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REVIEW

Current trends in hardware and software for brain–computer interfaces (BCIs)

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Abstract
A brain–computer interface (BCI) provides a non-muscular communication channel to people with and without disabilities. BCI devices consist of hardware and software. BCI hardware records signals from the brain, either invasively or non-invasively, using a series of device components. BCI software then translates these signals into device output commands and provides feedback. One may categorize different types of BCI applications into the following four categories: basic research, clinical/translational research, consumer products, and emerging applications. These four categories use BCI hardware and software, but have different sets of requirements. For example, while basic research needs to explore a wide range of system configurations, and thus requires a wide range of hardware and software capabilities, applications in the other three categories may be designed for relatively narrow purposes and thus may only need a very limited subset of capabilities. This paper summarizes technical aspects for each of these four categories of BCI applications. The results indicate that BCI technology is in transition from isolated demonstrations to systematic research and commercial development. This process requires several multidisciplinary efforts, including the development of better integrated and more robust BCI hardware and software, the definition of standardized interfaces, and the development of certification, dissemination and reimbursement procedures.

1. Introduction

Over the past 80 years, since Hans Berger first recorded electroencephalographic activity (EEG) from the scalp using silver wires and a galvanometer (Berger 1929), researchers and clinicians have continued to develop better instrumentation and clinical applications that can detect and/or use EEG and other brain signals. One of these clinical applications is a brain–computer interface (BCI) (Vidal 1973) that might restore communication to people with severe motor disabilities. BCI instrumentation consists of hardware and software. BCI hardware records brain signals either non-invasively (e.g., EEG, magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS)) or invasively (e.g., electrocorticography (ECoG), local field potentials (LFP), single-unit activity) using a series of devices (i.e.

sensor, biosignal amplifier and analog-to-digital converter). BCI software then translates these brain signals into device output commands and provides feedback to the user.

Up to the present day, BCI research and development has mainly focused on basic research and laboratory demonstrations of various BCI applications (Farwell and Donchin 1988, Wolpaw *et al* 1991, Pfurtscheller *et al* 1993, Birbaumer *et al* 1999, Taylor *et al* 2002, Pfurtscheller *et al* 2003, Gao *et al* 2003, Wolpaw and McFarland 2004, Schwartz *et al* 2006, Coyle *et al* 2007, Müller *et al* 2008, Velliste *et al* 2008, Bin *et al* 2009, McFarland *et al* 2010, see Wolpaw *et al* 2002 for review). As BCI research is evolving from isolated demonstrations to systematic investigations, it has become clear that BCI hardware and software require features such as real-time capability (Guger *et al* 1999, 2001, Mason and Birch 2003, Schalk *et al* 2004, Cincotti *et al* 2006, Berger *et al* 2007, Wilson *et al* 2010) and high bandwidth and sensitivity (Crone *et al* 1998, Schalk 2008), that existing hardware and software often did not provide. In response, different vendors (e.g., g.tec, BrainProducts, Tucker-Davis Technologies, Ripple, etc) have produced hardware devices that are optimized for BCI or related research. These research systems can capture EEG, ECoG or single-neuron activity in real time from up to 512 channels, and sample these signals at up to 50 kHz with very high sensitivity (e.g., 24-bit resolution, 250 mV sensitivity). This BCI hardware is interfaced with BCI software that is based either on general-purpose BCI frameworks such as BCI2000 (Schalk *et al* 2004, Mellinger and Schalk 2007, Schalk and Mellinger 2010) or OpenVIBE (Renard *et al* 2010), or on custom software. Using these research-grade systems, groups around the world are now beginning to demonstrate clinical efficacy of BCIs in patients with severe motor disabilities (Kübler *et al* 2005, Sellers *et al* 2006, Vaughan *et al* 2006, Nijboer *et al* 2008, Cincotti *et al* 2008, Stavisky *et al* 2009, Guger *et al* 2009, Sellers *et al* 2010, see Mak and Wolpaw 2009 for review), thereby beginning the translation of research findings into clinical practice.

In addition to these academic efforts that focus on clinical applications of BCI technology, some commercial vendors have begun to provide consumer-grade applications to both able-bodied and disabled people. Such consumer applications include augmented communication devices (IntendiX, http://www.intendix.com) and gaming systems (MindFlex, http://www.mindflexgames.com, Allison *et al* 2007, Fairclough 2008, Blankertz *et al* 2010, see Reuderink 2008 for review). Other types of commercial applications may use BCI technology to detect different covert states in a subject (Zander and Jatzev 2009, Bahramisharif *et al* 2010, Baernreuther *et al* 2010). This approach provides the basis for emerging applications such as neuromarketing (e.g., Neurofocus, http://www.neurofocus.com, Pradeep 2010) or defense applications (e.g., Honeywell, AugCog helmet, St. John *et al* 2005, Dorneich *et al* 2009, Kotchetkov *et al* 2010).

