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Brain-computer interface technologies: from signal to action

Abstract: Here, we present a state-of-the-art review of the research performed on the brain-computer interface (BCI) technologies with a focus on signal processing approaches. BCI can be divided into three main components: signal acquisition, signal processing, and effector device. The signal acquisition component is generally divided into two categories: noninvasive and invasive. For noninvasive, this review focuses on electroencephalogram. For the invasive, the review includes electrocorticography, local field potentials, multiple-unit activity, and single-unit action potentials. Signal processing techniques reviewed are divided into time-frequency methods such as Fourier transform, autoregressive models, wavelets, and Kalman filter and spatiotemporal techniques such as Laplacian filter and common spatial patterns. Additionally, various signal feature classification algorithms are discussed such as linear discriminant analysis, support vector machines, artificial neural networks, and Bayesian classifiers. The article ends with a discussion of challenges facing BCI and concluding remarks on the future of the technology.

Keywords: BCI; brain-computer interface; EEG; electroencephalogram; Fourier transform; Laplacian filter; signal processing; wavelet transform.

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Introduction

Current challenges in rehabilitation have created the need to develop a viable and effective path of communication between the brain and the exterior environment. This technology is often called brain-computer interface (BCI), also known as brain-machine interface or neural interface system (NIS; Hsu, 2011, 2012; Luis de Mello et al., 2011; Lopez-Gordo et al., 2012; Manyakov et al., 2012). The purpose of these devices is to create a bridge between an individual's intent and the outer world through brain signals (Schwartz et al., 2006; Birbaumer and Cohen, 2007; Donoghue et al., 2007; Hatsopoulos and Donoghue, 2009; Nicolelis and Lebedev, 2009; Scherberger, 2009; del Riego et al., 2011). This technology can help a diversity of patients with various challenges ranging from multiple neuromuscular diseases such as amyotrophic lateral sclerosis (ALS) and cerebral palsy to those with trauma in the brain or the spinal cord (Donoghue, 2008). These complications impact the lives of approximately two million people in the US alone and millions more in the rest of the world (Ficke, 1992; Murray and Lopez, 1996; Gustavsson et al., 2011; Larkindale et al., 2013).

Other potential applications may come from amputation or muscle deformation. These amputations can be the result of unattended fractures, war wounds, or pathophysiologic conditions such as diabetes or tumors (Esquenazi, 2004). Individuals with such experiences suffer not only from the trauma, but their everyday life is affected adversely and permanently (Stansbury et al., 2007). These challenges have created an increasing interest in the development and improvement of BCI technologies. This article presents a state-of-the-art review of the representative research performed on BCI technologies. This review is divided into five sections: components of a BCI, signal acquisition approaches, signal processing techniques, devices currently used, and concluding remarks.

Components of a BCI

A BCI is a multicomponent device that measures brain signals to uncover the subject's intentions. The three basic components in a BCI are signal acquisition, signal processing, and effector device (Figure 1). This depiction is a simplified perspective because each of these components includes other mechanisms and operations. The signal acquisition component records the signal created by the brain. This acquisition can be either invasive or noninvasive, difference to be discussed in detail in the

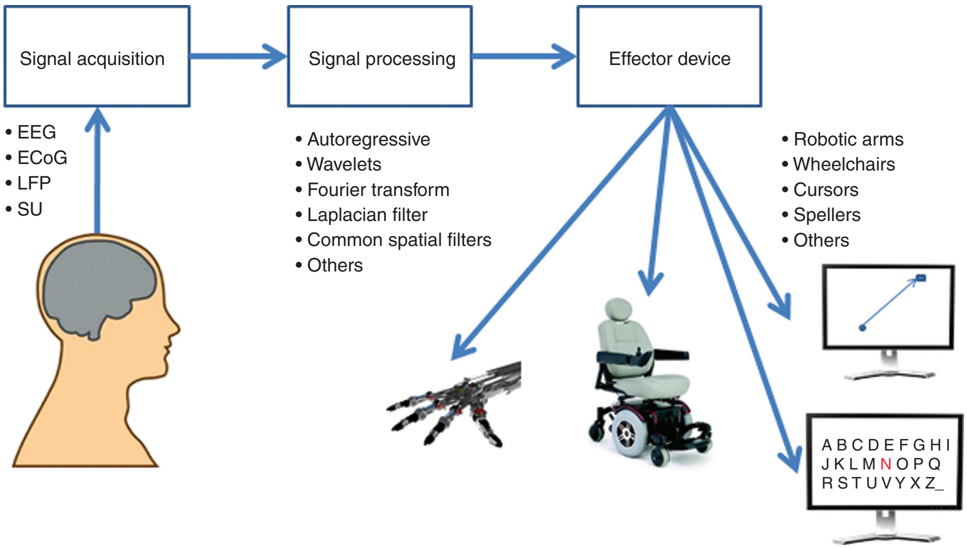

Figure 1 Basic components of a BCI: a brain signal acquisition device, a signal processing system, and an effector device. The purpose of BCI technology is to create a path of communication to control a prosthetic device, a spelling setup, or a computer cursor.

following section. The signal processing component analyzes the signal, with the goal of discovering features and markers to be translated into desired actions. A great deal of research has been conducted on the improvement of the signal processing aspect of BCI. The last component is the effector device, which can be a computer cursor (Wu et al., 2003), a prosthetic arm (Hochberg et al., 2006, 2012; Chao et al., 2010; Collinger et al., 2013), a speller (Krusienski et al., 2008), or a wheelchair (Galán et al., 2008; Iturrate et al., 2009; Li et al., 2013).

