Brain–Computer Interfaces Handbook  
Technological and Theoretical Advances  
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Brain–Computer Interface

Publication details
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Published online on: 10 Jan 2018

How to cite :-  Chang S. Nam, Inchul Choi, Amy Wadeson, Mincheol Whang. 10 Jan 2018,  
Brain–Computer Interface from: Brain–Computer Interfaces Handbook, Technological and Theoretical Advances  
CRC Press  
Accessed on: 07 Jun 2023  

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1 Brain–Computer Interface

An Emerging Interaction Technology

Chang S. Nam, Inchul Choi, Amy Wadeson, and Mincheol Whang

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Abstract

During the last decades, a new capability has emerged by which the human brain can directly communicate with the environment, called a brain–computer interface (BCI), brain–machine interface (BMI), direct neural interface, or mind–machine interface (MMI). The BCI community has witnessed a substantial amount of work done on BCI technologies and many successful BCI applications. However, continuing effort is still needed to further optimize the capabilities, robustness, and usability of BCI systems for human use, including those who suffer from muscular disabilities such as amyotrophic lateral sclerosis, brainstem stroke, and severe cerebral palsy. This chapter reviews the state of the art of BCI as an emerging human–computer interaction technology. We first introduce a BCI classification scheme, along with different types of the signal recording methods and brain signal patterns for BCI operation. Next, the most commonly used signal processing techniques and feature extraction techniques are explained, in addition to classification methods used for identifying the user’s intentions. Finally, we present and discuss various types of BCI applications with an emphasis on the future of BCI research and development through inter- and multidisciplinary collaborations and ongoing communication among neuroscientists, engineers, psychologists, human factors professionals, clinicians, and rehabilitation specialists.

1.1 INTRODUCTION

Individuals with healthy motor functions may take for granted the complicated biological, chemical, and electrical processes that occur within their body in order for them to easily communicate and interact with the outside world. Although the processes are complex, healthy individuals are able to complete them without much thought or effort. However, when certain neuron pathways are severed or degeneration brought on by an injury or a disease occurs, what once were simple tasks may become impossible or very cumbersome to complete.

During the last decades, a new capability has emerged by which the human brain can directly communicate with the environment, called a brain–computer interface (BCI), brain–machine interface (BMI), direct neural interface, or mind–machine interface (MMI). BCI is defined as “a communication system in which messages or commands that an individual (Nam 2012) sends to the external world do not pass through the brain’s normal output pathways of peripheral nerves and muscles” (Wolpaw et al. 2002, p. 769). That is, BCIs offer a way of bypassing typical nerve pathways by providing novel output pathways in order to interact with a variety of applications that replace, improve, enhance, restore, and supplement the human user’s central nervous system output (Klein & Nam 2016; Nijholt & Nam 2015; Wolpaw & Wolpaw 2012). This is especially important for individuals with compromised neural tracts. For example, there are nearly 2 million people in the United States alone and many more worldwide who suffer from severe motor disabilities (Ficke 1992). Moreover, nearly 500,000 people suffer from locked-in syndrome worldwide (Moore & Kennedy 2000). Though research into brain–computer interfacing technology is still in early
phases on these benefits, many significant developments have been made. BCI applications now enable individuals, in particular those with severe motor impairments but cognitively intact, to write sentences (Birbaumer et al. 2000; Li et al. 2010, 2014), control an unmanned aerial vehicle control (Shi et al. 2015) and a prosthetic (Tyler-Kabara et al. 2015), play video games (Beveridge et al. 2015), perform a collaborative work (Li & Nam 2015, 2016; Nam et al. 2013), and create arts (Mullen et al. 2015), all through brain signal acquisition, signal processing, and interpretation.

BCI systems consist of several sequential steps, which can be divided into four categories: brain activity pattern generation, signal acquisition, feature extraction, and classification. First, brain activity can be represented by electrical activity, magnetic fields created by electrical activity, and blood oxygenation, and it differs in spatial and temporal characteristics depending on stimulus type, stimulus intensity, mental effort, and mental status. Second, brain activity can be measured through various brain imaging techniques in the signal acquisition phase. The appropriate technique should be chosen according to the type of brain activity to be measured and the purpose of the measurement, largely divided into invasive and noninvasive methods. Third, in the feature extraction step, only the important and interesting brain activities are extracted from the measured brain signals. Finally, the extracted brain features are analyzed through various algorithms to classify the user’s current intention and status.

In addition, BCI systems can be categorized as either active, reactive, or passive depending on the user’s attention and efforts (Brouwer et al. 2013; Mühl et al. 2014; Zander et al. 2010). While active/reactive BCI systems use brain activity that occurs with external stimuli (reactive BCI) or modulated mental efforts (active BCI) to directly control the application, passive BCI systems use spontaneously generated brain activity such as users’ cognitive state to utilize an additional signal to support and compensate ongoing human–computer interaction (Choi et al. 2017; Garcia–Molina et al. 2013; Khan & Hong 2015; Kim et al. 2017; Lim et al. 2012). In this chapter, only active and reactive BCIs will be introduced.

The goal of this chapter is to provide an overview of the state of the art of BCI as an emerging human–computer interaction technology. The outline of the chapter is as follows. This section features an example of illustrating how a typical BCI works, along with a classification scheme with which to catalog BCI systems. Section 1.2 discusses two main types of recording methods and six different brain signal patterns for BCI operation. Section 1.3 describes the most commonly used signal processing techniques that deal with artifacts and some of the feature extraction techniques that have become increasingly popular in BCIs. Section 1.4 covers different classification methods used for identifying the user’s intentions. Section 1.5 introduces various types of BCI applications. Finally, the conclusions are drawn in Section 1.6.

1.1.1 How Does a BCI Work?

Imagine being completely unable to move. You want to communicate, but cannot speak or even move your eyeballs. You cannot even use general assistive technologies such as an eye tracker and speech recognition system, because they still require some degree of motor control such as eyeball control and vocal-cord vibration. BCIs can offer an effective communication alternative purely through the use of human brain signals. Take a look at an anecdotal story illustrating how a person with severe motor disability can write an e-mail to his daughter, Samantha, using a P300-based BCI, along with a BCI system framework in Figure 1.1.

1.1.2 How Can BCIs Be Categorized?

In general, BCI systems can be categorized by brain signal pattern, stimulus modality, mode of operation, operation strategy, and recording method. Figure 1.2 illustrates how BCI systems compare against each other based on these criteria.

There are many kinds of brain signal patterns that can be used to communicate with a BCI (Bryant et al. 2016; Wadeson et al. 2015). A brain signal is a set of electrical impulses that flows on groups of active neurons (for more details, see Section 1.3). BCIs that are categorized by brain
Brain signals rely on different arrangements of impulses to communicate with the specific application. An example of a brain signal is P300 event-related potentials (ERPs) that reach a maximum positive peak in voltage about 300 ms after a stimulus onset (e.g., through the so-called oddball paradigm). Compared with other brain signals, P300 ERPs require little initial training—a huge advantage as compared to other brain signal types (Li et al. 2010; Powers et al. 2015). P300 can be evoked by visual, auditory, tactile, and even olfactory or gustatory paradigms (Linden 2011).

Another widely used brain signal type is steady-state evoked potentials (SSEPs), which are the electrical activity of the brain in response to stimulation of specific sensory nerve pathways, as distinct from spontaneous potentials. There are three kinds of SSEPs: steady-state auditory evoked...
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potentials (SSAEPs), usually recorded from the scalp but originating at the brainstem level (Hill et al. 2012); steady-state visually evoked potentials (SSVEPs) found within the occipital lobe of the brain caused by focusing on a steady pattern of visual stimuli, such as a regularly flashing light (Nam et al. 2015); and steady-state somatosensory evoked potentials (SSSEPs), a sinusoidal electrophysiological brain response elicited from mechanical vibrotactile stimulation delivered to the glabrous skin (e.g., fingertip), which is modulated by selective spatial attention (Giabbiconi et al. 2004). Among many SSEPs, SSVEP-based BCIs that utilize flickering light sources with different frequencies from either LED or LCD displays are well studied, because they could provide the quickest and most reliable path to communication (Volosyak 2011; Wang et al. 2008; Zhu et al. 2010). For example, when the user concentrates on a target stimulus with a certain frequency, that same frequency is synchronized to a certain area according to the modality (e.g., visual cortex for visual stimuli), and the amplitude at the frequency of the target stimulus is higher than those of the nontarget stimuli. The BCI system uses these distinct brain patterns to perform different actions (e.g., directions, on/off, and typing) according to the user’s selective attention (Müller-Putz & Pfurtscheller 2008; Muller et al. 2011; Wang et al. 2011a). A lesser used brain signal method is slow cortical potentials (SCPs), which are shifts in the cortical electrical activity lasting from several hundred milliseconds to several seconds (Gevensleben et al. 2014). Finally, there is sensorimotor rhythm (SMR), involving event-related desynchronization/synchronization (ERD/ERS), brain activity associated with imagining motor behavior.