In summary, applications of BCI technology fall into the following four categories: basic research, clinical/translational research, consumer products, and emerging applications. All these four categories use BCI hardware and software, but have different sets of requirements. For example, while basic research needs to explore a wide range of system configurations, and thus requires a wide range of hardware and software capabilities, applications in the other three categories may be designed for relatively narrow purposes and thus may only need a very limited subset of capabilities. The following sections summarize different technical issues for these four categories of BCI applications.

2. Basic research

Basic BCI research and development is based predominantly on recording and analysis of electrophysiological brain signals. These brain signals can be classified into three categories that depend on the source of signal recordings: (i) EEG signals, which are recorded from electrodes on the scalp; (ii) ECoG signals, which are recorded from electrode grids on the surface of the brain; (iii) single-unit activity that is recorded from electrode arrays implanted within the brain.

The number of channels that are recorded usually varies from 8–64 for EEG (Sharbrough *et al* 1991), to 32–192 for ECoG (Lesser *et al* 2010), to 100–300 for single-unit recordings (Maynard *et al* 1997). The brain signals recorded from these modalities vary substantially in their amplitudes and frequencies (EEG: 50 μV, 0–50 Hz; ECoG: 500 μV, 0–300 Hz; extracellular single unit activity: 100 μV, 0.3–30 kHz, see Niedermeyer and Lopes da Silva 1993 for review). Because signals also vary substantially in amplitude across frequencies (Miller *et al* 2008, 2010), it is difficult to acquire these three signal categories with the same amplifier and analog/digital converter. This issue is compounded by safety requirements that are prescribed by regulatory authorities such as the Food and Drug Administration (FDA) in the US, the European Commission (CE) in Europe, and the Ministry of Health, Labor, and Welfare (MHLW) in Japan. For that reason, current BCI hardware is usually tailored for only one category of signals and the extraction of one set of features. In consequence, laboratories may need to purchase a dedicated set of BCI hardware for each of these signals. At a system cost of several hundred to one thousand dollars per channel, this becomes an expensive proposition.

The integration of these dedicated sets of acquisition hardware into the laboratory requires connecting different hardware interfaces to electrodes and behavioral sensors. This usually requires additional hardware (e.g., head-stages, pre-amplifiers and behavioral data acquisition) to acquire signals from other sources and to prevent artifacts that affect the signal-to-noise ratio.

The coordinated acquisition, analysis, and storage of brain and behavioral signals recorded by these sets of acquisition hardware remain complex. It requires communication and synchronization of various software interfaces. These interfaces may be synchronous (e.g., stream-based) or asynchronous (e.g., event-based) and their timing and sampling rate may vary (Wilson *et al* 2010). General-purpose BCI software frameworks such as BCI2000 (Schalk *et al* 2004, Mellinger and Schalk 2007, Schalk and Mellinger 2010) or OpenVIBE (Renard *et al* 2010) provide readily available solutions to acquire, analyze and store brain and behavioral signals. However, standardization of software beyond such packages does not exist yet.

In summary, standardization and integration of hardware and software continues to remain an issue for BCI research and development.

3. Clinical/translational research

The translation of BCIs into clinical practice provides a primary impetus and focus for BCI research, and is thus of great interest to funding institutes such as the NIH. Groups around the world are demonstrating the clinical efficacy of BCIs (Kübler *et al* 2005, Sellers *et al* 2006, Vaughan *et al* 2006, Nijboer *et al* 2008, Cincotti *et al* 2008, Stavisky *et al* 2009, Guger *et al* 2009, Sellers *et al* 2010, see Mak and Wolpaw 2009 for review), and the NIH lists 11 active investigational clinical BCI trials (http://clinicaltrialsfeeds.org).

These investigational studies currently use experimental-grade BCI hardware and software that were developed for basic research and suffer from high cost and complexity, proprietary standards, and lack of robustness (Cincotti *et al* 2006). The translation of this experimental-grade BCI hardware and software into product-grade clinical BCI instrumentation is challenging. It requires the integration of BCI hardware and software into clinical environments as well as improvements to clinical applicability, robustness, usability, and cost/benefit ratio (Kübler *et al* 2006). Besides these engineering tasks, the development of clinical certification (Higson 2002), reimbursement (Raab and Parr 2006), and dissemination procedures all require attention.

