CHAPTER

BCI in practice

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Abstract

Brain–computer interfaces are systems that use signals recorded from the brain to enable communication and control applications for individuals who have impaired function. This technology has developed to the point that it is now being used by individuals who can actually benefit from it. However, there are several outstanding issues that prevent widespread use. These include the ease of obtaining high-quality recordings by home users, the speed, and accuracy of current devices and adapting applications to the needs of the user. In this chapter, we discuss some of these unsolved issues.

Keywords

Brain–computer interface, Home use, Neurotechnologies

People with severe motor disabilities require alternative methods for communication and control. A brain–computer interface (BCI) is a system that does not depend on the brain's normal output pathways of peripheral nerves and muscles. It measures brain activity and converts it into an artificial output that replaces, restores, enhances, supplements, or improves natural CNS output (Wolpaw and Wolpaw, 2012).

Given the complexity of recording and interpreting brain signals, it is not surprising that most BCI studies take place in a laboratory with healthy subjects or with target populations with expert supervision. To be useful, a BCI must be available, reliable, and serviceable outside the laboratory. Further, the application must be useful to the target population. That is, a BCI must provide a safe and effective solution to an important problem most of the time for most of the people who need it. This chapter seeks to provide information and insight into the practical matters that must be addressed for BCIs to be useful in the everyday lives of people who need them.

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1 OVERVIEW OF COMMON BCI SYSTEMS

In this section, we present a brief overview of several BCI systems that could be used for practical applications. Our intent is not an exhaustive review, but rather to highlight some of the features of these systems. A variety of signals can be measured and have the potential for use in a BCI. They include electrical, magnetic, metabolic, chemical, thermal, and mechanical responses to brain activity and signals recorded from the spinal cord. Questions about which kind of brain signal are best for which application is an empirical question. The overall goal is to use the brain signal that provides sufficient information content for controlling the BCI device with required reliability, safety, longevity, and cost effectiveness (Wolpaw and Wolpaw, 2012; Wolpaw et al., 2002). To date, most BCI studies have focused on replacing or augmenting communication and control using electrophysiological signals recorded from the scalp (electroencephalography, EEG), from the surface of the cortex (electrocorticography, ECoG), or from the activity recorded from single cortical neurons. The ultimate usefulness of each of these methods hinges on the range of communication and control applications it can support and on the extent to which its disadvantages can be overcome.

Here, we wish only to provide a brief summary of the more common alternatives and focus on issues that arise when one tries to apply these to end users. It is worth noting that improvements in these methods are continually being proposed.

BCI methods that rely on epidural or subdural recordings (Schalk et al., 2008) as well as those involving electrodes penetrating the brain (Hochberg et al., 2006; reviewed in Homer et al., 2013) offer superior spatial resolution over surface recordings. Whether or not increased spatial resolution is of sufficient benefit for communication and control and outweighs the cost and the increased health risk to the subject remains uncertain (McFarland et al., 2010). In addition, current invasive methodologies have not yet solved problems rising from long-term stable recordings (Groothuis et al., 2014; Kozai et al., 2015). To date, all clinical studies involving these methods have required expert supervision. Advances in materials and methods may reduce the risks, and further study may demonstrate increased utility (reviewed in Huggins et al., 2014).

Sensorimotor rhythm or SMR-based BCI has been the focus of research and development for over two decades (Pfurtscheller and McFarland, 2012). These BCIs rely on the fact that the execution, or imagined execution, of limb movement induces changes in rhythmic activity recorded over sensorimotor cortex (Pfurtscheller and Aranibar, 1979). Changes in SMRs can be detected on the scalp by EEG (eg, McFarland et al., 2000) and magnetoencephalography (MEG) (eg, Jurkiewicz et al., 2006) or on the surface of the brain by ECoG (eg, Graimann et al., 2002; Leuthardt et al., 2004; reviewed in Pfurtscheller and McFarland, 2012). Most often, BCIs that rely on SMRs use linear regression algorithms to translate SMR amplitudes into cursor movements on a computer display (eg, Wolpaw et al., 1991). More recent developments of this approach have produced the most complex multidimensional SMR-based BCI control realized to date (McFarland et al., 2010; Wolpaw and

McFarland, 2004). Using an approach based on classification, Guger et al. (2003) report that 56 of 60 nondisabled subjects achieved classification accuracies of 60% or better on a two-choice task after two sessions of training. In one example, an SMR-based BCI spelling application realized spelling by dividing the alphabet into four parts. Users reached a single letter through a series of three successive selections (Wolpaw et al., 2003). Importantly, these users required many days of training to master this task.