Signal acquisition

The signal acquisition component can be divided into two categories: noninvasive and invasive. The invasive denomination is used when the device pierces through skin, skull or even brain matter (Millán and Carmena, 2010). For noninvasive, this review focuses on electroencephalogram (EEG), although other technologies have been explored with limited practicality such as functional magnetic resonance imaging (fMRI; Wessberg et al., 2000; Martins et al., 2011; Rangaprakash et al., 2013), near-infrared spectroscopy (NIRS; Sitaram et al., 2006), and magnetoencephalography (MEG; Mellinger et al., 2007; Ahmadlou et al., 2013). For the invasive, the review includes electrocorticography (ECoG), local field potentials (LFP), multiple-unit activity (MUA), and single-unit (SU) action potentials (Figure 2). These signals are recorded through sensors or electrodes that range from multiple scalp electrodes, single electrodes, or arrays (Liao et al., 2012). There are two main paradigms in which signals are typically recorded: synchronous and asynchronous. In the synchronous paradigm (Besio et al., 2011; Han et al., 2011), signals are handled through cues and specific time windows. This approach is typically used with signals that have time-dependent behavior or occur in very specific instances. On the contrary, the asynchronous paradigm acquires the signal with no specific cues to the subject over a broader time window. This latter approach appears to be the future direction of BCI where the user can use the device at will (Müller-Putz and Pfurtscheller, 2008).

Noninvasive signal acquisition (EEG)

Noninvasive EEG is the preferred method for a vast majority of BCI researchers (Birbaumer, 2006a). This preference stems from the ease of use and no-risk noninvasive nature of this approach. Yet, these advantages are often accompanied by challenges such as low spatial resolution and difficulty of managing signal-to-noise ratios (Cabrerizo et al., 2012; Cong et al., 2012). Additionally, other brain activities might supress or conceal the desired signal, thus affecting signal quality. Often, spatial filters are introduced to enhance the EEG signals that can improve feature classification significantly. In addition, by not crossing the skin barrier, researchers must deal with artifacts such as electromyographs (EMG; electrical activity from muscles above/in the eye and/or cranial muscles; Pfurtscheller et al., 2000) and/or electrooculographs (EOG; changes

A

Method	Signal Name	Spatial Resolution	Sensor Location
Non-invasive	EEG	3 cm	Scalp
Invasive	ECoG	.5 cm	Above Cortex
	Local Field Potential (LFP)	1 mm	Inside Cortex
	Single Unit Action Potential (SU)	.2 mm	

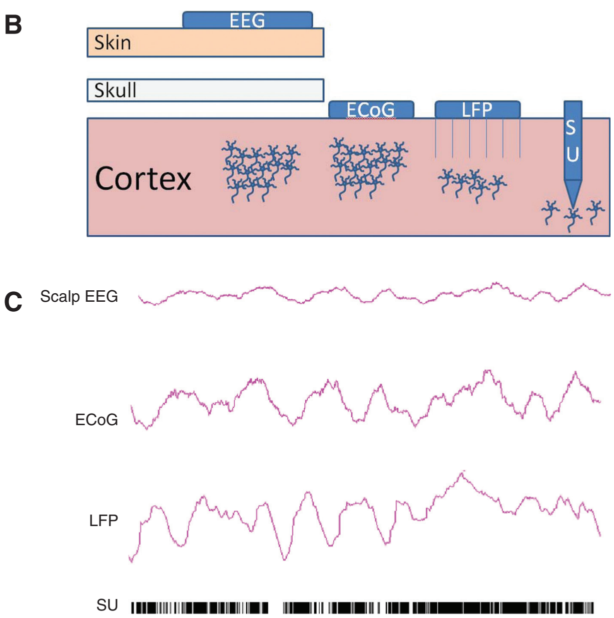

Figure 2 BCI signal's depth, neuron population, and signal waveform. (A) Table summarizing the different levels for signal acquisition with corresponding locations and spatial resolution. (B) Diagram showing electrode locations for different signals. (C) Example signals from different locations. Noninvasive scalp EEG is the most distant of the sensors. Being over the scalp, there is no perforation. This provides a disadvantage of distance, collecting noise and interference from other sources making the signal less visible. Invasive sensors cross both the scalp and the skull providing a more detailed and accurate signal. The spatial resolution increases as the distance of the sensor from its focus is reduced.

in electrical potential occurring between the front and back of the eyeball as the eyes move between two fixed points; Furdea et al., 2012). Because of these limitations, EEG-based BCI was initially thought to be capable of only binary (yes/no) responses, but this was disproven when two-dimensional (Wolpaw et al., 2004) and even three-dimensional controls were experimentally achieved (McFarland et al., 2010). The EEG is often acquired through 32 or 64 channels that measure voltage changes on the scalp over time (Figure 3; Martis et al., 2012).

Through the use of EEG, distinct types of signals can be observed, which relate to specific neuronal or motor behavior (Pasqualotto et al., 2012). The most typical are P300 (Finke et al., 2009), visual evoked potentials (VEP), sensorimotor rhythms (SMR; Pfurtscheller et al., 2000), and slow cortical potentials (SCP). Some artificially generated signals are shown to demonstrate typical characteristics of these signals (Figure 4). VEPs and P300 are event-related potentials that are tied with outside stimulus and are modulated by the subjects' attention to their environment. VEPs are generated from visual sensory stimulation, usually flashing lights, to achieve a neuronal synchronization with a similar frequency (or harmonic) to the flash of light presented. P300 are evoked potentials that occur when the subject observes an expected event unfold from a seemingly chaotic environment – similar to finding a puzzle piece lost in a table or the sight of a friend in a group of strangers (Farwell and Donchin, 1988). Researchers use this low probability event, called oddball paradigm, to evoke P300 expecting a consistent appearance of the wave after a 300 ms window. Event-related synchronization (ERS) or amplitude suppression known as event-related desynchronization (ERD) are closely related to SMRs. Generally found in the EEG α/β band (<30 Hz), SMRs can be generated by the imagining or realization of movements. SCPs are synchronized polarizations of synaptic potentials that can be voluntarily regulated by the