In addition to the difficulties in translating BCI technologies, it remains unclear whether clinical BCI systems will ever be a viable alternative to other established (i.e. muscle-based) and emerging (e.g., bionic) assistive devices. Currently established and emerging assistive clinical devices tend to provide a better cost/benefit ratio and are easier to use and disseminate (Majaranta and Räihä 2002, Berger and Glanzman 2005, Pylatiuk and Döderlein 2006, Schalk 2008).

If clinical BCI systems are to become widely used, they need to either improve on their performance or complement established and emerging assistive devices. Hybrid BCIs, i.e. the combination of a BCI with other BCIs or existing assistive systems, follow a current trend that addresses this issue (Allison *et al* 2010, Millán *et al* 2010, Pfurtscheller *et al* 2010, Zander *et al* 2010). In any case, the current lack of product-grade BCI hardware and software and standardized procedures impedes the translation of BCIs into clinical practice.

4. Consumer products

The growing interest in and maturity of the field of BCI research have opened up different avenues for application of BCI technology in commercial contexts.

Commercial BCI devices measure signals from the brain and turn them into outputs that provide value to the customer. As with many other novel technologies, it is currently unclear in what situations BCI devices can provide maximum value for the largest number of users. Several manufacturers are currently exploring these questions by offering commercial BCI-like devices. These companies include Emotiv (http://www.emotiv.com), Neurosky (http://www.neurosky.com) and OCZ Technology (http://www.ocztechnology.com).

The success of widespread dissemination of commercial BCI devices depends on reducing the barriers to acquiring and using these systems. This requirement entails several challenges that relate mainly to cost and ease of use. The cost of a typical (i.e. research-based) BCI system is usually at least 5000 dollars—too much for most consumer products. Reducing these costs is mainly a technical problem that can be solved, but does require appropriate resources. Improving ease of use mainly relates to improving EEG electrode technology. Typical EEG electrodes are wet, i.e. they require the application of conductive electrode gel, and usually have to be applied by trained experts who abrade the skin mildly. In contrast, widespread application requires that electrodes can be applied without gel and the associated mildly abrasive procedures. Different strategies have been proposed to address this problem. The first strategy is to create 'dry' electrodes, i.e. electrodes that can function with a dry interface between electrodes and the scalp. Different types of dry electrodes have been proposed (Popescu *et al* 2007, Matthews *et al* 2007, Sullivan *et al* 2008, Sellers *et al* 2009, Gargiulo *et al* 2010) and are currently distributed by commercial vendors (e.g., Nouzz (http://nouzz.com), Quasar (http://www.quasarusa.com)), but at least some still have unsolved problems with robustness. The second strategy is to create 'active' electrodes, i.e. electrodes that do require the application of conductive gel, but amplify the EEG signal at the electrode, which minimizes the need for skin abrasion. Active electrodes are provided by many commercial vendors of EEG equipment, but typically are quite expensive and still require an additional biosignal amplifier and analog-to-digital converter. The third strategy is to actively shield the connection between the electrode and distant biosignal amplifier. This possibility is currently only implemented by one commercial vendor (Twente Medical Systems International (http://www.tmsi.com)). Their system utilizes actively shielded cables that prevent capacitive coupling that also minimizes the need for abrading the skin.

Finally, improving ease of use also requires that operation of the BCI software should be as easy as possible. This requires that it can adapt efficiently to fluctuations in brain signals caused by changes in the subject's brain state or environmental or other noise.

In summary, it is currently unclear to what extent BCI performance will further improve, and when and to what extent BCI technologies will find commercially viable applications in consumer areas.

5. Emerging applications not related to communication and control

Since their origin, BCIs have focused mainly on communication and control. The resulting studies have developed a body of knowledge and technology, including portable hardware and novel methods for extracting and reliably classifying relevant aspects of brain signals. This knowledge has applications beyond the development of traditional BCIs. Some of these applications challenge the current definition of BCIs.