There are two recording methods for use in BCIs (for more details, see Section 1.2). The safest and most prevalent of these methods is noninvasive (Han et al. 2015). This method requires equipment that either touches the scalp such as electroencephalogram (EEG) or near-infrared spectroscopy (fNIRS) or is otherwise outside of the cranium such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), or positron emission tomography (PET). Although there is controversy in categorizing PET as a noninvasive brain imaging method because of the radio-tracer injection process, they were classified as noninvasive methods in this chapter because they did not require surgical intervention (Coyle et al. 2007; Krepki et al. 2003; Vallabhaneni et al. 2005). Unlike noninvasive methods, invasive techniques require surgery in order to place signal receptors within the brain (Birbaumer 2006). Examples of invasive recording methods are intracortical neuronal recording and electrocochleography (ECoG).

Another way to categorize BCIs is through their Operation Strategy. This is the way in which a BCI elicits brain signals during use. A BCI that utilizes Selective Attention presents users with auditory, visual, or tactile stimulation that can elicit brain signal responses (e.g., Allison et al. 2008; Zhang et al. 2010). Cognitive Efforts, another operation strategy, rely on biofeedback to train users to maintain a desirable level of brainwave frequency amplitude (e.g., Kamiya 1971). Some BCIs employ the unique operation strategy of Motor Imagery, which allows the user to imagine muscle movements, in order to cause a spike in neuronal activity in the motor cortex (e.g., Pfurtscheller & Neuper 2006).

The Mode of Operation for a BCI is the underlying way in which brain signals are elicited. They are either synchronous or asynchronous. Synchronous BCIs are cue based; information is presented to the user in order to elicit certain brain signal responses (e.g., Hazrati & Erfanian 2010). Asynchronous BCIs, on the other hand, are self-paced; they are controlled through user intention in the user’s desired timing (e.g., Leeb et al. 2007).

Finally, BCIs can be categorized by their Stimulus Modality, or the form in which stimulus is presented to the user: visual (e.g., Sellers & Donchin 2006), auditory (e.g., Nijboer et al. 2008), tactile (e.g., Brouwer & van Erp 2010), or hybrid, which combines multiple BCIs such as imagined movement and visual attention, or P300 and SSVEP (Pfurtscheller et al. 2010a; Yin et al. 2013).

1.2 SIGNAL ACQUISITION METHODS

BCIs require a neuroimaging or neurophysiological device to acquire and transmit the brain signals from brain to computer. In general, neuroimaging methods are categorized by invasiveness of
the recording methods, but can be further classified by spatial/temporal resolution, direct/indirect measurement, and complexity/price. Each recording technique has strengths, weaknesses, and specific uses that help researchers decide which device is relevant to their study. Figure 1.3 visually compares different recording methods discussed in more detail in the following sections.

1.2.1 NONINVASIVE RECORDING METHODS

A noninvasive recording technique uses sensors placed on the skin, such as the scalp, or machinery that surrounds the cranium in whole. Two types of noninvasive recording methods discussed in this section include (1) direct measures that detect electrical (e.g., EEG) or magnetic activity (e.g., MEG) of the brain, and (2) indirect measures of brain function reflecting brain metabolism or hemodynamics of the brain (e.g., fMRI, fNIRS, and PET) that do not directly characterize the neuronal activity. Unlike invasive recording methods, these noninvasive techniques do not require surgery, internal chemical or machine implantation, or needle insertion in order to receive and record neural activity (Bhattacharyya et al. 2015).

1.2.1.1 Electroencephalography

One of the most popular noninvasive neurophysiological recording techniques is electroencephalography, or EEG. This method measures electrical activity in the brain through the use of surface electrodes placed on the scalp (Niedermeyer & da Silva 2005). The first human EEG was recorded by Hans Berger, a German psychiatrist, in 1924.

The neurophysiological origin of EEG signals is the pyramidal neurons of the cortex (Cantor & Evans 2013). An electrical impulse is sent down the axon and into the synapse every time neurons are fired during excitation. Since electrical signals are not able to cross neuronal boundaries, a chemical reaction is created between neurons. This chemical reaction is triggered by the electrical impulse and causes an action potential. An action potential is the process of neuron depolarization, followed by repolarization. Chemical information can begin flowing through the synaptic cleft when a neuron is at its resting polarization level. The flow causes the depolarization, and repolarization is necessary before more chemical information can flow through the synapse again (Nunez 1995). EEG measures the electrical current, which Teplan explained as “that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex” (Teplan
Because of the distance and impedance of bone and skin between the electrodes and the cerebral cortex, the EEG cannot accurately detect single neuron excitations. Instead, the EEG picks up local current flows on groups of active neurons within the cerebral cortex (Teplan 2002; Tonet et al. 2006).

Neural oscillations that are observed in EEG signals are popularly called “brainwaves,” reflecting different aspects when they occur in different locations in the brain (Table 1.1). These brainwaves are identified by frequency (in hertz or cycles per second) and amplitude in the range of microvolts (μV or 1/1,000,000 of a volt). Each brainwave has its own set of characteristics representing a specific level of brain activity and mental states (Mühl et al. 2014). For example, Delta brainwaves reflect slow, loud, and functional mental states that prevail during the late sleep (Steriade et al. 1993), while the power decrease at the alpha band correlates to the presence of mental imagery (Pfurtscheller & Lopes da Silva 1999).

In order to record EEG signals, a head set consisting of an EEG cap with at least three electrodes (i.e., a ground, a reference, and a recording electrode) is needed (Figure 1.4b). In addition, an amplifier, an A/D converter, and a computing device (such as a computer) are necessary (Nicolas-Alonso & Gomez-Gil 2012). Electrodes are typically made of silver, silver chloride, or gold and can be considered wet, which requires conductive gel to be placed between electrode and scalp, or dry, where the electrode is placed directly onto the skin (Peng et al. 2015, 2016). Measurements from all electrodes are referred to one common electrode, called “reference” electrode (Schalk & Mellinger 2010). The active and reference electrodes serve as the signal receptors for potential difference comparisons. The ground electrode serves as the baseline of brainwave signals that helps weed out irrelevant data from the active and reference signals.

Correct EEG electrode placement is important to ensure proper location of electrodes in relation to cortical areas so that they can be reliably and precisely maintained from individual to individual. The international 10/20 system has been an internationally recognized standard system for electrode positioning with 21 electrodes for half a century (Homan et al. 1987; Jasper 1958). Under the 10/20 system, the skull is divided into six areas from nasion to inion with interval rates of 10%, 20%, 20%, 20%, 20%, and 10% (Fp: frontopolar, F: frontal, C: central, P: parietal, and O: occipital, respectively), and also divided into the same ratios from left to right preauricular points (T3: temporal, C3: central, Cz, C4, and T5, respectively) (Klem et al. 1958). With the advent of multichannel EEG acquisition systems and the concurrent development of topographic and tomographic signal