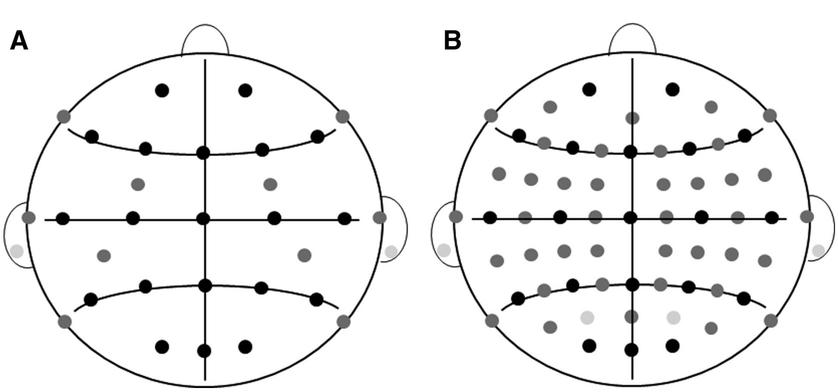

Figure 3 Typical 32-electrode (A) and 64-electrode (B) array for EEG signal acquisition.

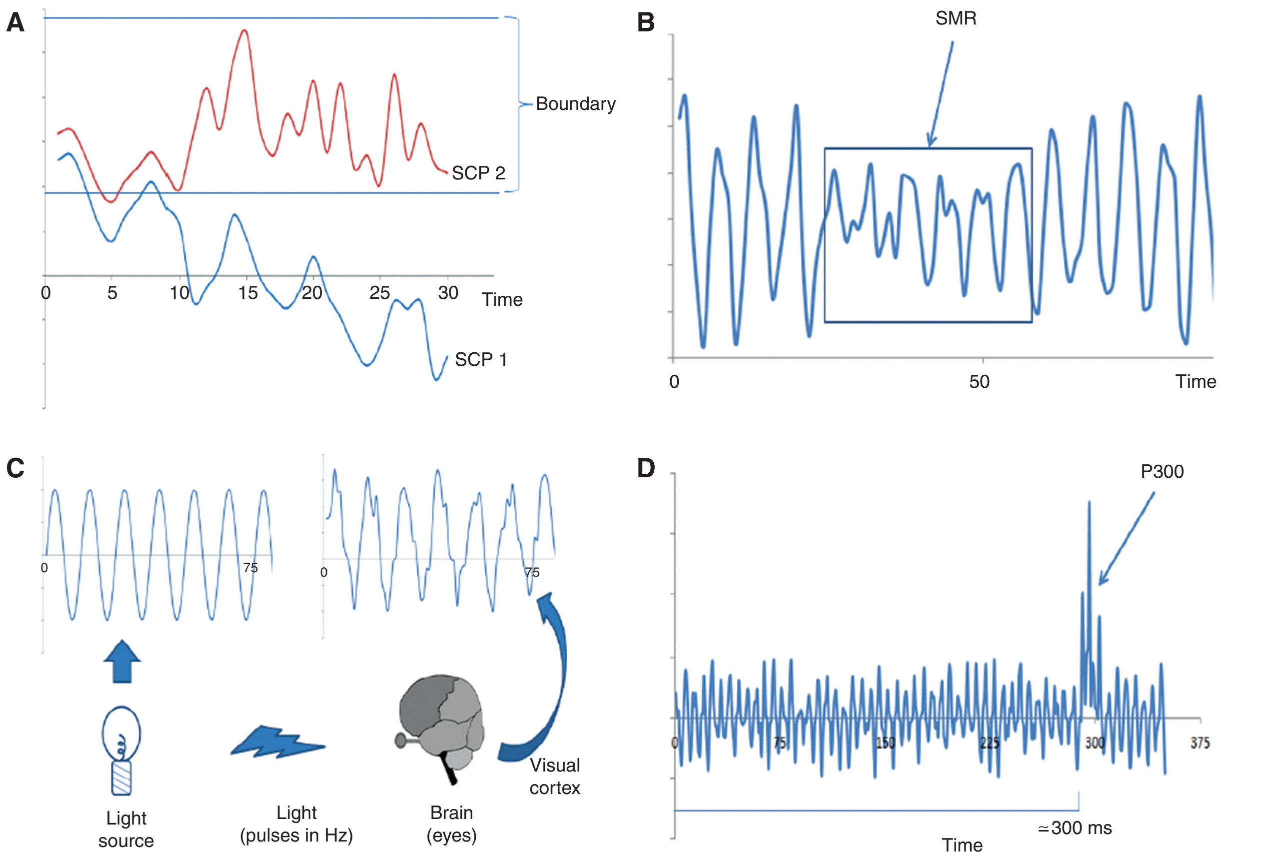

Figure 4 Sample EEG signal types.
(A) SCPs are synchronized synaptic potentials that can be voluntarily regulated by the subject through positive reinforcement. (B) SMRs are sensorimotor rhythms generated by the imagining of movements and like SCPs can be voluntarily controlled. (C) VEPs are signals acquired on the visual cortex, which possess similar frequencies to visual stimulus. (D) P300 are evoked potentials that occur when the user is faced with an unexpected event such as finding a puzzle piece lost in a table or the sight of a friend in a group of strangers and appear approximately 300 ms after the stimulus.

subject through positive reinforcement. The SCP, like the SMR, can be voluntarily controlled through training.

