Brain-Computer Interfaces for Neuropsychological Rehabilitation

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This paper provides a short introduction to brain-computer interfaces for use by individuals lacking normal muscle control. The emphasis is on EEG-based methods that use electrical signals recorded non-invasively from the brain for communication and environmental control. Following a general overview, three influential methods are presented along with further resources for designing brain-computer interfaces. Most of the material here was adopted with only minor changes from two excellent comprehensive reviews [2, 54], which the interested reader is encouraged strongly to read.

BCIs in a neuropsychological context

Target populations. Many disorders can disrupt the neuromuscular channels through which an individual communicates or controls his or her external environment. Amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases impair either the neural pathways that control muscles or the muscles themselves. Those most severely affected may lose all voluntary muscle control, including eye movements and respiration, and may be completely locked into their bodies, unable to communicate in any way.

Alternatives for restoring function. Other than repairing the physical damage caused by these disorders, there are three options for restoring communication and control. One is to expand the repertoire of remaining neuromuscular pathways. Muscles that remain under voluntary control can substitute for paralyzed ones. For example, people largely paralyzed by brainstem lesions can often use eye movements to answer questions, give simple commands, or even operate word processing programs [24, 25]. Another option is to restore function by detouring around breaks in the neural pathways. For example, muscles above the level of a spinal cord lesion can control electrical stimulation of paralyzed muscles below [11, 15, 19]. The final option is to provide the brain with a new output channel that does not rely on peripheral nerves and muscles, in other words a direct brain–computer interface (BCI).

Brain measures for BCI. A variety of methods for monitoring brain activity might in principle provide the basis for a BCI. These include electrophysiological methods (both scalp recordings and more invasive methods), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and functional near-infrared imaging (fNIR). Many of these methods are technically demanding and expensive (fMRI and MEG), and those that depend on blood flow (fMRI and fNIR) are less amenable to rapid communication than those employing electrical or magnetic signals. So far, only electrophysiological methods ─ which are sensitive to brief mental events, can function in most environments, and require relatively simple and inexpensive equipment ─ have been able to provide the basis for a practical BCI.

Suitable applications and users. Current BCIs are suitable for basic environmental control (e.g. temperature, lights, television), answering yes/no questions, internet browsing, and word processing at slow rates. They might also operate devices like a wheelchair and simple neuroprostheses or orthoses, like those providing hand grasp to people with cervical spinal cord injuries [28, 43]. Nevertheless, 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. Other options for communication or environmental control may have little to offer them, so that even the simplest BCI-based abilities (e.g. to say 'yes' or 'no') could be valuable.

Invasive vs. noninvasive BCIs. As mentioned, electrophysiological methods can be invasive or noninvasive. BCIs based on the noninvasive methods employ electroencephalographic signals recorded from the scalp surface (EEG). The electrophysiological signals employed to date for invasive BCIs include (1) action potentials from nerve cells or nerve fibers [17, 18], (2) synaptic and extracellular field potentials [38, 50], and (3) electrocorticograms [26, 29]. While the signal-to-noise ratios for these invasive measures is better than that for scalp-recorded EEG, they are still associated with medical risks and have yet to show clear advantages for patients. Thus, EEG-based BCIs are likely to be preferred by many patients and researchers for some time to come [2]. Moreover, advances in EEG-based BCIs continue to be made, some of which are described below.

Three examples of EEG-based BCI

Slow cortical potentials. Scalp-recorded EEG is in part composed of slow changes in voltage, which are thought to originate from dendrites of pyramidal neurons in superficial layers of the cerebral cortex [3]. These voltage changes occur over a timescale of 0.5–10.0 sec 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 [1, 47]. Birbaumer and his colleagues have shown in numerous studies that people can learn to modulate their SCPs in order to control movement of an object on a computer screen [4, 5, 9]. This acquired ability provides the basis for a BCI tested extensively as a means of communication in people with late-stage ALS [21].

Typically, SCPs recorded from electrodes on the scalp surface are used to control the vertical position of a cursor on a computer screen displaying two alternative choices, one at the top of the screen and the other at the bottom. Selection of an alternative takes 4 sec. During an initial 2 sec period, the system measures a baseline voltage level for the user. During the next 2 sec (Figure 1), the user selects the top or bottom alternative by decreasing or increasing voltage from the baseline level by a criterion amount. A similar SCP-based BCI can be employed as well in the auditory or tactile modality [5]. Users train in several 1–2 hour sessions per week over weeks or months. When they consistently achieve accuracies 75%, they are switched to a language support program.