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<table>
<thead>
<tr>
<th>Brainwave</th>
<th>Sample Pattern</th>
<th>Frequency (Hz)</th>
<th>Amplitude (μV)</th>
</tr>
</thead>
<tbody>
<tr>
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<td><img src="image" alt="Delta" /></td>
<td>0.5–4</td>
<td>100–200</td>
</tr>
<tr>
<td>Theta</td>
<td><img src="image" alt="Theta" /></td>
<td>4–8</td>
<td>5–10</td>
</tr>
<tr>
<td>Alpha</td>
<td><img src="image" alt="Alpha" /></td>
<td>8–12</td>
<td>20–80</td>
</tr>
<tr>
<td>SMR</td>
<td><img src="image" alt="SMR" /></td>
<td>12–15</td>
<td></td>
</tr>
<tr>
<td>Beta</td>
<td><img src="image" alt="Beta" /></td>
<td>15–25</td>
<td>1–5</td>
</tr>
<tr>
<td>Gamma</td>
<td><img src="image" alt="Gamma" /></td>
<td>25–60</td>
<td>0.5–2</td>
</tr>
</tbody>
</table>
source localization methods, however, the international 10/20 system has been extended to higher-density electrode settings such as the 10/10 and 10/5 systems, allowing more than 500 electrode positions (for the effectiveness of 10/20-derived systems, see Jurcak et al. 2007). Figure 1.4a and b demonstrate the 10/20 international system of electrode placement and an example montage based on the 10/10 system, respectively. To accurately identify the location of scalp electrodes, anatomical landmarks should be determined for the essential positioning of the electrodes: (1) the nasion, which is the point between the forehead and the nose; (2) the inion, which is the lowest point of the skull from the back of the head and is normally indicated by a prominent bump; (3) the pre-auricular points anterior to the ear. The numbers “10” and “20” refer to the fact that the distances between adjacent electrodes are either 10% or 20% of the total front–back or right–left distance of the skull. Each site has a letter to identify the lobe (i.e., F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal, and Occipital, respectively), the Z(ero) to refer to an electrode placed on the midline, and

![Diagram of electrode placement](image)

**FIGURE 1.4** (a) The 10/20 international system of electrode placement. (b) An example montage based on the 10/10 system, which measures O1 and O2 with Oz bipolar method to elicit SSVEPs.
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a number to identify the hemisphere location (i.e., odd and even numbers referring to the left and right hemispheres, respectively). Also note that the smaller the number, the closer the position is to the midline. In Figure 1.4b, for example, electrode O1 identifies the left occipital, C4 identifies the right central, P3 identifies the left parietal, and A1 identifies the left ear reference.

Currently, EEGs are among the most popular techniques for brain–computer interfacing technology, making up 68% of BCI research articles published in 2007–2011 as shown in Figure 1.5 (Hwang et al. 2013). It is noninvasive, inexpensive, and portable, making it a popular device in current research. It does not, however, provide high spatial quality information on the location of brain signal activation. In addition, it is mathematically difficult to accurately compute the distribution of currents within the brain that generated these signals. This is referred to as the “inverse problem” (Castaño-Candamil et al. 2015).

1.2.1.2 Magnetoencephalography

MEG is another recording technique for noninvasively measuring the magnetic fields generated by neuronal activity of the brain. When active neurons generate electric currents, a miniscule magnetic field is created (Hämäläinen et al. 1993). This magnetic field is impossible to detect from the activation of a single neuron, but when many neurons fire together, a larger and more easily detectable magnetic field is created. MEG combines functional information from the magnetic field recordings with structural information from other anatomical images, such as magnetic resonance imaging (MRI).

The hardware required includes the MEG scanner that is equipped with a superconducting quantum interference device or SQUID that was invented in the 1960s as a sensor of magnetic field changes. The principle features of MEG are as follows: (1) a direct measure of brain function, (2) a very high temporal resolution on the order of milliseconds, (3) an excellent spatial resolution with millimeter precision, and (4) a noninvasive method that does not require the injection of isotopes or exposure to x-rays or magnetic fields (Uhlhaas 2015).

Despite MEGs having better spatial resolution and very similar temporal resolution to EEG, they are used less in BCI research—accounting for only 2% of relevant literature (Figure 1.5). This is likely due to the nonportability and high cost. In addition, MEG requires highly sensitive instrumentation and sophisticated methods, such as a magnetically shielded room for eliminating environmental magnetic interference (Tonet et al. 2006).
1.2.1.3 Functional Magnetic Resonance Imaging

Functional magnetic resonance imaging or functional MRI (fMRI) is a noninvasive, functional neuroimaging method that indirectly measures neuronal activity of the brain by identifying the hemodynamic response, known as the blood oxygen level–dependent (BOLD) contrast.

The fMRI principle is based on the so-called neurovascular coupling in which neuronal activation and metabolism with regional cerebral blood flow (rCBF) and regional cerebral blood oxygenation (rCBO) are tightly coupled (Lindauer et al. 2010). When neurons fire, the surrounding blood of the firing neurons experiences a decrease in oxygenated blood, and then a rapid increase in rCBF and oxygen metabolism (cerebral metabolic rate of oxygen, CMRO2) as more oxygenated blood and glucose flow to the area for use in energy consumption (Dunn et al. 2005). The increased oxygen metabolism then converts the oxyhemoglobin in the blood (oxy-Hb) to the deoxygenated blood (deoxy-Hb). On the other hand, a disproportionately large increase in rCBF leads to a washout of deoxy-Hb from the activation area, resulting in a decrease of deoxy-Hb and an increase of oxy-Hb (Lindauer et al. 2001). It has long been suggested that rCBF increases exceed CMRO2 increases by a factor of 2–10 (Lin et al. 2008). Deoxygenated blood transmits greater magnetic fields, interfering with the MRI’s magnetic field. However, oxygenated blood creates less intense magnetic fields and therefore interferes with the MRI less, allowing activated neuron areas to be viewable owing to an increase in oxygenated blood flow (Weiskopf et al. 2004).

fMRI data imagery is shown very close to the blood flow, within approximately 1 mm of accuracy and within approximately 1 s of oxygenated blood flow increase (Nicolas-Alonso & Gomez-Gil 2012). That is, fMRIs offer highly accurate spatial information that could be very useful for detailed BCI tasks, but their temporal resolution is quite slow compared to techniques such as EEG or MEG. In addition, fMRI does not measure neural activity directly, but allows for inference of neural activity from measured blood volume and blood flow. Other downfalls include size, and expense of use, making them ineffective and impractical for everyday purposes. Research articles discussing fMRI-BCIs accounted for only 2% of the literature (Figure 1.5).

1.2.1.4 Functional Near-Infrared Spectroscopy

Similar to fMRI, functional near-infrared spectroscopy (fNIRS) relies on the changes in oxygenated and deoxygenated blood in the cerebral cortex. Oxygenated and deoxygenated blood absorb light at different rates. For example, deoxygenated blood absorbs more light below 800 nm light, while oxygenated blood does above 800 nm (Giardini et al. 2000; Wilcox et al. 2008). fNIRS takes advantage of the differences in light absorption to detect neuronal activity.

The hardware required for fNIRS includes an infrared light source, a light detector, signal processing devices, and a computing device such as a computer (Nicolas-Alonso & Gomez-Gil 2012). Through the use of an infrared light placed on the scalp and a light detection device placed nearby, levels of neuronal activation can be detected. The infrared light penetrates the scalp and bone and the upper level of the cerebral cortex and, depending on the amount of oxygenated or deoxygenated blood in the area, a certain amount of light is allowed to pass through, and some light is reflected back out of the scalp (Tonet et al. 2006). This penetrating light is identified by the light detector. As discussed in Section 1.2.1.3, neuron firings cause oxygenated blood to rush to the surrounding area, bringing glucose for energy. This shift in blood oxygen levels causes the light to act differently, providing a change in the signal sent to the light detector, which is then processed and recorded.

fNIRS BCIs are not nearly as popular as EEG systems. Research articles focused on fNIRS BCIs accounted for just 3% of the relevant published material (Figure 1.5). Coyle and colleagues (2007) found that fNIRS BCIs can be accurately and simply commanded through motor imagery and proper light and detector placement. Because of the latent nature of the blood flow response to neuron activated sites in the cerebral cortex, the temporal resolution is slower in fNIRS than in EEG or invasive methods that we will discuss in Section 1.2.2. In addition, fNIRS signals are vulnerable to motion and pulse artifacts caused by physical motions and heartbeats during the measurement,
respectively (Matthews et al. 2008). Thus, fNIRS should be preprocessed with elaborate artifact removal methods, such as ICA and wavelet, to improve the signal-to-noise ratio (SNR) before feature extraction. fNIRS is also limited to detecting changes in the surface areas of the brain, as the infrared light can only penetrate so far. It is, however, a portable and inexpensive option, making it a decent candidate for home settings (Castermans et al. 2014).

