCI) operation: signal and noise during early training sessions. *Clin. Neurophysiol.* 116, 56–62 (2005).
- 135 Fatourechi M, Bashashati A, Birch GE, Ward RK. Automatic user customization for improving the performance of a self-paced brain interface system. *Med. Biol. Eng. Comp.* 44, 1093–1104 (2006).
- 136 Kaiser J, Perelmouter J, Iversen IH et al. Self-initiation of EEG-based communication in paralyzed patients. *Clin. Neurophysiol.* 112, 551–554 (2001).
- 137 Shiffrin RM, Schneider W. Automatic and controlled processing revisited. *Psychol. Rev.* 91, 269–276 (1998).
- 138 Willingham DB, Salidis J, Gabrieli JDE. Direct comparison of neural systems mediating conscious and unconscious skill learning. *J. Neurophysiol.* 88, 1451–1460 (2002).
- 139 Wilhelm B, Jordan M, Birbaumer N. Communication in locked-in syndrome: effects of imagery on salivary pH. *Neurology* 67, 534–535 (2006).
- 140 Kübler A, Neumann N. Brain–computer interfaces – the key for the conscious brain locked into a paralyzed body. *Frog. Brain Res.* 150, 513–525 (2005).
- 141 Wang Y, Wang RP, Gao XR, Hong B, Gao SK. A practical VEP-based brain–computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 234–239 (2006).
- 142 Robbins RA, Simmons Z, Bremer BA, Walsh SM, Fischer S. Quality of life in ALS is maintained as physical function declines. *Neurology* 56, 442–444 (2001).
- 143 Lule D, Kurt A, Jurgens R et al. Emotional responding in amyotrophic lateral sclerosis. *J. Neurol.* 252, 1517–1524 (2005).
- 144 Müller GR, Neuper C, Pfurtscheller G. Implementation of a telemonitoring system for the control of an EEG-based brain–computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 54–59 (2003).
- 145 Kübler A, Mushahwar VK, Hochberg LR, Donoghue JP. BCI meeting 2005 – workshop on clinical issues and applications. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 131–134 (2006).
- 146 Neuper C, Scherer R, Reiner M, Pfurtscheller G. Imagery of motor actions: differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG. *Brain Res. Cogn. Brain Res.* 25, 668–677 (2005).
- Highlights the importance of subject strategy in BCIs. Providing unambiguous instructions to patients could facilitate training.
- 147 Kennedy P. Comparing electrodes for use as cortical control signals: tiny times, tiny wires or tiny cones on wires: which is best? In: *The Biomedical Handbook (3rd Edition)*. Braziano J (Ed.). CRC Press LLC, FL, USA (2006).
- 148 Delorme A, Makeig S. EEG changes accompanying learned regulation of 12-Hz EEG activity. *IEEE Trans. Neural Syst. Rehabil. Eng.* 11, 133–137 (2003).
- 149 Hinterberger T, Birbaumer N, Flor H. Assessment of cognitive function and communication ability in a completely locked-in patient. *Neurology* 64, 1307–1308 (2005).
- 150 Hinterberger T, Veit R, Wilhelm B, Weiskopf N, Vatine JJ, Birbaumer N. Neuronal mechanisms underlying control of a brain–computer interface. *Eur. J. Neurosci.* 21, 3169–3181 (2005).
- 151 Kübler A, Nijboer F, Mellinger J et al. Patients with ALS can use sensorimotor rhythms to operate a brain–computer interface. *Neurology* 64, 1775–1777 (2005).
- 152 Goncharova II, McFarland DJ, Vaughan TM, Wolpaw JR. EMG contamination of EEG: spectral and topographical characteristics. *Clin. Neurophysiol.* 114, 1580–1593 (2003).
- 153 Fonseca C, Cunha JPS, Martins RE et al. A novel dry active electrode for EEG recording. *IEEE Trans. Biomed. Eng.* 54, 162–165 (2007).
- 154 Trejo LJ. Development of a hybrid EEG sensor for brain-computer interfaces. Presented at: *International Workshop on Brain-Computer Interface Technology, HCI*. July 22–27, Beijing, People's Republic of China 2007.
- 155 Blankertz B, Müller KR, Curio G et al. The BCI competition 2003: progress and perspectives in detection and discrimination of EEG single trials. *IEEE Trans. Biomed. Eng.* 51, 1044–1051 (2004).
- The first BCI data analysis competition. These competitions have since resulted in many papers and encouraged new researchers and directions.
- 156 Blankertz B, Müller KR, Krusienski DJ et al. The BCI competition III: validating alternative approaches to actual BCI problems. *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 153–159 (2006).
- 157 Yordanova J, Kolev V, Polich J. P300 and α event-related desynchronization (ERD). *Psychophysiology* 38, 143–152 (2001).
- 158 Fu KMG, Foxe JJ, Murray MM, Higgins BA, Javitt DC, Schroeder CE. Attention-dependent suppression of distracter visual input can be cross-modally cued as indexed by anticipatory parieto-occipital α -band oscillations. *Cogn. Brain Res.* 12, 145–152 (2001).
- 159 Tanaka K, Matsunaga K, Wang HO. Electroencephalogram-based control of an electric wheelchair. *IEEE Trans. Robotics Automation* 21, 762–766 (2005).
- 160 Starner TE. Wearable computing for the developing world. *IEEE Pervas. Comp.* 4, 87–91 (2005).
- 161 Tregubov M, Birbaumer N. On the building of binary spelling interfaces for augmentative communication. *IEEE Trans. Biomed. Eng.* 52, 300–305 (2005).
- 162 Wills SA, MacKay DJC. DASHER – an efficient writing system for brain–computer interfaces? *IEEE Trans. Neural Syst. Rehabil. Eng.* 14, 244–246 (2006).
- 163 Pfurtscheller G, Neuper C. Future prospects of ERD/ERS in the context of brain–computer interface (BCI) developments. *Frog. Brain Res.* 159, 433–437 (2006).
- 164 Dobkin BH. Brain–computer interface technology as a tool to augment plasticity and outcomes for neurological rehabilitation. *J. Physiol.* 579(Pt 3), 637–642 (2007).
- 165 Tecchio F, Porcaro C, Barbuti G, Zappasodi F. Functional source separation and hand cortical representation for a brain–computer interface feature extraction. *J. Physiol.* 580(Pt 3), 703–721 (2007).
- 166 Zhou J, Yao J, Deng J, Dewald J. EEG-based discrimination of elbow/shoulder torques using brain computer interface algorithms: implications for rehabilitation. *Conf. Proc. IEEE Eng. Med. Biol. Soc.* 4, 4134–4137 (2005).