Some researchers have suggested the use of various cognitive strategies as alternatives to the use of motor imagery (eg, Curran et al., 2003; Vansteensel et al., 2010). However, it is important that a communication and control devices not co-opt cognitive resources that would normally be involved in how the user decides to use the device. In this regard, use of motor systems normally used in functions such as typing or speaking become automatic with practice. This also appears to be the case with SMR control (McFarland et al., 2010).

Like SMRs, movement or movement imagery is associated with relatively slow changes in the voltages recorded over the sensorimotor cortex, called slow cortical potentials (SCPs). SCPs typically consist of negative potential shifts that precede actual or imagined movement or cognitive tasks (eg, mental arithmetic Birbaumer et al., 1990). An SCP is typically followed by a biphasic wave referred to as the movement-related potential (Colebatch, 2007). SCP BCI users learn to produce SCP changes that can be detected by a BCI and used for control. This training requires repeated sessions over weeks or months (Birbaumer et al., 1999). In a typical SCP-based BCI, the user communicates through a series of binary selections until the alphabet is parsed (Perelmouter et al., 1999). While Krepki et al. (2007) described improvements, Allison et al. (2012) emphasize that compared with other methods, SCP-based BCIs remain slow.

Steady state visual evoked potential (SSVEP)-based BCIs depend on changes in SSVEPs (eg, Gao et al., 2003; Middendorf et al., 2000). In this approach, the subject views one or more stimuli that each oscillate at a unique constant frequency. When the subject focuses attention on one stimulus, the corresponding frequency can be detected in the EEG activity recorded over occipital areas of the brain. Hence, an SSVEP-based BCI can infer a user's intent by measuring the EEG activity at a specific frequency or frequencies recorded over occipital areas of the brain and achieve high information transfer rates (Chen et al., 2013; Nakanishi et al., 2014). BCIs using SSVEPs have been described as dependent; ie, they use EEG features that depend on the ocular-motor muscles that control eye movements and thus not appropriate for individuals who lack muscle control (Wolpaw et al., 2002). Allison et al. (2008) reported that two spatially overlapping stimuli produced differences in SSVEPs, and Zhang et al. (2010) reported that subjects using a similar approach averaged online classification accuracy of $72.6 \pm 16.1\%$ after 3 days of use. In addition, several groups have reported that people can use a binary SSVEP-based device with eyes closed (Hwang et al., 2015; Lim et al., 2013). Thus, SSVEP-based BCIs might support BCI control in people who are currently considered locked in. Guger et al. (2012a) report that 96% of

53 able-bodied subjects attained an accuracy of 80% or above with a four-choice SSVEP BCI that required virtually no training.

The P300-based matrix speller, originally described by Farwell and Donchin (1988), holds promise for providing BCI-based communication to users with severe motor disabilities (Vaughan et al., 2006). A P300 is the response that occurs when a subject recognizes a rare target stimulus (Sutton et al., 1965). Since the P300 signals the subject's recognition of the target event without the requirement for an overt response, it represents a useful signal for BCI. In the original P300-based BCI speller paradigm, a 6×6 matrix of 36 items (ie, characters and numbers) is presented on a screen and the user attends to the desired item (ie, the target), while different groups of items flash rapidly. About 300 ms after the target item flashes, a positive deflection occurs in the EEG, the P300 event-related potential (ERP). The P300-based BCI can usually identify the target item with a high rate of accuracy. Guger et al. (2009) reported that 89% of 81 able-bodied subjects were able to spell with an accuracy greater than 80% after just 5 min of data collection for system calibration. The P300 speller paradigm has been well studied. According to an Ovid search in early 2016, over 80 studies have examined aspects of P300-based BCI control and applied it to problems like communication, environmental, wheelchair, and robotic control.