1.2.1.5 **Positron Emission Tomography**

PET is a noninvasive, three-dimensional (3D) radiation or nuclear medicine imaging technique that is used to measure the functional processes within the human body, including neural activity (Stollfuss et al. 2015). The PET principle is based on the phenomenon of positron annihilation. That is, when a positron passes through matter, two photons are simultaneously emitted in almost exactly opposite directions. This method relies on a positron-emitting tracer atom that is introduced into the bloodstream in a biologically active molecule, such as fludeoxyglucose, which acts similarly to glucose in the body. Fludeoxyglucose will concentrate in areas with higher metabolic needs. Over time, this tracer molecule emits positrons, which are detected by a sensor. The spatial location of the tracer molecule in the brain can be determined based on the emitted positrons. This allows researchers to construct a 3D image of the areas of the brain that have the highest metabolic needs, typically those that are most active (Townsend 2008).

In general, the arrangement of a PET machine consists of coincidence detectors, scintillating crystals, and block detectors. However, most BCI research utilizing PET is limited to clinical studies because of its disadvantages, including its high cost and lower half-life of the radionuclide (Bhattacharyya et al. 2015; Boecker et al. 2002; Grafton et al. 1996; Winstein et al. 1997).

1.2.2 **Invasive Recording Methods**

Invasive recording methods are neuroimaging techniques in which the electrodes make direct contact with brain tissue. These methods can provide more accurate spatial and temporal information, but come at a greater risk to the individual. Two types of invasive recording methods—electrocorticography (ECoG) and intracortical neuron recording (INR)—are discussed in this section.

1.2.2.1 **Electrocorticography**

ECoG is also referred to as intracranial EEG, a method of recording electrical impulses with electrodes that are placed on the brain in order to bypass impeding material such as the scalp and skull. The physiology behind ECoG is the same as that for EEG, but sensitivity in ECoG is greater because of the close nature of the electrodes to the neurons. In order for the electrodes to be placed on the surface of the cortex, surgery involving removing part of the skull is required. A group of electrodes spaced about 1 cm apart from each other are placed lightly on either the epidural or subdural layer of the brain. The spacing and grouping of the electrodes are kept consistent through the use of clear, flexible grid structure. Electrodes can be placed temporarily and patients can complete tasks while cognizant during the surgical procedure or they can be placed permanently for use outside of the operating room.

ECoG offers higher temporal (Henle et al. 2013) and spatial resolution than EEG (e.g., tenths of millimeters vs. centimeters) (Freeman et al. 2003), broader bandwidth (e.g., 0–500 Hz vs. 0–50 Hz) (Staba et al. 2002), higher characteristic amplitude (i.e., 50–100 μV vs. 10–20 μV) (Schalk & Mellinger 2010), and far less vulnerability to artifacts such as EMG (Ball et al. 2009) or ambient noise (Schalk & Mellinger 2010). Leuthardt and colleagues found that users of ECoG BCIs had a quicker training rate than those who used EEG BCIs (Leuthardt et al. 2004). Invasive techniques accounted for 32% of the literature over the 2007–2011 period (Figure 1.5). Even still, the invasive nature of ECoG poses obvious risks, including the chance that electrodes can unintentionally move...
from their initial placement. In addition, patients are also at risk of postoperative infection and tissue reaction (Castermans et al. 2014; Daly & Wolpaw 2008; Mestais et al. 2015). Furthermore, the long-term stability of ECoG signals has not been well researched.

1.2.2.2 Intracortical Neuron Recording

INR is a technique that allows for neuronal activity in the gray matter of the brain to be recorded. Just like the EEG and ECoG, this technique relies on the electrical impulses of the brain. Through the use of a penetrating electrode made of glass, platinum or tungsten, placed near or within a neuron cell body, electrical currents are able to be observed. This technique can be so precise it detects one single neuron, known as single unit activity (SUA). Or it can be used to detect multiple neuronal impulses, known as multi-unit activity (MUA). Or more generally, INR can identify local field potentials (LFPs), which are the electrical impulses in the surrounding area of the electrode placement (Homer et al. 2013).

Research into INR began with animal subjects and has since been applied to humans—especially those with severe motor disorders. Coupled with ECoG, research into BCIs using these methods accounted for 32% of the literature (Figure 1.5). The spatial resolution of INR is very detailed and surpasses all other types of invasive and noninvasive neuroimaging techniques, whether recording SUA, MUA, or LFPs. The temporal resolution is similar to that of ECoG. This method has associated risks, including the diminishing of signal acquisition through the electrode over time, tissue damage, foreign body rejection, or electrode movement within the brain (Gunasekera et al. 2015).

1.2.3 Brain Signal Patterns for BCI Operation

Every BCI is created to respond to a certain type of brain signal. Figure 1.6 illustrates the most popular types of brain signals used for operating BCIs. What follows is an overarching review of the brain signal patterns in terms of their physiological bases, initial training requirement for use, and the rate at which information is transferred from brain to application. However, only neuroelectric signals, such as EEG, are discussed in the following sections, because it not only can cover most of brain patterns (P300, SSEP, and ERD/ERS) as shown in Figure 1.2 but also is the most studied BCI system because of its simplicity in application (Niedermeyer & da Silva 2005).

1.2.3.1 P300 ERPs

The P300 wave is an ERP component of the EEG that reaches a maximum positive peak in voltage about 300 ms after a stimulus onset (Figure 1.6). It is most commonly elicited in an “oddball” paradigm when a subject responds to target stimuli that occur infrequently and irregularly within a series of standard stimuli that occur frequently and regularly (Huettel & McCarthy 2004). The amplitude of the P300 wave is maximal at central and parietal scalp regions (e.g., Pz), varying with the improbability of the targets. Its latency is proportional to the difficulty of discriminating the target stimulus from the standard stimuli (Picton 1992). The stimulus can be visual (Bledowski et al. 2004), auditory (Musiek et al. 2005), or even tactile (Brouwer & van Erp 2010).

Since the P300 response to external stimuli is automatic, initial training is not required to teach users to control their brain signals. A short training may be necessary for certain applications using the P300 wave owing to complicated interfaces or for the sake of the classification algorithm (discussed in Section 1.4). Guger et al. (2009) found that healthy individuals were able to achieve high accuracy levels with very little training time. The high levels of accuracy coupled with the low-cost, easy-to-use EEGs used to measure this response make the P300 wave a useful and popular tool for BCIs. P300 BCIs can also provide the user with a large amount of options to choose.

1.2.3.2 Steady-State Evoked Potentials

When presented with steady-state (i.e., vibratory in nature) stimuli, the rhythmic brain activity in the associated cortical area will be generated, mimicking the frequency of the stimuli (Figure 1.6).
The stimulus can be visual, auditory, or even tactile. For example, SSVEPs are currently the most popular choice for brain signals in BCI operations. SSSEPs to be elicited by vibrotactile stimuli (Severens et al. 2010) and SSAEPs to be elicited by auditory stimuli (Hill et al. 2012) have also been used in BCI research.

BCIs that use SSVEPs as their control signal usually have lights or other stimuli that flash at differing frequencies. Each light or pattern is linked with a control option (e.g., direction, on/off, etc.) for the BCI application. For example, a 9-Hz flickering light-emitting diode (LED) is for turning on TV, while an 11-Hz LED is for turning off TV. Selections are made through users focusing on whichever stimulus is associated with the action they want to perform. The neuroimaging device records the frequency of the brain signals and interprets the selection. SSVEP BCIs do not require
training and provide the quickest and most reliable communication in EEG BCIs (Volosyak 2011; Wang et al. 2008; Zhu et al. 2010). However, as SSVEP BCIs required eye gaze and focus, they may not be suitable for users with severe motor disabilities and those who are visually impaired (Nicolas-Alonso & Gomez-Gil 2012). Moreover, staring for long periods of time at flashing lights or stimulus may also induce fatigue.

1.2.3.3 Sensorimotor Rhythms

SMRs are brainwave patterns recorded in the somatosensory and the motor cortices (Figure 1.6). These patterns can change due to either movement or imagined movement. There are two rhythms relevant to SMRs: the Mu band (7–13 Hz, alpha band present in the somatosensory and motor cortices) and the Beta band (14–30 Hz). Real and imagined movement creates what are known as event-related desynchronization (ERD) and event-related synchronization (ERS).