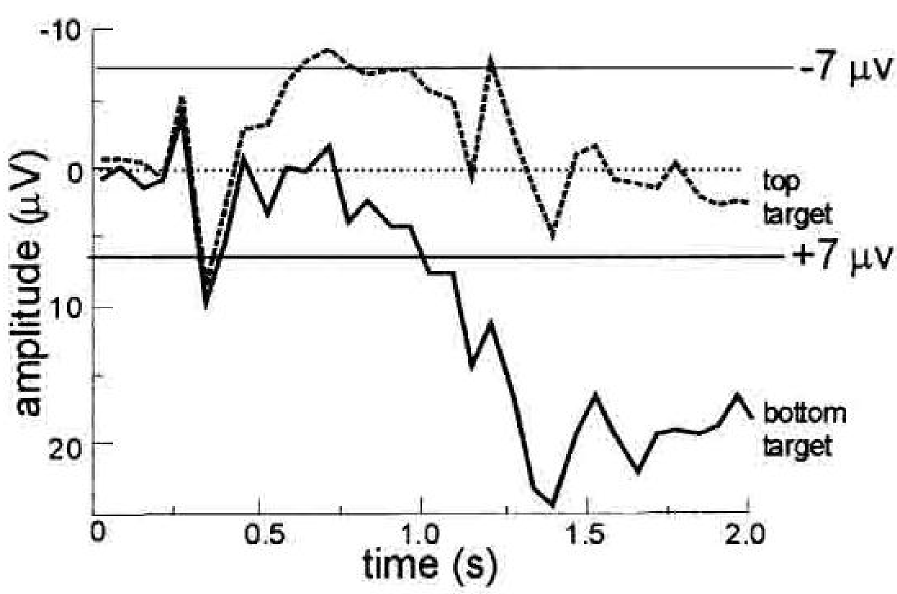

Figure 1. Slow Cortical Potential (SCP) BCI (modified from [23]). Scalp EEG is recorded from the vertex. Users learn to control SCPs to move a cursor towards a target at the bottom (more positive SCP) or top (more negative SCP) of a computer screen [4, 5, 23].

The language support program [39, 40] enables the user to choose a letter or letter combination by a series of two-choice selections. In each selection, the choice is whether or not to accept a set of one or more letters. The first two selections choose between the two halves of the alphabet, the next two choose between two halves of the selected half, and so on until a single letter is chosen. A backup or erase option is provided. With this basic system, users who have two-choice accuracies of 65–90% can write 0.15–3.0 letters/min, or 2–36 words/hour. This rate can be markedly increased by a predictive algorithm that uses initial letters of a word to select words from the user's vocabulary. A stand-by mode allows users with electrodes securely glued to their scalp to access the system 24 h/day by producing a specific sequence of positive and negative SCPs [16], which is essentially a key for turning the BCI on and off.

P300 event-related potential. Infrequent or particularly significant stimuli, when interspersed with frequent or routine stimuli, typically evoke a characteristic response in peoples' EEG. This response occurs regardless of stimulus modality (e.g. visual or auditory) or level of abstraction (e.g. sensory or semantic), has a characteristic distribution of voltage across the scalp (usually largest over parietal cortex), and requires that the eliciting stimulus be attended [7, 52, 53]. Because it is positive and often occurs with a latency of around 300 ms, this event-related EEG component is known as the "P300."

Donchin, Farwell, and their colleagues have employed the P300 in a BCI where users view a 6 x 6 matrix of letters, numbers, and/or other symbols or commands [8, 10]. Every 125 ms, a single row or column flashes, with each row and column flashed once in a complete trial of 12 flashes. The user chooses the contents of a cell in the matrix by counting how many times the row or column containing that cell flashes. The average EEG response to the flash of each row and column is computed, and P300 amplitude for each possible cell (row-column combination) is computed. As Figure 2 shows, P300 is prominent only in the EEG responses to flashed rows or columns containing the cell with the choice. This effect enables the BCI to identify a series of choices (e.g. letters) selected by the user.