P300 spelling devices generally average EEG over multiple stimulus sequences in order to improve accuracy. This creates a speed-accuracy trade-off since longer sequence runs produce more accuracy at the expense of speed. Schreuder et al. (2013) evaluated rules for the early termination of stimulus sequences based on dynamic determination of the discriminability of the data collected from the current trial. Most methods worked well. Mainsah et al. (2015) showed that dynamic stopping could increase communication rates in patients with amyotrophic lateral sclerosis (ALS). Furthermore, the patients preferred this method.

The design of the P300 speller matrix also has a considerable impact on performance. For example, Townsend et al. (2010) reported on use of a paradigm that used virtual matrices that were reordered prior to display on the screen. This procedure prevented a given potential target from flashing twice on successive epochs and minimizes the extent to which adjacent stimuli flash within the same epoch. Townsend et al. (2010) found that the use of the virtual matrix paradigm resulted in better performance and user acceptance in both healthy volunteers and ALS participants. Zhang et al. (2012) showed that the use of facial stimuli produced superior classification over simply highlighting an icon. Allison and Pineda (2003) showed that larger matrices with more elements evoked larger P300 responses. This effect could be due in part to the fact that increases in target-to-target interval enhance P300-based performance (McFarland et al., 2011).

Each of the BCI approaches discussed so far has its strengths and weaknesses. For example, an SMR-based BCI can provide relatively rapid graded multidimensional control. However, available methods require extensive training, and the training requires expert supervision. Furthermore, it is unknown if people with severe disabilities can tolerate such training regimes. SSVEP-based BCIs allow for a relatively high information transfer rate without extensive training, but there are concerns about the requirement of good eye control. Invasive methods pose some medical risk. However, many people with disabilities express a desire to use implanted devices (Blabe et al., 2015).

The P300-based method designed by Farwell and Donchin (1988) has great advantages. The ERPs appear to be stable over time (Sellers et al., 2010), do not require extensive training (Guger et al., 2009), and have information transfer rates that compare to other augmentative and assistive communication devices. Yeom et al. (2014) report about 50 bits per minute, and more recently, Townsend and Platsko (2016) report 100 bpm. A P300-based BCI also has several important disadvantages. The matrix-based speller requires vision (McCane et al., 2014). Furthermore, such methods may rely, in part, on the users' ability to move their eyes (Brunner et al., 2010; Treder and Blankertz, 2010). Thus, this method may be especially problematic for people with ALS who, late in disease, have both impaired vision and weakened oculomotor control. For example, McCane et al. (2014) report that visual impairment was the principal obstacle for about 30% of individuals with ALS who were unable to use a P300-based visual speller. These visual impairments primarily involved some aspect of motor control (eg, diplopia, nystagmus, ptosis) that could potentially interfere with seeing the flashing items well enough to achieve high accuracy.

2 SOME ISSUES IN APPLICATIONS FOR END USERS

Nijboer (2015) suggests that BCI technology should be designed for usability rather than reliability. From this perspective, it is important to consider the needs of a potential patient population in designing a BCI system as user acceptance is the ultimate test of success. Studies using questionnaires indicate that patients are interested in using BCI systems (Huggins et al., 2011, 2015), but that current systems do not meet their requirements for speed, accuracy, and ease of use. While system performance (ie, speed and accuracy) is important to end users, other aspects of usability also need to be considered. For example, Liberati et al. (2015) report that participants in a focus group emphasized the need for ALS patients to retain their sense of agency by being able to control their environment without asking for help (eg, turn the lights on and off, control the television, answer the doorbell, regulate the temperature in a room, and get somebody's attention).

There are several possible ways to evaluate the impact of BCI systems on the needs of users. Perhaps the most straightforward approach is to determine how often the BCI devices are used. The assumption here is that individuals will use devices that meet their needs more often. However, BCI researchers should be aware that all assistive technologies face certain barriers to acceptance and that these should be taken into account (Baxter et al., 2012).