ERD is the decrease in frequency band amplitude in the sensorimotor areas of the brain related to movements or imagined movement. ERS is the increase in frequency band amplitude in the
sensorimotor areas immediately after movement or imagined movement (Graimann et al. 2010). Mu band ERD starts right before movement onset, reaches the maximal ERD shortly after movement onset, and recovers its original level within a few seconds. In contrast, the beta band shows a short ERD during the initiation of movement, followed by ERS that reaches the maximum after movement execution. This ERS occurs when the Mu rhythm is still attenuated (Nicolas-Alonso & Gomez-Gil 2012). In order for the signal emitting from these movements or imagined movements to be strong enough, the area of usage in the brain needs to be large enough. The hands, feet, and tongue are represented over large areas of the somatosensory and motor cortices owing to the complex and regular motion they produce. BCIs using SMRs often use the imagined movement of feet, hands, or tongue for the purposes of control (Graimann et al. 2010). Since outside stimulation is not required for this BCI type, and the brainwaves and interactions with the BCI are controlled by thought processes, training—sometimes extensive training—is required, employing techniques such as operant conditioning.

1.2.3.4 Slow Cortical Potentials

Generalized changes in the polarization levels of superficial cortical neurons are known as slow cortical potentials (SCPs) (Strehl et al. 2014). A change in the direction of negative polarity is associated with increased cortical activity or movement, while a change in the direction of positive polarity is associated with decreased cortical activity and calm (Figure 1.6). SCPs are generally analyzed through the Thought Translation Device. Extensive and intensive training is required, using individualized cognitive and behavioral strategies (Studer et al. 2014). SCPs take anywhere from 1 s to several seconds to develop, and therefore the information transfer rate is quite slow compared to SSVEP and visual P300, which does not allow for much efficiency in use. Similar to SMR BCIs, SCP BCIs do not rely on external stimulus such as visual stimuli of SSVEP in order to elicit brainwave patterns to use to influence the interface. Instead, users control their thought processes in order to interact with the BCI.

1.3 IMPROVING SIGNAL QUALITY AND FEATURE EXTRACTION METHODS

In this section, we briefly discuss some methods to improve signal quality and extract important features (e.g., Nicolas-Alono & Gomez-Gil 2012). First, a discussion of the different artifacts, their primary causes, and the main methods used to remove them is presented. Next, spatial filtering techniques used to enhance the quality of brain signals are discussed. Finally, an example illustrating how artifact removal methods and spatial and temporal filtering techniques are implemented in an SSVEP-based BCI system is presented, along with a summary of the feature extraction techniques widely used for BCI applications.

1.3.1 Removing Noisy Signals and Artifacts

The raw signals recorded from the brain during the signal acquisition stage often contain other information that reduces signal quality (Wittenberg et al. 2017). This extra information is collectively known as “noisy signals” or “artifact” and is added by environmental and physiological sources (Wolpaw & Wolpaw 2012). The initial step in feature extraction is to remove the artifacts and excess noise because their presence hinders BCI performance. Figure 1.7 gives an overview of the different artifacts and their primary causes.

Since eye blinking, heart rate, and movement are all uncontrollable body functions that unavoidably intrude on the desired brain signal output necessary for controlling a BCI, preventative measures need to be taken. The signals caused by physiological sources are counteracted by recording electrical output at, or near, the site of the source so that those signals can be temporally compared to the overall brain signal recording. When a shift in the brain signal correlates to the signal recorded by the EKG, EOG, or EMG, that signal is no longer considered for controlling the BCI.
Other unavoidable electrical signals that interfere with brain signal data stem from power lines, incorrect electrode contact, and electrode drift. The electrode drift indicates abnormal peaks and trends in EEG signals, and it can be caused by eye-related artifacts, electrode cable movements, and unstable electrode contacts. A notch filter is applied at 60 Hz (main frequency in the United States) or 50 Hz (main frequency in Europe) to remove power line data from the incoming signal, while statistical analysis and visual monitoring are used to overcome irrelevant signals from issues with the EEG cap.

1.3.2 Spatial Filtering

The purpose of a spatial filter is to enhance sensitivity to particular brain sources, improve source localization, and suppress certain artifacts (Krusienski et al. 2012). Two main types of spatial filtering methods have been commonly used for BCIs: referencing and data-dependent spatial filters.

1.3.2.1 Referencing Methods

Electric potentials are only defined with respect to a reference electrode that needs to be placed on a presumably “inactive” zone such as the mastoid, earlobe, nose, or base of the neck. Since no position on the scalp can have zero potentials, however, several methods have been used to eliminate task-unrelated background noise from the electrodes (Lee et al. 2017). Example methods include the common average reference (CAR), surface (small or large) Laplacian, and bipolar reference (Figure 1.8).

FIGURE 1.7 Artifacts and noise sources, causal factors, and removal methods. EKG/ECG, electrocardiography; EMG, electromyography; EOG: electrooculography.

FIGURE 1.8 The example of referencing methods. (a) Small and larger surface Laplacian method: inner four grid circles are used for the small surface Laplacian method while outer four checkers are used for the large surface Laplacian method. (b) Bipolar and CAR method: grid circles are used for the bipolar method while checkers are used for CAR method.
The choice of the EEG reference is a critical issue, because it can improve the SNR of the electrical activities at target and reference sites (Vatta et al. 2005) and may produce topographic distortion if not appropriately selected (Alhaddad et al. 2012).

1.3.2.1.1 Bipolar Reference
The simplest referencing method is bipolar reference, which is performed by measuring a potential difference between two electrodes placed anteriorly and posteriorly or to the left and right of the target position, or with bipolar chains. A bipolar reference is calculated by subtracting the secondary electrode \( j \) from the recording electrode \( i \):

\[
V_{\text{bipolar}(i,j)} = V_{(i)} - V_{(j)}. 
\]

One advantage of bipolar reference is that it is easy to remove artifacts with relatively less electrodes, which occur at the same temporal, on the same position, and with the same amplitude such as eye blinking and jaw clenching. Moreover, it can easily detect spatial differences over a larger area by chain bipolar reference (Evans & Abarbanel 1999). For these reasons, bipolar reference has been commonly used for BCI applications, including motor imagery BCIs (e.g., Ramoser et al. 2000) and SSVEP-based BCIs (e.g., Wang et al. 2004). The disadvantages, however, are that measuring a specific position is not possible because of indirect measurement and that the information from the electrode could be cancelled out when the brain activities at two positions are temporally and spatially similar to each other (Arciniegas et al. 2013). An example of the bipolar method is shown in Figure 1.8a with grid circles while the gray circle is the target electrode.

1.3.2.1.2 Surface Laplacian Reference
The surface Laplacian reference methods can enhance EEG spatial resolution by filtering out spatially broad features among nearest-neighbor or next–nearest-neighbor electrodes. The procedure can be expressed in the following formula:

\[
V_{\text{LAP}(i)} = V_{(i)} - \sum_{j \in S(i)} w_{i,j} V_{(j)}, 
\]

where \( w_{i,j} = \frac{1}{d_{i,j}} \) and \( d_{i,j} = \sum_{j \in S(i)} \frac{1}{d_{i,j}} \).

where \( S_{(i)} \) is the subset of the four adjacent electrodes surrounding the target electrode \( i \) (i.e., anterior, posterior, left and right). If the distance from the target electrode \( i \) to an adjacent electrode \( j \), \( d_{i,j} \), is identical for all \( j \)'s, then \( w_{i,j} \) is just a reciprocal of the number of adjacent electrodes, 0.25. Note that the electrodes are not weighted according to their distance (Schalk & Mellinger 2010).

The advantages of the surface Laplacian reference method are that it can be used as a spatial filter to eliminate spatial noise (McFarland et al. 1997) and that it is a reference-independent approach (Tenke & Kayser 2005). However, it is limited in its ability to detect widely distributed brain activity on both the target and adjacent electrodes. An example of small (large) surface Laplacian methods is shown in Figure 1.8b where grid (checkerboard) circles are for adjacent electrode, while the gray circle is the target electrode.
1.3.2.1.3 Common Average Reference

The CAR is one of the common referencing methods where the potential is averaged over all electrodes (including the recording electrode) and is subtracted from the recording electrode. The procedure can be expressed in the following formula:

\[ V_{\text{CAR}(i)} = V(i) - \frac{1}{N} \sum_{j=1}^{N} V(j), \]

where \( N \) is the total number of electrodes used for the recording and \( V(j) \) is the potential between the recording electrode \( i \) and the reference electrode \( j \).