In BCI, the typical setup for P300 spellers works randomly lighting one letter at a time on a screen. The appearance of the P300 wave is recorded when the expected letter is activated and observed by the subject. Typically, the letters flash in a random order a number of times per trial. Krusienski et al. (2008) used a stepwise linear discriminant analysis (SWLDA) to optimize P300 speller performance. The SWLDA approach, similar to a linear regression, seeks to model an observation with linear combinations of features or measurements. They experimented on channel selection, channel reference, removal of redundant features, and optimal values of features and concluded that only the spatial selection of channels statistically affected the P300 detection and thus the speller performance. Jin et al. (2012a) evaluated the effect of target-to-target intervals and flash patterns in a P300 speller. The target-to-target intervals are defined as the time between targets. Flash patterns are generated based on the total number of flashes per trial per letter.

Steady-state VEPs (SSVEPs) are extensively used in BCI research due to their high signal-to-noise ratio and straightforwardness. These evoked potentials are generated by flashing lights at specific frequencies that can be observed in the neuronal activity of the visual cortex. The typical setup for SSVEP-BCI is to have subjects observe flashing lights in the surrounding area (monitor or prosthetic device) allowing the BCI to correlate the observed light with a desired action (cursor control or robotic arm movement). The disadvantage of SSVEPs comes with the need to have gaze control for which patients with different neuromuscular diseases do not have. Müller-Putz and Pfurtscheller (2008) demonstrated the use of an SSVEP-BCI to control asynchronously an electrical prosthesis in four subjects.

Recent experiments have tried to uncover a better understanding of SMR generation and its relation to motor behavior. Researchers have questioned whether SMRs are just an epiphenomenon or perhaps comprise a relevant component in the physiologic transmission of information in motor control (Kilgard et al., 2007). Boulay et al. (2011) studied six able-bodied individuals using EEG-BCI and SMR and concluded that SMR signals posses a causal role on regulation of behavior, thus confirming the usability of SMRs in BCI. Researchers have also looked at the advantages of continuous adaptation in translation accuracy in both SMRs and P300. More recently, SMRs have been used to provide communication to minimally conscious patients using single switch BCI (Müller-Putz et al., 2013).

SCPs stand as the most challenging signals to acquire from EEG. The training of SCPs can be long (months to years) and may not be successful (Pasqualotto et al., 2012). Using fMRI, researchers have identified the areas where SCPs are generated, which can be used to expedite BCI training (Hinterberger et al., 2004, 2005). Iversen et al. (2008) demonstrated the possibility of training an ALS patient to control SCPs and that patients with ALS still possess SCPs even in the late stages of the disease.

Invasive signal acquisition (ECoG, LFP, MUA, and SU)

For a signal to be considered invasive, the recording approach must cross the scalp-skull level. These signals have been explored mostly in animals and only to a limited extent in human cases (Georgopoulos et al., 1986; Chapin et al., 1999; Leuthardt et al., 2004; Krusienski and Shih, 2010). For human experimentation, researchers must deal with a range of challenges from recording instability to minimizing the risk/benefit ratio.

ECoG

ECoGs are acquired from the cortical surface of the brain and bear great similarity to scalp EEGs in their characteristic shape and are often called intracranial EEG (iEEG). ECoGs are often obtained from severely epileptic and Parkinsonian patients (Wu et al., 2010; Andres et al., 2011; Liu et al., 2013) and sometimes from patients with major depressive disorder (MDD; Ahmadlou et al., 2012a). In the case of epileptic patients, subdural electrode arrays are surgically implanted over multiple cortical areas (fronto, parietal, and temporal) in foci related to the source of the neurologic disorder. This provides researchers with a window of 4 to 5 days from the implantation of the electrode to surgical resection of the foci. In most occasions, researchers must acquire data during clinical observation in the presence of a physician only, which limits greatly experimental procedures. The ECoG, being closer to the brain, provides a higher spatial resolution and signal clarity than noninvasive scalp EEG.

By providing a clearer signal, ECoG has been used in the context of BCI for some time. Using ECoG, Chao et al. (2010) achieved asynchronous decoding of arm motion in monkeys. Through this decoding, they were able to acquire kinematics with high degrees of freedom. Their decoder was used for months without experiencing any effect in accuracy or signal fidelity. Davis et al. (2011) recorded ECoG signals wirelessly to continuously monitor epileptic episodes in canines, with the goal of creating a better platform for communication between the implant and BCI. This experiment provided over a year of data in six dogs and a potential platform for a wireless and more stable BCI.

LFP, MUA, and SU

In contrast to ECoG, LFP, MUA, and SU cross the cortical surface to record inside the brain matter. LFP reaches to a small group of neurons recording their field potentials (Bansal et al., 2012), whereas MUA and SU record the action potentials of single neurons (Maynard et al., 1997; Carmena et al., 2003; Collinger et al., 2013). Research involving LFPs, MUA, and SUs are mostly done in animals with few human exceptions (Hochberg et al., 2006, 2012; Collinger et al., 2013). These methods provide the highest spatial resolution yet are the most invasive, typically causing damage to tissue surrounding the recording site and cells in the area (Navarro et al., 2005). In addition, these sensors must be designed to be biocompatible to withstand the biologically active environment of the brain to attain reliable and continuous recordings through time (Donoghue, 2008).

Using SU recordings in rats, Laubach et al. (2000) studied the learning of movement and activation of motor cortex neurons. They observed neuronal firing rate and pattern over time. The authors correlated this activity with motor learning and the activation of new cortical areas, thus observing a predictable behavior suitable for BCI applications.

While making SU recordings in monkeys, Carmena et al. (2005) observed that one neuron might have different contributions to a single action. A neuron participating in motion generation in one time window may remain silent in another. This observation proved that single-neuron participation was nonstationary, pointing out the need for considering a larger pool of neurons for future BCI applications.