Another approach is to consider how BCI systems impact the quality of life of users. However, this approach is not so simple, and many psychologists have opted for evaluating constructs related to mood and affect. For example, depression is related to quality-of-life ratings. Kübler et al. (2005) report that the incidence of depression in ALS is quite variable, ranging from none to clinically depressed. Yet, quality of life was rated by Kübler as satisfactory. In a review of the literature, McLeod and Clarke (2007) found that quality of life as assessed by questionnaire varied more with social support and hopelessness than with the physical state of the patient. Well-being is often treated as synonymous with quality of life and happiness. However, it is important to consider whether questionnaires can effectively measure these constructs (World Health Organization, 2012). Indeed, it may be very difficult to validate constructs for which there are not established criteria. Questionnaires designed to measure the quality of life of someone with a particular diagnosis, for example, ALS, may reflect the investigators' point of view rather than validated psychological constructs (eg, Simmons et al., 2006). There are complex relationships between measures purported to assess satisfaction with life, subjective happiness, and self-reflection (Lyke, 2009). A further complicating factor is that the value an individual might place on life may change as death appears closer (King et al., 2009).

Perhaps the most common BCI study involves the evaluation of potential prediction algorithms (Lotte et al., 2007; Pasqualotto et al., 2012), often using data from archived BCI competitions that involve healthy subjects (eg, Blankertz et al., 2006; Sajda et al., 2003). For the most part, these data sets do not involve transfer between sessions. Data set 1 described by Blankertz et al. (2006) is an exception in that training and test sets were recorded on different days. Likewise, data set 2b described by Tangermann et al. (2012) was concerned with session-to-session transfer. Both of these competition data sets involved motor imagery without feedback. In general, the competition data sets do not approximate data that would be encountered in the field. Individuals who could actually benefit from use of a BCI would most likely have a neurological disorder, and the data would be collected over many separate sessions, often under less than favorable recording conditions. In addition, feedback would be inevitable. In any case, the results reported in these studies vary widely (eg, fig. 1 from Blankertz et al., 2006), due in large part to the skill of the analysts. Further, when prediction algorithms are compared within the same group, the differences are often not large (eg, Krusienski et al., 2006).

Optimizing recordings is one of the more important issues in adapting BCI systems to individuals who might actually benefit from their use. Potential users have expressed concerns about the mess, inconvenience, and discomfort of wet electrodes (Peters et al., 2015). As these same users also expressed concerns about system accuracy, potential alternative sensors should be developed to produce quality recordings. While it has been stated that current wet gel recordings provide an excellent signal (Chi et al., 2010), they are probably less than optimal for several reasons. If the electrode density is too great, bridging can occur so that two or more sensors are electrically coupled (Alschuler et al., 2014). In addition, current generation surface sensors are susceptible to a variety of noise sources due to variations in impedance. Ferree et al. (2001) have asserted that high electrode impedance has little effect beyond power-line noise that can be easily filtered out. However, Kappenman and Luck (2010) showed that high impedance increased the noise level of the EEG primarily at lower frequencies and reduced the signal-to-noise ratio of the P3 response.

In addition to overall impedance levels, fluctuations due to unstable electrode contact can produce large artifacts in the EEG. While it might seem that completely paralyzed subjects are unlikely to produce movement artifacts, use of a respirator can produce rather large movement-related artifacts and involuntary reflexes may be present.

There are a number of alternative sensor designs that might be used in a BCI system. The emotive EPOC system uses moistened felt pads and a semirigid support that is less accurate but quicker than conventional electrode positioning (Mayaud et al., 2013). The locations of the pads are also largely restricted to sites on the perimeter of traditional recording montages which are more prone to EMG contamination (Goncharova et al., 2003). Guger et al. (2012b) describe the g.SAHARA dry electrode that consists of a series of eight gold-plated pins that are mounted in a conventional cap that does not limit electrode locations. Both of these rely on low impedance resistive contact with the scalp. In contrast, Sellers et al. (2009) describe a sensor by QUASAR that uses hybrid combination of high impedance resistive and capacitive contact with the scalp.