Websites

- 201 McFarland DJ, Sarnacki WA, Wolpaw JR. Reach and select with a noninvasive brain – computer interface in humans: emulating full mouse control. Program No. 520.9. Abstract Viewer/Itinerary Planner. Washington DC. *Soc. Neurosci.* (2005).
www.sfn.org
- 202 Nijboer F, Mellinger J, Matuz T *et al.* Comparing sensorimotor rhythms, slow cortical potentials, and P300 for brain–computer interface (BCI) use by ALS patients. Program No. 520.13. Abstract Viewer/Itinerary Planner. Washington DC. *Soc. Neurosci.* (2005).
www.sfn.org
- 203 2D cursor control with scalp-recorded sensorimotor rhythms
[www.bciresearch.org/html/2d_control_8tn.html](http://bciresearch.org/html/2d_control_8tn.html)
- 204 Nature. Supplementary information. Video 1
www.nature.com/nature/journal/v442/n7099/supplinfo/nature04970.html
- 205 Moore MM, Tomori O, Yadav A. The Brainbrowser: a brain computer interface for internet navigation. Program No. 421.23. Abstract Viewer/Itinerary Planner. Washington DC. *Soc. Neurosci.* (2004).
www.sfn.org
- 206 BCI2000
www.bci2000.org
- 207 Allison BZ, McFarland DJ, Wolpaw JR *et al.* An independent SSVEP BCI. Program No. 707.8. Abstract Viewer/Itinerary Planner. Washington DC. *Soc. Neurosci.* (2005).
www.sfn.org
- 208 Sellers EW, Vaughan TM, McFarland DJ *et al.* Daily use of a brain–computer interface by a man with ALS. Program No. 256.1. Abstract Viewer/Itinerary Planner. Washington DC. *Soc. Neurosci.* (2006).
www.sfn.org
- 209 Allison BZ, Graimann B, Gräser A. Why use a BCI if you are healthy? International Conference on Advances in Computer Entertainment. Salzburg, Austria. (2007) (Abstract).
<http://hmi.ewi.utwente.nl/brainplay07/contributions>
- 210 Graimann B, Allison BZ, Gräser A. New applications for non-invasive brain–computer interfaces and the need for engaging training environments. International Conference on Advances in Computer Entertainment. Salzburg, Austria (2007) (Abstract).
<http://hmi.ewi.utwente.nl/brainplay07/contributions>

Affiliations

- *Brendan Z Allison, PhD*
Experienced Researcher,
iAT, University of Bremen,
Otto-Hahn-Allee NW1, N1151,
28359 Bremen, Germany
Tel.: +49 421 218 3344
Fax: +49 421 218 4596
allison@iat.uni-bremen.de
- *Elizabeth Winter Wolpaw, PhD*
Professor Emerita (Siena College),
Consultant, Laboratory of Nervous System
Disorders, Wadsworth Center, New York State
Department of Health, PO Box 509, Albany, NY 12201-0509, USA
Tel.: +1 518 473 3631
Fax: +1 518 486 4910
wolpaw@siena.edu
- *Jonathan R Wolpaw, MD*
Professor and Laboratory Chief,
Laboratory of Nervous System Disorders,
Wadsworth Center, New York State Department
of Health and State University of New York,
PO Box 509, Albany, NY 12201-0509, USA
Tel.: +1 518 473 3631
Fax: +1 518 486 4910
wolpaw@wadsworth.org
www.bciresearch.org