Chase et al. (2012) used SU recordings in monkeys to observe primary motor neuron adaptation capabilities to errors in motor tasks. Assuming a linear encoding model, the authors extracted preferred directions from neurons and studied their changes when presented with a perturbation. They argue that error reduction was attributed to a global re-aiming adaptation from the population instead of individual re-tuning of neurons strengthening the idea of using larger neuronal populations.

Using a 96-electrode array on a monkey, Bansal et al. (2012) compared the information encoded within certain frequency bands of LFPs and SUs resulting from primary motor cortex (M1) and ventral premotor area (PMv). They examined the impact of movement encoded in both LFPs and SUs within the M1 and PMv and concluded that a large enough pool of SUs (>16 neurons) provides better or equal information than LFPs, but including LFPs improves robustness for BCI applications.

More recently, MUAs have been demonstrated in the BCI field as a recording method. This approach acquires multiple neuronal activities that can be isolated in multiple channels. It was used recently to demonstrate robotic control in tetraplegic patients (Hochberg et al., 2006, 2012). Collinger et al. (2013) demonstrated a seven degrees-of-freedom robotic arm used by a tetraplegic patient. Their application allowed the subject to move the robotic arm freely in a three-dimensional workspace achieving a 91.6% mean success rate.

Hybrid signals

A recent trend in BCI signal acquisition, called hybridization or hybrid BCI, is the use of more than one signal type (Figure 5; Nam et al., 2011). These devices can range from two different BCIs working together to physiologic devices such as EMG or EOG being added to the BCI. These additional signals can work within the BCI system to turn it on or change control states for a more accurate and robust operation.

Another type of signal used in a hybrid BCI is motion-onset VEPs (M-VEPs), a type of VEP evoked by motion instead of flashing frequency (Torriente et al., 1999). Jin et al. (2012b) proposed a hybrid BCI using P300 and M-VEP. Their experimentation was designed to assess M-VEP performance for BCI, test hybrid feasibility, and find possible alternatives for BCI operation. Another notable aspect of the research is the use of color stimulation. The hybrid approach yielded a mean classification accuracy of 96%, higher than using stand-alone P300 and M-VEP BCIs.

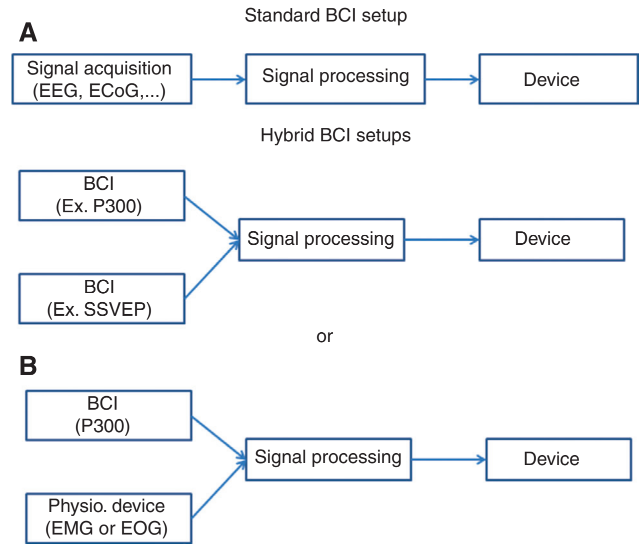

Figure 5 Standard BCI setup vs. hybrid BCI setup.
(A) Example of standard BCI setup including signal acquisition, signal processing, and device. (B) Examples of a hybrid BCI. These systems acquire and use more than one type of signals to improve the operation of the BCI.

Signal processing: feature extraction

After the signal is acquired by any of the aforementioned mediums, it has to be processed. This task is performed by the signal processing component. In a BCI system, this component consists of two major steps: feature extraction and feature translation/classification. The feature extraction is the process of evaluating the acquired signal and identifying potential signal features or markers (Acharya et al., 2011, 2012; Hou et al., 2011; Cong et al., 2013; Hsu, 2013). A signal extraction algorithm is used to discover the features that correlate most strongly with the subject's intent. The result from the extraction is sent to a feature classification algorithm that relates the extracted feature with the output device used. Effective and accurate feature extraction and classification (Ahmadlou and Adeli, 2010a) are of paramount importance for the success of the BCI. Many signal processing techniques have been used in BCI research (McFarland et al., 2006; Waldert et al., 2009). The most common ones are reviewed in this section.

Feature extraction is the most important and challenging aspect of BCI signal processing because of the complex processes involved in the brain. Feature extraction algorithms must deal with the source of the signal, which is often noisy and complex, and detect features of interest. For the discovery of these features, researchers rely on time-frequency and/or temporal-spatial analysis. The most common techniques used in time-frequency analysis include Fourier transforms (FT), autoregressive (AR) models, wavelet transform, and Kalman filters (KF). The temporal-spatial techniques typically used are Laplacian filter and common spatial patterns (CSP).

Time-frequency methods

Fourier transforms

FT is one of the oldest and most widely used methods for signal processing and BCI. Discrete FT (DFT) is often used to convert time series functions into a frequency domain representation using discrete samples of a continuous time signal. Diez et al. (2011) used DFT in an EEG-BCI experiment with six human subjects to decode high-frequency SSVEP to achieve asynchronous control of a computer cursor. Advantages of high frequencies (>30 Hz) attainable in SSVEP are lower visual fatigue (due to less perceived flickering) and less interference with the α band (an information-rich frequency band). The authors set a monitor with four light-emitting diodes (LEDs) above, below, and to each side of the monitor. Each LED flickered at a slightly different frequency (37, 38, 39, and 40 Hz) representing the four possible cursor movements (up, down, right, and left). Subjects were asked to control the cursor through different mazes by gazing at the one of the four flickering lights and determine direction. Using a linear combination of Fourier series, some researchers have tried to quantify the relationship between two or more brain signals usually using measures based on FT of the signal. Krusienski et al. (2012) compared three such measures: coherence, spectral power, and the phase-locking value (PLV) of two EEG signals obtained from seven able-bodied users trained on a simple one-dimensional/two-target cursor control task. They conclude that 'spectral power produced classification at least as good as PLV, coherence, or any possible combination of these measures.' This was expected because all signals were obtained from the same area of the brain – sensorimotor cortex. Other applications of fast FT (FFT) in BCI are reported in Chin-Teng et al. (2008).