Guger et al. (2012b) report that dry and gel-based electrodes (g.SAHARA vs g.BUTTERFLY wet electrodes) produced similar results with a P300-spelling device used by healthy individuals. Nijboer et al. (2015) report that a 32-channel BioSemi headset produced higher accuracy than 8-channel g.SAHARA and 14-channel Emotive systems. There was no significant difference between the BioSemi system and the g.SAHARA system when performance based on the same eight electrodes was compared. Hairston et al. (2014) compared the EPOC and QUASAR systems as well as the B-Alert X-10, with the BioSemi system, which they considered a "gold standard." They report on usability and comfort, but did not consider quality of the signal or how it might impact performance. Hairston et al. (2014) state that only the BioSemi system accommodates variations in both head size and shape. They rated the B-Alert system next in terms of accommodation. The EPOC and QUASAR systems could produce uncomfortable pressure points and movement artifacts when they do not fit properly. As noted by Chi et al. (2010), dry electrodes require that new mechanical solutions be devised since they are much more difficult to secure to the patient's scalp. This may create a potential trade-off between comfort and recording quality.

Design of the BCI user interface can also have a considerable impact on usability. Mason and Birch (2000) noted that many user applications require infrequent, asynchronous input. In contrast, existing BCI applications require a user response synchronized with a regularly occurring BCI system stimulus display. Asynchronous input can be a challenge as many EEG signals can generate a high rate of false positives. The solution to this problem depends on the task design as well as the particular EEG signal used. Mason and Birch (2000) based their approach on producing a system with a low false-alarm rate. In contrast, Kaiser et al. (2001) trained two paralyzed patients to learn to regulate SCPs in order to turn the BCI system on.

Communication rates can also be enhanced by the use of information available in the sequential probabilities in language. For example, Da Silva-Sauer et al. (2016)

found increased communication rates using the T9 system and word prediction similar to that employed by many mobile phones. Another alternative is to use language priors in the classifier that determines the users' intent (Delgado Saa et al., 2015).

Even with all of these various enhancements, some severely disabled patients cannot use current BCI systems. As discussed earlier, visual impairments appear to be a major factor in preventing some individuals with ALS from using a P300-based speller (McCane et al., 2014). This has led to considerable effort to develop BCI systems based on alternative sensory modalities (eg, Halder et al., 2010; Nijboer et al., 2008a). So far these systems that use alternative sensory modalities do not appear to provide communication rates comparable to the visual P300 speller. In addition, the logic of using alternative sensory modalities assumes that these will provide a solution to the difficulties that prevent effective BCI operation for some users with ALS. This assumption requires additional study. There is some evidence that ALS may also be associated with auditory processing difficulties (Pekkonen et al., 2004). Furthermore, poor BCI performance might also be associated with ALS-related dementia (Swinnen and Robberecht, 2014) which would not be corrected by substitution of sensory modalities.

3 STUDIES WITH END USERS

Over the past decade, BCI researchers have begun to explore the BCI capacities of people severely disabled by injury or disease. The results to date indicate that many people with severe disabilities might use BCIs for communication and control (eg, Jarosiewiczn et al., 2015; reviewed in Vaughan et al., 2012). By far the largest number of BCI studies to date has included people with ALS (Marchetti and Priftis, 2015). People with ALS have learned to use P300-based BCIs (eg, Nijboer et al., 2008b; Silvoni et al., 2013), SCPs (eg, Birbaumer et al., 1999), and SMR-based BCIs (eg, Neuper et al., 2003; Kübler et al., 2005) to operate spelling devices. Recently, one study reported success with an individual with ALS who was completely locked in (Gallegos-Ayala et al., 2014). Many aspects of the paradigm have been manipulated in on- and off-line studies, eg, rate (McFarland et al., 2011) and stimulus presentation (Townsend and Platsko, 2016; Yeom et al., 2014). These studies suggest strongly that customization may be an important factor for success and indicate that ERPs from the entire time interval used for classification are likely involved in classifier performance (Bianchi et al., 2010; McCane et al., 2015).