BCI technology can also provide the basis for novel applications that go beyond restoration of function. Such novel and emerging applications that are not related to communication and control may include detection of covert behavior (Zander and Jatzev 2009, Bahramisharif *et al* 2010, Baernreuther *et al* 2010), biofeedback, sleep control, treatment of learning disorders, functional and stroke rehabilitation, and the use of brain signals as biomarkers for diagnosis of diseases or their progression (Georgopoulos *et al* 2007). Some of these opportunities have begun to be exploited commercially, e.g., neuromarketing (Neurofocus, http://www.neurofocus.com, Pradeep 2010) and defense applications (Honeywell, AugCog helmet, Dorneich *et al* 2009, St. John *et al* 2005). The ability of BCI feedback to induce cortical plasticity (Fetz 1969, Taylor *et al* 2002, Carmena *et al* 2003, Wolpaw and McFarland 2004, Leuthardt *et al* 2004, Miller *et al* 2010) may provide the basis for therapeutic tools that restore the brain function. Such therapeutic tools are currently under development for reducing seizures (Monderer *et al* 2002, Walker and Kozlowski 2005, Sterman and Egner 2006), treating attention deficit or hyperactivity disorders (Monastra *et al* 2005), improving the cognitive function in the elderly (Angelakis *et al* 2007), managing pain (deCharms *et al* 2005), and improving motor function in stroke patients (Buch *et al* 2008, Daly *et al* 2009, Ang *et al* 2010, see Daly and Wolpaw 2008 for review). One of the characteristics of these emerging applications is that they are often targeted toward larger markets than traditional BCIs.

In summary, emerging applications not related to communication and control may provide additional drive for development of BCI hardware and software.

6. Standardization

As described in the previous sections, the translation of BCI hardware and software from isolated demonstrations to systematic investigations and commercial products requires efforts in different disciplines (Berger *et al* 2007). The lack of defined technical standards has become an important impediment to the integration of those efforts. As an example, it is currently difficult to mix and share hardware devices (e.g., EEG headsets, amplifiers), tools (e.g., Bianchi *et al* 2009), and software modules (e.g., classifiers) that originate from different laboratories or manufacturers. While there have been isolated efforts to define and implement a common model for BCI operation (Mason and Birch 2003), a standard way in which they exchange information through well-defined interfaces (Quitadamo *et al* 2008), and general-purpose BCI software (Bianchi *et al* 2003, Schalk and Mellinger 2010, Renard *et al* 2010), these efforts do not yet completely encompass all aspects of hardware connectivity, file formats for storing any kind of information (e.g., biosignals, classifiers outputs, feedback rules), or all software interfaces (in particular with third-party software).

Standardization of the technical basis for hardware and software interfaces has been shown to facilitate the translation from isolated demonstrations to systematic investigations and commercial products (Tassey 1997). On the other hand, standardization, if poorly designed or timed, impedes innovation (Tassey 2000). However, if well designed and timed, standardization will facilitate the coordinated development of future BCI hardware and software. For example, as a first step, connectors between EEG caps and biosignal amplifiers could easily be standardized without overly stifling innovation.

7. Conclusions

BCI hardware and software are currently in a transition from isolated demonstrations to systematic research and commercial development. Successful and continuing transition requires that BCI hardware and software further improve in speed, accuracy, price, and robustness, and consequently the cost/benefit ratio. For example, to match the cost/benefit ratio of conventional assistive communication devices, product-grade BCI spelling devices may require maintenance-free spelling performance of more than 10 words per minute at close to 100% accuracy for less than 15 thousand dollars (e.g., MyTobii P10 eye-tracker system, Tobii Technology AB, Sweden, http://www.tobii.com). To facilitate necessary improvements, an ecosystem of product-grade BCI systems and components needs to be developed. The requisite efforts include the development of better integrated and more robust BCI hardware and software, the definition of standardized interfaces, and the development of certification, dissemination and reimbursement procedures.

We expect that these efforts will create an ecosystem of increasingly compatible BCI hardware and software that will enable the translation of BCIs into clinical practice, as well as the rapid development and dissemination of commercial consumer applications and additional applications that are not related to communication and control. The detailed aspects for creating an ecosystem of product-grade BCI hardware and software, and the likely societal impact of this ecosystem, require further investigation.

The creation of this ecosystem may be hindered by factors such as defensive intellectual property strategies, and the lack of patent pools and commercial interests. It is also possible that unresolved ethical considerations, such as privacy and liability, will eventually impede the proliferation of BCIs (Haselager *et al* 2009, Kübler *et al* 2006).

In summary, current trends in hardware and software for brain–computer interfaces (BCIs) are the transition from isolated demonstrations to systematic research and commercial development, and steady, albeit slow, improvements in BCI performance parameters. We anticipate that these trends will drive the creation of an ecosystem of increasingly compatible BCI hardware and software that is likely to facilitate the increasing application of BCIs to the needs of people with and without disabilities.

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