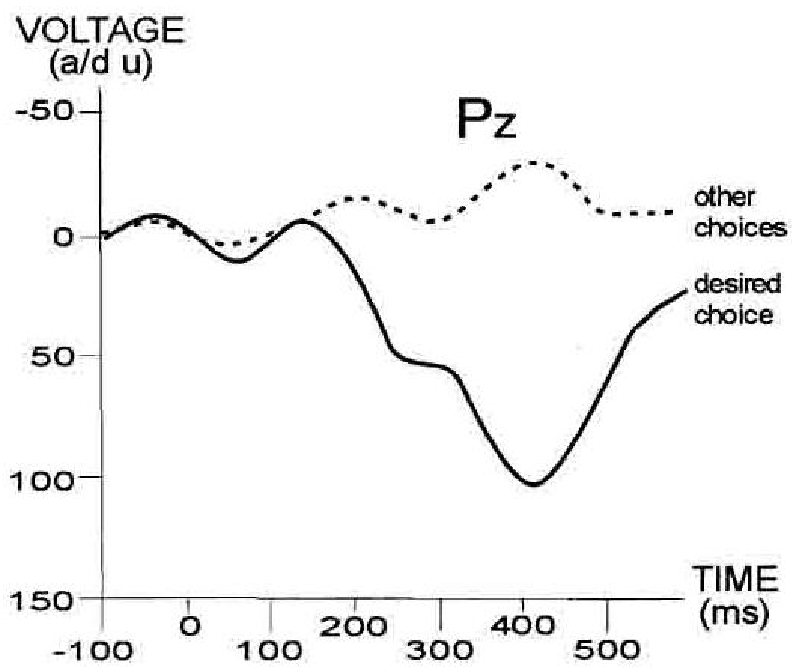

Figure 2. P300 BCI (modified from [23]). A matrix of possible choices is presented on a screen, and EEG is recorded from centro-parietal scalp while these choices flash in succession. Only the choice desired by the user evokes a large P300 [8, 10].

In both experiments and simulations, different algorithms for identifying users' choices have been evaluated and the relationship between various parameters (e.g. number of trials per choice) and BCI accuracy 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 that further improvement in speed should be possible. In people with visual impairments, auditory or tactile stimuli might be used [14, 48]. One advantage of a P300-based BCI is that, because the P300 depends on an unlearned reaction to improbable or pertinent stimuli, it may require minimal user training. A possible disadvantage is that P300 responses in a BCI are likely to change over time, as they have been found to do in conditioning protocols [14, 34, 48, 51]. Studies up to now have been short-term. With longer term use, the P300 could conceivably diminish [46] or become enhanced. Thus, adaptive algorithms for identifying users' choices that recalibrate over time are likely to be especially important for this type of BCI.

Sensorimotor rhythms. When not engaged in processing sensory input or motor output, the sensory or motor cortices of awake people often produce 8–12 Hz EEG activity [12, 13, 20, 37]. This idling activity, called mu rhythm when focused over sensorimotor cortex or visual alpha rhythm when focused over visual cortex, is thought to be produced by thalamocortical circuits [30, 37]. Mu rhythms are usually accompanied by 18–26 Hz beta rhythms, some of which have a different topography and/or timing than mu, and thus constitute an independent feature of EEG [32, 41, 42]. One reason these rhythms provide good signals for EEG-based BCIs is their association the brain's normal motor output channels. Bodily movements are typically accompanied by a decrease in mu and beta rhythms, which is greater over the scalp contralateral to a moved hand. This decrease has been labeled 'event-related desynchronization' or ERD [41, 44]. Its opposite, an increase in rhythm, or 'event-related synchronization' (ERS) occurs after movement and with relaxation [41]. Especially relevant for use in a BCI is that ERD and ERS do not require overt movement, but occur also during motor imagery and preparation [32, 45].