AR model

The AR model attempts to estimate a given data set, or signal, by linear weighted sum of prior values. It is an efficient method because it uses only linear regression equations to make the predictions. Most of the information extracted from the signal is through the conversion of the time domain into the frequency domain and finding spectral amplitudes in the frequency domain. An optional use for AR model is to directly use the acquired values (or coefficients) as features instead of the frequency spectrum.

Wolpaw et al. (2004) presented an application of AR model in EEG-BCI using frequency amplitudes from μ (8–12 Hz) and β (18–26 Hz) bands for two-dimensional control of a computer cursor on human subjects. The amplitudes in μ and β bands were modulated through motor imagery, making the cursor move in the horizontal or vertical direction. With this control, the subject was able to move the cursor to one of eight predefined locations on a screen. Other applications of AR model can be found (Guger et al., 2001; Kübler, 2005; Vidaurre et al., 2006; Mehta et al., 2011).

Wavelet

A more recent time-frequency analysis technique is the wavelet transform that has been used in many fields from image and pattern recognition (Ghodrati Amiri et al., 2012; Jiang et al., 2012; Lin et al., 2012; Tao et al., 2012; Xiang and Liang, 2012) to automated EEG-based diagnosis of neurologic and psychiatric disorders (Adeli and Ghosh-Dastidar, 2010). This methodology has been applied to epilepsy (Adeli et al., 2003, 2007; Ghosh-Dastidar and Adeli, 2007, 2009; Ghosh-Dastidar et al., 2008), Alzheimer's disease (Adeli et al., 2005, 2008; Ahmadlou et al., 2010a, 2011; Sankari and Adeli, 2011; Sankari et al., 2012), autism spectrum disorder (ASD; Ahmadlou et al., 2010b, 2012b), attention-deficit and hyperactivity disorder (ADHD; Ahmadlou and Adeli, 2010b, 2011; Ahmadlou et al., 2012c), and MDD (Ahmadlou et al., 2012a). The approaches presented in the aforementioned papers have demonstrated the power of wavelets as denoisers and feature extractors and their effectiveness in brain signal processing. Wavelet uses the concept of resonance to acquire features within a specific frequency band. The main concept in wavelet analysis is to decompose a given signal into scale components in both frequency and time domains. This decomposition allows specific frequency bands to be extracted, processed, and/or analyzed. This signal processing technique is especially helpful for nonperiodic/nonstationary signals with discontinuities.

The discrete wavelet packet transform (DWPT) provides more coefficients than the conventional discrete wavelet transform (DWT), representing additional subtle details of a signal and can be considered a generalization of DWT (Jiang and Adeli, 2004). One of the challenges of EEG signal processing is the location of the optimal subject-based band, the slight difference found in subjects' frequency bands due to physiologic differences. Yang et al. (2007) proposed an adaptive subject-based feature extraction using DWPT. The authors determined the best wavelet basis for the most suitable frequency subbands for signal representation. They tested the idea on three different motor imagery tasks: playing basketball using the left hand, playing basketball using the right hand, and braking using the right foot. Hsu et al. (2012) classified single-trial left finger lifting and resting EEGs obtained from male and female human subjects using Daubechies wavelets and amplitude modulation. Another application of wavelet can be found in Donchin et al. (2000).

Kalman filter

KF, or linear quadratic estimation, is an algorithm used to estimate unknown variables from measurements that contain noise or inaccuracies. The algorithm works with a series of inputs and recursive measurements to achieve its statistically optimal estimates. The filter will estimate a variable including noise, and once estimated, it will use weights to adjust the estimation in a recursive manner. The advantage of the KF is its ease of use for real-time data analysis. Malik et al. (2011) applied a steady-state KF (SSKF) on ECoG data obtained from two patients to assess its computational efficiency against standard KF. The authors recorded LFPs using a silicon microelectrode over the precentral gyrus opposite the dominant hand. The cursor velocity and position were decoded using SSKF and KF. SSKF displayed improved computational efficiency over stand-alone KF proving a potential method for online neuroprosthetic control. Gupta and Ashe (2009) compared linear multiple regression analysis with KF for LFP signals obtained from recorded motor cortex neurons in nonhuman primates. The authors were able to decode endpoint forces from the hand accurately, thus potentially improving the BCI operation. Other applications of KF can be found (Sykacek et al., 2004; Gage et al., 2005; Koyama et al., 2010; White et al., 2010).

Spatiotemporal techniques

Laplacian filter

The methods in previous sections were applied on time series independent of their spatial distribution on or in the brain. The methods covered in this section deal with multiple signals distributed over the brain (Figure 6). Laplacian filters are a family of signal processing techniques that observe the change of behavior of spatially distributed signals. Mostly used for image processing, Laplacian filters can delineate signal changes between spatial locations obtained from electrodes over the scalp. As such, they provide a useful tool for spatiotemporal processing of BCI signals.