The CAR works well if small signal sources need to be identified in very noisy recordings (Cooper et al. 2003) or when 30 or more electrodes are used (Schmidt & Segalowitz 2007). The advantage of the CAR method is that it can measure spatially broad activities that cannot be measured by bipolar or surface Laplacian reference methods (Carmeli et al. 2012). An example of the CAR method is shown in Figure 1.8a with checkerboard circles while the gray circle is the target electrode.

1.3.2.2 Data-Dependent Spatial Filtering

It is often hard to know the exact characteristics of relevant brain activity. In this case, a spatial filter can be derived directly from each BCI user’s data. Three common methods for deriving data-dependent spatial filters are introduced: principal component analysis (PCA), independent component analysis (ICA), and common spatial patterns (CSP).

1.3.2.2.1 Principal Component Analysis

PCA is a nonparametric statistical data analysis method for significant feature extraction and data reduction, which is accomplished by re-expressing a data set (Shlens 2014). In PCA, EEG data can be explained as a linear combination of principal component coefficients and associated weights by finding the eigenvectors of a covariance matrix (Kayser & Tenke 2003). The principal components of the signals can be derived by the singular value decomposition method (Wall et al. 2003). The EEG signal matrix with \( n \) rows of temporal data (sampled data) and \( m \) columns of spatial data (channels) can be decomposed into three components such as \( U \), \( S \), and \( V \) matrices as

\[ X = USV^T, \]

where \( U \) is an \( n \times m \) matrix with \( U^TU = I \), \( S \) is an \( m \times m \) diagonal matrix, and \( V \) is an \( m \times m \) orthonormal matrix with \( V^TV = VV^T = I \). Then, the covariance matrix as is written as

\[ C = \frac{1}{n-1} XX^T = \frac{1}{n-1} US^2U^T, \]

The eigenvectors and corresponding eigenvalues of \( XX^T \) are calculated, and then select \( m \) eigenvectors have the largest \( m \) eigenvalues for the new basis because higher eigenvalues present more data characteristics than lower eigenvalues.

PCA has been proven especially effective at reconstructing the signals with fewer artifactual components in EEG signals (e.g., Boye et al. 2008) and reducing feature space dimensionality (e.g., McFarland et al. 2006).
Brain–Computer Interface

1.3.2.2 Independent Component Analysis

The biological signals are measured by a set of electrodes, where each electrode receives an unknown combination of the source signals. ICA is a useful technique to separate unobserved and independent signals from the mixed signal containing artifacts such as facial EMG and blinks with the assumption that these signals are mutually independent (McMenamin et al. 2010). In the simple ICA, it is assumed that there are \( n \) random \( x_i \) arranged into a vector \( \mathbf{x} = (x_1, x_2, \ldots, x_m)^T \), which are linear combinations of \( n \) unknown independent variables \( s_i \) arranged into \( (s_1, s_2, \ldots, s_n)^T \) (Mozaffar & Petr 2002). Thus, the linear combination form of the model is presented as

\[
\mathbf{X} = \mathbf{AS},
\]

where \( \mathbf{X} \) consists of the \( N \) observed signals, \( \mathbf{A} \) is an unknown \( m \times n \) “mixing matrix” that contains mixing coefficients, and \( \mathbf{S} \) is a matrix consisting of coefficients \( s_i \).

Then, the goal of ICA tries to find a best possible estimation of unmixing or separation matrix \( W, W \approx A^{-1} \), such that

\[
\mathbf{Y} = \mathbf{WX} = \mathbf{W(AS)} = \mathbf{S} = \mathbf{S}.
\]

While any ICA algorithm can be used to estimate the one-dimensional ICA components, large computational savings can be held by using an algorithm that makes use of pre-whitening such as FastICA.

Because of the main advantage of ICA of not requiring a priori knowledge or hypotheses, it has been commonly used as a preprocessing tool (e.g., Gao et al. 2010) or a classifier (Chiappa & Barber 2006). The shortcoming of the basic ICA estimation is, however, that the high computational cost comes about as a result of using high dimensions (Hyvärinen & Oja 2000).

1.3.2.2.3 Common Spatial Patterns

CSP is a data-driven supervised decomposition technique that transforms the multichannel EEG signal into a variance matrix to discriminate between two different classes (for a detailed theoretical description of CSP, see Wang et al. 2005). CSP helps to discriminate vague spatial information such as ERD/ERS effects among EEGs by maximizing the variance for one class while minimizing variance for the other classes (Blankertz et al. 2008; Lemm et al. 2005). CSP and its improved versions (e.g., wavelet common spatial pattern, WCSP; common spatio-spectral pattern, CSSP; common sparse spectral spatial pattern, CSSSP) have provided good results for synchronous BCIs, but less effective for asynchronous BCIs (Nicolas-Alonso & Gomez-Gil 2012) because of the nonstationary EEG properties (Galán et al. 2008).

Assuming a single-trial EEG data matrix, \( \mathbf{X}_{\text{NsS}} \), consisting of \( N \) channels and \( S \) samples per channel, the normalized covariance matrix is

\[
C_{c1} = \frac{X_{c1}X_{c1}^T}{\text{trace}(X_{c1}X_{c1}^T)}, \quad C_{c2} = \frac{X_{c2}X_{c2}^T}{\text{trace}(X_{c2}X_{c2}^T)}, \quad C_c = C_{c1} + C_{c2},
\]

where \( \text{trace}(XX^T) \) is the sum of diagonal elements of \( XX^T \). The composite spatial covariance, \( C_c \), and the factored composite spatial covariance are given as

\[
C_c = C_{c1} + C_{c2} = U_c \lambda U_c^T,
\]
where $U_C$ is a matrix of normalized eigenvectors with corresponding diagonal matrix of eigenvalues $\lambda$. The whitening transformation matrix is given as

$$P = \sqrt{\lambda} U_C^T.$$

Finally, the CSP projection matrix will be $W = U^T P$.

### 1.3.3 Feature Extraction: SSVEPs

In this section, we describe a feature extraction procedure with an EEG-based SSVEP BCI example. Assume that there is a robot that can move four directions in a grid cell environment. A user can control the robot by gazing at one of four flashing LED stimuli (i.e., flickering at 7, 13, 17, and 23 Hz) that correspond to directional commands (up, down, left, and right, respectively). A starting position of the robot is randomly set and the user moves the robot via a BCI system to hit a target position. The robot moves one cell from its current location when the classification of BCI detects one of the four SSVEP features. The classification is made only if the amplitude of one of the frequencies exceeds a certain threshold within the most recent 5 s of EEG data. Otherwise, the robot will not move and will stay at its current position.

EEG data record at a sampling rate of 512 Hz on the occipital area (O1 and O2). The recorded EEG data are first filtered by a 5-Hz high-pass filter, a 75-Hz low-pass filter, and a 60-Hz notch filter. The filtered EEG data are refined by the artifacts removal procedure, and subtract O1 channel to O2 channel by using the bipolar reference method. Then, the EEG data are transformed into the frequency domain by fast Fourier transform (FFT). The time window for FFT is 5 s and a 1-s (512 data points) sliding time window is used, so one decision can be made every second. For each time window, the power values of the fundamental, second, and third harmonics for each frequency are summed up. For example, the power value of 23, 46, and 69 Hz will be summed up for the stimulus of 23 Hz. If the maximum power sum value among four values is two times bigger than the average of the others, then the robot will move one cell from its current location to the corresponding direction of the maximum power frequency. Otherwise, the robot stays in its current position. This procedure will continue until the robot arrives at the target position.

### 1.4 Feature Classification Methods

One important element in BCI operations is a data classifier, or a classification algorithm, that aims at automatically determining a user’s intention by classifying extracted brain features. Comprehensive reviews on the classification techniques used for BCIs have been given elsewhere (e.g., Bashashati et al. 2007; Lotte et al. 2007; Nicolas-Alonso & Gomez-Gil 2012). Thus, this section is restricted to present three types of the commonly employed classifiers to design EEG-based BCI systems and highlights their most important properties for BCI applications: linear classifiers, artificial neural network classifiers, and hidden Markov model classifiers.