However, not all individuals with ALS are able to use these BCI systems. In fact, many of those who have participated in BCI studies retained alternative means to communicate (Kübler and Birbaumer, 2008). As discussed earlier, several factors could account for this lack of success for individuals with advanced ALS, including oculomotor dysfunction (reviewed in Sharma et al., 2011); extinction of goal-oriented behavior (Kübler and Birbaumer, 2008) and dementia (Hochberg and Anderson, 2012). Designs that capitalize on the P300 and related ERPs, but do not require visual acuity, have reduced information transfer rates but have not been tested extensively in populations they are meant to serve (eg, Hill et al., 2014Klobassa et al., 2009; Sellers and Donchin, 2006; Treder et al., 2010).

More recently, P300 spelling devices have been installed in users' homes and maintained by their caregivers (Holz et al., 2015; Sellers et al., 2010; Wolpaw et al., 2016). While these systems still require technical support, most of the day-to-day support for use is handled by the caregivers. These systems face all the problems that face BCI researchers, and in addition, some that are the purview of assistive technology (Huggins and Zeitlin, 2012).

Like any device deployed in the home, components must be safe and simple to use and maintain. However, monitoring success and providing ongoing training and technical support present some issues that are unique to BCI devices (eg, placement and care of the cap). Without capable and motivated caregivers, long-term BCI home use is currently not possible (Wilkins et al., 2009). Current BCIs available for home use also require some ongoing technical support. This is dependent on consistent Internet connections for data transfer and regular contact if support is to be done remotely.

Successful home use of a BCI system requires a home environment that can support its use. The immediate environments of people with severe disabilities are often crowded with much essential equipment, including ventilators, mechanical beds, wheelchairs, and so forth. Thus, significant sources of electrical noise and intermittent artifacts may be present. For example, the ventilators essential to the survival of many prospective BCI users often cause high-frequency electromagnetic and low-frequency mechanical (ie, movement) artifacts (Young and Campbell, 1999).

System reliability for EEG-based BCI depends on good signal quality. Fig. 1 represents impedances recorded over 23 months of BCI home use by two different home users (for details of the method, see Krusienski et al., 2006; McCane et al., 2015). In every session represented here, the caregiver positioned an eight-channel cap and started the system after using diagnostic software (Wolpaw et al., 2016).

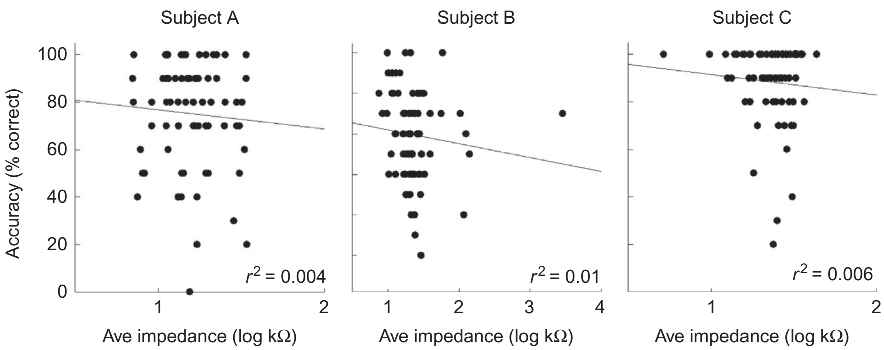

FIG. 1

The log of average impedance over eight channels for a copy-spelling calibration task for three BCI-24/7 home users over A (12 mos), B (11 mos), and C (12 mos).

This diagnostic software allows caregivers to measure impedance and regard EEG traces in order to judge record quality in order to determine BCI readiness. BCI performance on this copy-spelling task was unaffected at averaged impedances well over the laboratory standard. Likely, there are both system and subject qualities not currently captured by home system measures.

BCIs are currently used mainly by researchers in the laboratory. To see BCI realize its full potential BCIs must work well not only in the laboratory but also in real life. To meet these requirements, they must be simple to operate, require minimal expert oversight, be usable by the people who need them (ie, the BCI user, their caregivers, and/or their healthcare providers). Much more translational research is required if BCI is to fulfill its promise to its funders and to the people who need it.

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