Qin et al. (2005) reported a pilot study using source analysis, a technique for approximation of the source of an EEG signal, for the classification of motor imagery. The authors used various techniques to pre-process the signal including Laplacian filters, time-frequency analysis, band-pass temporal filtering, and independent components analysis (ICA; Al-Naser and Soderstrom, 2012) before performing the source analysis. Faller et al. (2012) applied Laplacian transform to EEG signals obtained from three channels for autocalibration of motor imagery BCI, performed classification using LDA (Garcia-Cuesta et al., 2011), and reported a calibration accuracy of 70%. Other

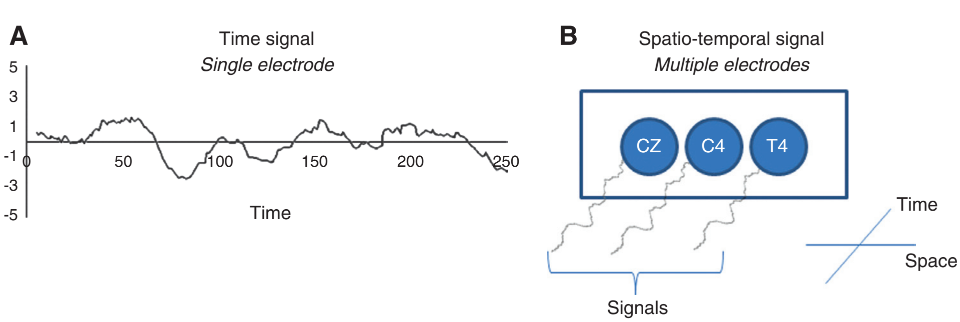

Figure 6 Time domain signal vs. spatial domain signal.
(A) Typical time series signal. (B) Typical spatiotemporal signal. A time-series signal is usually taken from a single electrode or recording site and is evaluated over time. On the contrary, spatiotemporal signals are a group of signals recorded over a grid. Operations applied to spatiotemporal signals may range from simple averaging of neighboring signals to elaborate transformations.

applications of Laplacian filters have been reported in by Millán et al. (2004) and Kamousi et al. (2005).

Common spatial pattern

A commonly used statistical approach used as a spatial filter for feature extraction in BCI is the CSP algorithm, a data-driven supervised statistical learning algorithm. It works by maximizing the variance of the spatially filtered signal of one class and minimizing the variance for the other class in a two-class BCI problem. This is formulated as a generalized eigenvalue problem where the largest and smallest eigenvalues are used to measure the difference between the two classes (Blankertz et al., 2011). Another application of CSP has been reported by Lemm et al. (2005).

Signal processing: feature classification/translation

The second component of signal processing is responsible for translating the features with desired actions or controls. The translation (or classification) algorithms use statistical or discriminative methods to place the feature into classes. Proper algorithms must be selected for each problem, otherwise faulty representation of the observed features or operational errors in the BCI may result. The following approaches are reviewed: LDA, support vector machines (SVM; Jumutc et al., 2011; Wandekokem et al., 2011; Dai et al., 2012), neural networks (NN; Ahmed et al., 2011; Colici et al., 2011; Rossello et al., 2012; Tomasevic et al., 2012; Yamanishi et al., 2012), and Bayesian classifiers (Saliminejad and Gharaibeh, 2012). A review of EEG-BCI classification algorithms up to 2007 is presented in by Lotte et al. (2007). This review will discuss more recent applications of the aforementioned techniques.

LDA is a linear method that seeks to minimize the interclass variance while maximizing the distance between means of two classes. LDA assumes the data possess a normal distribution and separates them using a linear hyperplane. For a multiple-class problem, a generalization of LDA is used called multiple discriminant analysis (MDA), which applies several hyperplanes to separate the features. LDA and other linear discriminant methods, however, cannot solve nonlinear classification problems effectively, which commonly occur in the context of BCI (Linderman et al., 2008). Iturrate et al. (2009) use SWLDA for classification of a noninvasive P300 BCI for the automated navigation of a wheelchair. Other applications of LDA have been reported by Lemm et al. (2005), Galán et al. (2008), and Finke et al. (2009).

SVM, similar to LDA, uses hyperplanes to distinguish different classes. The major difference between the two is in the application of an optimal hyperplane that maximizes the distance between the hyperplane and each class using support vectors (boundary points between classes to be differentiated). Through the optimal hyperplane, SVM achieves a higher generalization for the classification, thus becoming more robust. SVM classifiers can be converted into nonlinear classifiers by converting the feature space into a higher-dimensional space using a kernel function, usually Gaussian or radial basis function (RBF; Junfei and Honggui, 2010; Patrinos et al., 2010; Wu et al., 2010). Spüler et al. (2012) used a RBF SVM to improve performance for P300 classification. Furdea et al. (2012) use RBF SVM for classification in a pseudo lie detection test along with several other classification methods including LDA. They report the best classification results by RBF SVM. Other examples of SVM are presented by Rakotomamonjy and Guigue (2008) and Hsu et al. (2012).

NNs are used extensively in many fields including the BCI field. They are capable of approximating any continuous function and solve multiple-class classification problems effectively (Freitag et al., 2011; Puscasu and Codres, 2011; Setiono et al., 2011; Graf et al., 2012; Hsiao et al., 2012; Osornio-Rios et al., 2012). White et al. (2010) used a combination of KF and NN to predict the user's intent for prosthetic limb control. Another application of NN in BCI is presented by Yang et al. (2007).

Bayesian classifiers set the decision boundaries based on probabilities in contrast to LDA, SVM, and NNs, which discriminate deterministically. Jin et al. (2012a) use a Bayesian LDA for the optimization of target-to-target intervals explained in the signal acquisition section above. Additional examples are presented by Shin et al. (2010) and Malik et al. (2011).