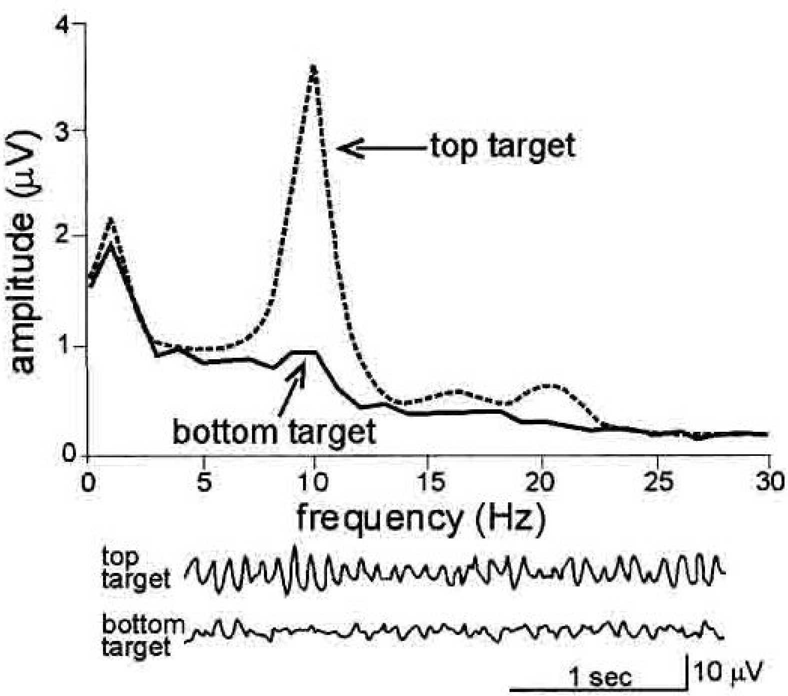

Figure 3. Sensorimotor rhythm BCI (modified from [23]). EEG is recorded over sensorimotor cortex. Users control the amplitude of a 8-12 Hz mu rhythm (or 18-26 Hz beta rhythm) to move a cursor to a target at the top of a screen, bottom of a screen or intermediate locations. Frequency spectra (top) for the 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 [31, 58].

Several BCIs based on mu/beta rhythm have been developed since the mid 1980s. Prominent among these is the system developed by Wolpaw, McFarland, and their colleagues [31, 57, 58] in which people use mu-or beta-rhythm amplitude to move a cursor to targets on a computer screen. Figure 3 illustrates the basic concept behind this BCI. In this example, the user increases the amplitude of 8–12 Hz mu rhythms 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.

With this BCI, users can move the cursor to answer spoken yes/no questions with accuracies of 95% [36, 59]. Users learn over a series of 40 min sessions to control cursor movement and participate in 2–3 sessions per week. Most (i.e. about 80%) acquire significant control within 2–3 weeks. In 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, they act without consciously thinking about the details of execution. Recent work has concentrated on developing precise one-dimensional control and on applying it to choosing among up to 8 different targets [33]. Users can also achieve independent control of two different mu-or beta-rhythm channels that enables them to move a cursor in two dimensions [55, 56].

Comparison of BCI methods. Performance on the above three types of BCI was compared in an NIH-funded project [2]. Specifically, the SCP-BCI, P300-BCI, and SMR-BCI were compared using a within-subject design for seven ALS patients who had not yet entered the final stages of paralysis. All patients achieved acceptable performance after 20 sessions with SMR-BCI training, four of the seven could spell with the P300-BCI, but none achieved acceptable performance rates with the SCP-BCI. Thus, in these patients (all of whom still had functioning vision), SMR-BCI and P300-BCI appeared to show the most promising results. Nevertheless, of the three approaches, the SCP-BCI has the most extensive track record with ALS patients and may prove to be the best option at later stages of the disease. For example, Birbaumer [2] reports training 32 patients with at various stages of ALS to use the SCP-BCI. Eventually, seven arrived at a state of almost complete paralysis but were able to continue to use the BCI. The SCP-BCI needs long training periods, sometimes months in the home of the patient (often paralyzed to a degree requiring artificial respiration). Letter selection speed is slow, e.g. one letter per minute, but speed may be less of an issue for late-stage ALS patients [6]. These patients have well-preserve cognitive functions (e.g. working memory), and many have considerable motivation to communicate [2].

Support for BCI development

All BCIs require software to perform numerous functions. These include recording and storage of brain signals, detection and classification of features in the signals, presentation of feedback and other stimuli, and overall coordination of all component activities. Moreover, the BCI must perform many of these functions online while being used for communication or control. To create such a complex set of software in its entirety requires considerable time and effort. Fortunately, there exists a website (http://www.bciresearch.org/BCI2000/bci2000.html) providing free software and documentation for a general purpose EEG-based system called BCI2000 [49]. This material, along with associated data storage and analysis tools, is available to those engaged in BCI research and development. More than 100 laboratories are now regular contributors to the BCI 2000 Web site, improving both the hardware and software modules. The aim is an inexpensive, easy-to-use, universal, noninvasive BCI that will accommodate SCP, P300, SMR, and other electrophysiological measures ─ one that will be used by a world-wide net of participants whose data collection and analysis will contribute to the continuous improvement and validity of BCI applications.

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