#### 1.4.1 Linear Classifiers

Linear classifiers are discriminant algorithms that use a linear function to classify the data into mutually exclusive and exhaustive classes, assuming that the data come from a Gaussian mixture model. Because of their structural simplicity, competitive accuracy, and very fast training and testing, linear classifiers are one of the most popular algorithms used to design BCI applications. Two main kinds of linear classifier are described: linear discriminant analysis (LDA) and support vector machine (SVM).
1.4.1.1 Linear Discriminant Analysis

The aim of LDA is to separate the classes using a line (the number of dimensions \( D = 2 \)), a plane (\( D = 3 \)), or a hyperplane (\( D > 3 \)) that maximizes the distance between the means of the classes (encoded in the between-class scatter matrix \( S_B \)) and minimize the intraclass variances (encoded in the within-class scatter matrix \( S_W \)). LDA works well under parametric assumptions (i.e., of the classes with equal class covariances) and linearity assumption (Duda et al. 2012). To solve a two-class problem \( \omega_i, i = 1, 2 \), for example, LDA seeks a good projection vector \( w^* \) that maximizes the criterion function:

\[
J(w) = \frac{\hat{\mu}_1 - \hat{\mu}_2^2}{S_1^2 + S_2^2} = \frac{\hat{S}_B}{\hat{S}_W} = \frac{w^T S_B w}{w^T S_W w},
\]

where \( \hat{\mu}_i \) is the projected mean vector of each class \( \omega_i \) in \( x \) and \( y \) feature space, and \( \hat{S}_i^2 \) measures the variability within class \( \omega_i \) after projecting it on the \( y \) space. The matrix \( \hat{S}_B \) (\( S_w \)) is called the between-class (within-class) scatter of the original feature vectors, while \( \hat{S}_B(S_W) \) is the between-class (within-class) scatter of the projected samples \( y \). Solving the generalized eigenvalue problem

\[
S_w^{-1} S_B w = \lambda w, \quad \text{where} \quad \lambda = J(w) = \text{Scalar}
\]

yields

\[
w^* = \arg \max_w J(w) = \arg \max_w \left( \frac{w^T S_B w}{w^T S_W w} \right) = S_w^{-1}(\mu_1 - \mu_2).
\]

The LDA technique has several advantages that make it suitable for determining a BCI user’s intention: low computational requirement and simple to use. In addition, LDA has given good results for motor imagery–based BCIs (e.g., Pfurtscheller 1999), P300 speller (e.g., Bostanov 2004), and asynchronous BCIs (e.g., Scherer et al. 2004). LDA has also been applied to multiclass BCI problems (e.g., Garrett et al. 2003), mainly using the “one-versus-the-rest” (OVR) strategy. The OVR method first constructs a set of binary classifiers, each one trained to separate class \( C_i \) from all other classes, and then uses the outputs of each binary classifier to predict one of the \( C \) classes (Ramage et al. 2009). However, some limitations of LDA should also be noted when considering this approach for BCI applications. For example, parametric assumptions (multivariate normality and equality of covariance matrices) and linearity assumption are particularly restrictive and can provide poor results on complex nonlinear EEG data (Garcia et al. 2003). LDA is sensitive to the presence of outliers (Duda et al. 2012) and often fails when the discriminatory information is not in the mean but rather in the variance of the data (Bostanov 2004).

1.4.1.2 Support Vector Machine

SVM is similar to LDA in that it is a binary classification algorithm that uses a discriminant hyperplane to distinguish two classes, but it is also different from LDA in that the selected best hyperplane for an SVM means the one with the largest margin (i.e., largest “gap” or “distance”) between the classes. The data points that are closest to or on the separating hyperplane (a linear decision surface) are called support vectors. SVMs have several advantages because of theoretical reasons such as good generalization properties (Bennett & Campbell 2000) and relative insensitive to over-training (Jain et al. 2000) and the curse of dimensionality (Burges 1998). The disadvantages of SVMs include a poor performance if the number of features is much greater than the number of
samples, an expensive \( n \)-fold cross-validation to calculate probability estimates, and a lower speed of execution (Bennett & Campbell 2000).

In addition to performing linear classification, SVMs can efficiently classify nonlinearly separable data using what is called the kernel trick. This method uses a kernel function \( K(x,y) \) to implicitly map the data into another high-dimensional feature spaces. The radial basis function (RBF) or Gaussian kernel is the most widely used kernel function in BCI research:

\[
K(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right).
\]

These RBF-based SVMs have been successfully applied to various BCI applications (e.g., Garrett et al. 2003). In addition, SVMs have provided good empirical results for synchronous BCI problems (e.g., Garrett et al. 2003), motor imagery–based BCIs (Lee & Choi 2003; Thomas et al. 2012), P3 speller (e.g., Krusienski et al. 2006; Rakotomamonjy & Guigue 2008; Salvaris & Sepulveda 2009), and multiclass BCI problems using the OVR strategy (Schlögl et al. 2005).

### 1.4.2 Artificial Neural Network Classifiers

One of the most successful for classification tasks in BCI applications is the so-called artificial neural networks or ANNs, a family of models inspired by biological neural networks (e.g., the structure of the human brain) (Wu et al. 2010). The key element of this paradigm is a large number of highly interconnected neurons or perceptrons, in which each neuron takes many input data, then, based on an internal weighting scheme, produces a single output that is often sent as input to another neuron. This section first describes the multilayer perceptron (MLP), the most widely used ANN for BCI applications, and then briefly presents other architectures of neural network used for BCIs.

#### 1.4.2.1 Multilayer Perceptron

The perhaps most widely used of all kinds of ANNs is the MLP, first proposed by Rumelhart et al. (1986). The MLP consists of a number of highly interconnected neurons or perceptrons organized into different layers. It has an input layer, an output layer, and in between one or more hidden layers. The MLP computes a single output from a set of (many) real-valued inputs \( x \) by forming a linear combination according to weighted connections between the inputs \( w \) and then possibly putting the output through some nonlinear activation function \( \phi \). With the bias \( b \), mathematically this can be written as

\[
y = \phi\left(\sum_{i=1}^{n} w_i x_i + b\right) = \phi(w^T x + b).
\]

There are important properties common to most ANNs and thus MLP (Forslund 2003):

1. **Learnability**: The ability to learn from examples to produce a certain output when presented with a certain input
2. **Generalizability**: The capability to produce good outputs even for inputs not encountered during training
3. **Nonlinearity**: Nonlinear information processing in each neuron, and hence a nonlinear mapping from an input space to an output space
4. **Fault tolerance**: Neural network systems that keep on functioning even if parts of them stop working
Because of these advantages, the MLP has been applied to many BCI problems such as binary (Palaniappan 2005), multiclass (Singha et al. 2007), synchronous (Haselsteiner & Pfurtscheller 2000), or motor imagery (Aguilar et al. 2015) BCIs.

### 1.4.2.2 Other ANN Architectures

The main advantage of the ANNs and thus MLP is that they are universal estimators (Hornik 1994). This means that a neural network can approximate any continuous function to an arbitrary degree of accuracy as the number of hidden layer neurons increases. However, it should also be noted that the universal approximation capability can make these ANN classifiers sensitive to overtraining, especially with noisy and nonstationary EEG data (Balakrishnan & Puthusserypady 2005). Thus, careful attention is required to select ANN architectures for BCI applications.

One of the most commonly used ANN architectures in the field of BCI is the Gaussian classifier, which has been successfully applied to motor imagery (Leeb et al. 2014) and asynchronous (Cincotti et al. 2003) BCIs. According to Lotte et al. (2007), several other ANN architectures have been used for BCI applications. Because of space limitations, we do not discuss these architectures. Interested readers can consult the corresponding references.

- Learning vector quantization (LVQ) neural network (e.g., Bascil et al. 2015)
- Fuzzy ARTMAP neural network (e.g., Palaniappan et al. 2002)
- RBF neural network (e.g., Hoya et al. 2003)
- Bayesian logistic regression neural network (BLRNN) (e.g., Penny et al. 2000)
- Adaptive logic network (ALN) (e.g., Kostov & Polak 2000)
- Probability estimating guarded neural classifier (PeGNC) (e.g., Felzer & Freisleben 2003)
- Finite impulse response neural network (FIRNN) (e.g., Haselsteiner & Pfurtscheller 2000)
- Gamma dynamic neural network (GDNN) (e.g., Barreto et al. 1996)

### 1.4.3 Hidden Markov Model Classifiers

A hidden Markov model (HMM) can be thought of as a bivariate stochastic process in which the most likely hidden state sequence that produces a given sequence of observations can be found using, for example, the well-known Viterbi algorithm (Hernando et al. 2005). Under an HMM, there are two basic assumptions:

1. The first-order Markov hypothesis: the current state is dependent only on the previous state.
2. The output independence hypothesis: the output observation at time $t$ is dependent only on the current state.