Devices

The final component of the BCI system is the output device. The initial purpose of BCIs was to provide a rehabilitation tool, but this purpose has now expanded to other applications (Lance et al., 2012). Because earlier BCI applications were intended for patients with severe neuromuscular disease, most of the output devices used in research are in the form of spellers or computer cursors (Kayagil et al., 2009; Shih et al., 2012). Further research intends to broaden this list by using augmented BCIs, which use improved sensors to acquire signals. BCI has been extended to nonrehabilitation purposes such as leisure and entertainment. Liao et al. (2012) demonstrated the use of wireless EEG-BCI for gaming control. The approach was to use attention levels to control an archery video game using the BCI. With three electrodes encased in a conductive fabric and foam setup, they were able to assess attention through FFT of the signal and demonstrated a reliable mechanism for control.

Galán et al. (2008) demonstrated asynchronous control for a wheelchair using EEG-BCI and a multiple LDA for feature extraction and a Gaussian classifier for classification. More recently, Huang et al. (2012) used ERS/ERD on both sides of the brain in an EEG-BCI to set different commands to control activation of a wheelchair.

BCI is also being used increasingly to control prosthetic or robotic devices. Pfurtscheller et al. (2003) used functional electrical stimulation (FES) in an EEG-BCI to control and restore hand grasp in a tetraplegic patient. Using foot motor imagery, the patient was able to control grasping of a cylinder with his disabled hand. Moritz et al. (2008) also used FES for wrist flexion in monkeys using cortical firing rates. Earlier approaches of movement control through BCI are given in Guger et al. (1999) and Lauer et al. (1999). Gancet (2012) presented the application of BCI to a lower limb exoskeleton for patients with spinal cord injury.

Cincotti et al. (2008) presented a BCI suite that provided control to multiple devices using a computer screen with icons each representing a device. It was tested for the directional control of a toy dog in a maze. This proposed suite has applications for control of in-house robots responding to the user's wish, such as opening the front door or calling for a caretaker.

Challenges

For BCI to move from the laboratory to real-life applications, a number of challenges must be overcome. Most BCI research is done under heavily controlled environment. The technology must reach a stand-alone status to be in the reach of patients and health providers (Fetz, 2007). Two possible setup approaches to BCI have emerged referred to as goal-oriented and control-oriented. The goal-oriented or cognitive BCI seeks to acquire the subject's objectives or desires instead of specific control. These systems require a complex output device to translate an objective such as 'reach a glass of water' to the action (Andersen et al., 2005, 2010). The output device needs to decipher obstacles and combination of movements to achieve the objective. The goal-oriented BCI attempts to mimic the complex pathway of motor control, which the control-oriented BCI bypasses (Figure 7).

Another challenge is the 'BCI illiteracy' (Hammer et al., 2012), that is, a percentage of people that are unable to use BCI due to advanced stages of neuromuscular diseases or other unknown reasons. In some cases, the patient is able to regain proficiency by switching from BCI approach. Yet, in some cases, such as in advanced stages of locked-in syndrome (LIS) or complete LIS (CLIS), the signals need for the BCI become challenging to acquire as the disease progresses (Birbaumer, 2006b; Kübler and Birbaumer, 2008).

For signal acquisition, invasive sensors currently face a reliability issue. These sensors lose signal quality with the passage of time due to the harsh environments inside the brain. They have not achieved the long-term reliability required for commercial applications (Schwartz et al., 2006). For noninvasive sensors, most require application of gels that make their implementation complicated and not ready-to-use. However, new sensors are currently being developed to overcome this problem (Liao et al., 2012). Another challenge is the long training times (Kreilinger, 2012) and to make single-trial classifications (Blankertz et al., 2011). Single-trial classification seeks to calibrate the device in one trial (or as close). Müller-Putz et al. (2005) reported training of an individual for an EEG-BCI using motor imagery in the relatively short time of 3 days, demonstrating the possibility of quicker training in the near future. These are only a sample of the challenges BCI currently faces.

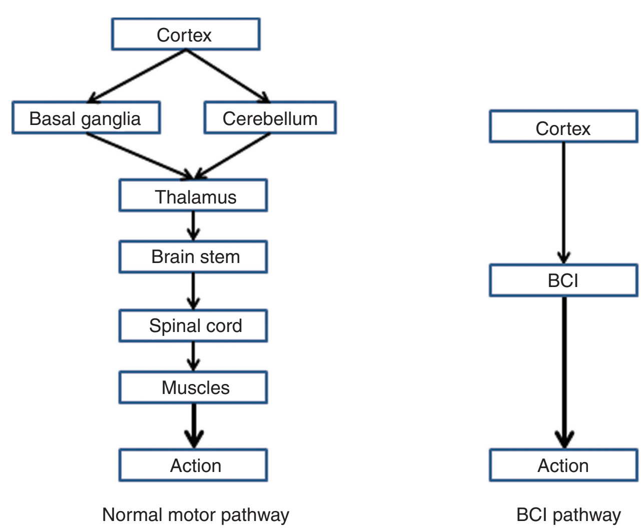

Figure 7 Normal central nervous system operation involves interaction of multiple components to produce motor action.
Current BCI only records actions of one of the components.

Conclusion

BCI holds a promising future for a broad range of applications. Current technological advances and applications in the field of BCI are growing fast. BCI, as a technology, has achieved a great deal of breakthroughs from control of robotic arms to three-dimensional cursor manipulation. A limited number of systems are currently in the market (Debener et al., 2012) and others under clinical trials (Malik et al., 2011). This number is expected to increase in the coming years.

Brilliant minds from around the world are doing research in BCI using multidisciplinary concepts and approaches. Growing exponentially in the past 15 years, BCI is a field with a bright future and great potentials for amazing technological breakthroughs.

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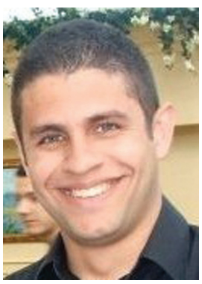

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