HMMs have been used in many other areas of speech recognition, computational biology, and fault detection, but they have also proven to be promising classifiers for EEG-based BCIs (e.g., Cincotti et al. 2003) and ECoG-based BCIs (e.g., Zhao et al. 2014). Table 1.2 summarizes different types of HMMs that have been used to analyze time series data such as EEG and ECoG as well as for BCI applications. HMMs have been applied to classify EEG signals on a motor imagery task. For example, Souza et al. (2012) compared the HMM and ANN classifiers for the spontaneous EEG, EEG of two-class MI, and EEG of real movement. The HMM was also used to classify single-trial EEG data during imagination of a left or right hand movement (Obermaier et al. 2001) and four-class single-trial motor imagery EEG data (Argunşah & Çetin 2010). Zhong and Ghosh (2002) compared the performance of several HMM and CHMM models for a multichannel EEG data classification. Chiappa and Bengio (2003) compared two Markovian models, HMMs and IOHMMs, on three mental tasks for an asynchronous BCI. Suk and Lee (2010) constructed a two-layer HMM for the classification of motor imagery EEG signals in a multiclass BCI paradigm. Recently, ECoG
signals have been used for more sophisticated motor task classification such as finger (Onaran et al. 2011) and hand movement (Zhao et al. 2014). For example, Onaran et al. (2011) applied a hybrid approach combining SVM and HMM to classify ECoG signals during finger movements. On the other hand, Zhong and Ghosh (2002) employed the CHMM on multichannel ECoG signals to classify brain signals during a multidirection hand movement task.

### 1.5 EXAMPLE BCI APPLICATIONS

Relying on different neuroimaging and neurophysiological techniques, control signals, feature extractions, and classifications, many interesting BCI systems have been developed for a wide variety of applications. This section serves to highlight the importance of BCI applications based on each control signal type and their implications for future research and development.

#### 1.5.1 P300-BASED BCIs

One of the more common control signal types is the P300 ERP (as discussed in Section 1.2.3.1). Its most prevalent usage has been the P300 Speller (Farwell & Donchin 1988), which paved the way for many other communication and control applications to be developed using and expanding on their work (Li et al. 2012; Nam et al. 2008). Table 1.3 gives an overview of many different P300-based BCI application resources, comparing control mechanisms and application objectives.

#### 1.5.1.1 Communication Applications

The P300 Speller is not only the most popular spelling application, but it was also the first of its kind (Nam et al. 2009, 2010, 2012). Since then, many researchers have expanded on Farwell and Donchin’s (1988) work to create more reliable, faster, and more accurate communication systems. To use the P300 Speller, the user gazes at the target letter while the system randomly flashes rows and columns. The user counts the number of flashes on the target letter and the BCI system then selects the letter with the highest probability with respect to rows and columns as described in the anecdotal story in Section 1.1.1 (Sellers & Donchin 2006). Much of the research has focused on changing the look of the interface in order to elicit either quicker or more intense ERPs. Furthermore, their research has been instrumental in the development of P300-based BCI applications, comparing control mechanisms and application objectives.

P300 ERPs that use visual stimulation may not be practical for users with decreased eyesight or eye movement ability. To overcome this limitation, P300-based BCIs relying on auditory and tactile stimulation have been researched. While visual, or a mixture of visual and auditory, stimulation...
### TABLE 1.3
Example P300-Based BCI Applications

<table>
<thead>
<tr>
<th>Application Type</th>
<th>Visual</th>
<th>Auditory</th>
<th>Tactile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communication</td>
<td>• Farwell &amp; Donchin 1988</td>
<td>• Furdea et al. 2009</td>
<td>• Circle: Brouwer &amp; van Erp 2010</td>
</tr>
<tr>
<td></td>
<td>• Krusienski et al. 2008</td>
<td>• Sellers et al. 2006</td>
<td>• Braille: van der Waal et al. 2012</td>
</tr>
<tr>
<td></td>
<td>• Hex-o-Spell type: Treder &amp; Blankertz 2010</td>
<td>• Furdea et al. 2009</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Checkerboard type: Townsend et al. 2010</td>
<td>• 2D: Höhne et al. 2010</td>
<td></td>
</tr>
<tr>
<td>Control Human-machine interaction (HMI)</td>
<td>• Robot: Bell et al. 2008</td>
<td>• Multi-class: Schreuder et al. 2010</td>
<td>• Robot: Mori et al. 2013</td>
</tr>
<tr>
<td></td>
<td>• Browser: Mugler et al. 2010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Virtual smart home: Holzner et al. 2009</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Internet browser: Mugler et al. 2008</td>
<td>• Game: Robinson et al. 2010</td>
<td>• Locked-in patients: Lugo et al. 2014</td>
</tr>
<tr>
<td>Entertainment</td>
<td>• 3D game: Finke et al. 2009</td>
<td>• Game: Robinson et al. 2010</td>
<td>• Game: Thurlings et al. 2013</td>
</tr>
<tr>
<td></td>
<td>• Game: Congedo et al. 2011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Virtual driving: Bayliss &amp; Ballard 2000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Chess: Kaplan et al. 2013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Art</td>
<td>• Painting: Holz et al. 2015; Münßinger et al. 2010</td>
<td>• Music: Vamvakousis &amp; Ramirez 2014</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Composing: Grierson 2008</td>
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</table>
has proven more effective than auditory stimulation alone (Sellers et al. 2006). BCIs using auditory stimuli are still viable for communication purposes (Furdea et al. 2009). Tactile stimulation has also proved effective (van der Waal et al. 2012), especially for users with the visual impairments discussed above.

1.5.1.2 Control Applications

P300-based BCI controls have many different uses such as human–machine interaction, entertainment and games, as well as art. Human–machine interaction encompasses robot control, wheelchair control, and many other human–device interactions. These types of applications are useful for individuals with physical disabilities, providing them with more independence and control over their environment. Certain devices are created to increase mobility, while others focus on control of in-home devices such as a TV or DVD player (Corralejo & Nicolás-Alonso 2014), and still others on robotic control to help with carrying tasks (Bell et al. 2008) and other odd jobs.

Although P300 ERPs are a popular control signal for many other BCIs, they are less popular in the entertainment area. This is perhaps due to the time it takes the computer to analyze the P300 data before making a decision and the nature of the task required by the user for P300 elicitation, which may not be well suited to game play (Kaplan et al. 2013). Even though they are not used regularly in BCI games, they are a prevalent choice in artistic BCIs. There are different types of artistic BCIs, ranging from musical applications that allow users to create music by visually selecting notes presented in a P300 Speller-type matrix (Miranda & Soucaret 2008) to a toolbox-style painting program that allows users to make creative choices with the options at their disposal (Münßinger et al. 2010). In-home artistic BCI usage (Holz et al. 2015) reignited the creative processes of two individuals presenting with amyotrophic lateral sclerosis (ALS), which increased their overall quality of life. Visual, auditory, and tactile stimulation applications have all been researched, although visual still appears to be the most popular for control purposes.

1.5.2 SSVEP-Based BCIs

Table 1.4 gives an overview of many different SSVEP-based BCI application resources, comparing control mechanisms and application objectives.

1.5.2.1 Communication

Most BCIs have developed from a need to make life easier for those who are physically disabled or suffering from a debilitating disease. Recent developments into SSVEP BCIs have geared toward making communication BCIs mobile friendly (Chi et al. 2012; Lin et al. 2013).

Other researchers (Wang et al. 2011b) have explored the development of an online chatting system using SSVEP BCIs, again seeking more independent and communally connected experiences for those with physical disabilities. SSVEP speller applications are becoming more present in the literature. One of the benefits of the SSVEP speller applications is that they require little to no training compared to P300 Spellers, are often quicker, and produce results with higher accuracies. Typically, in SSVEP systems, fewer options are presented at a time, but research into a QWERTY-style keyboard interface (Hwang et al. 2012) proved that increased speed and accuracies could still be accomplished with a large variety of choices. Communication applications using auditory steady-state responses (ASSRs) and SSSEPs have not shown to be as feasible or effective as those using SSVEPs, but research is still being conducted to attempt to implement these types of systems (Hill & Schölkopf 2012; Muller-Putz et al. 2006).

1.5.2.2 Control

SSVEP systems can provide users with a relatively simple and reliable means of interacting with their surroundings. Human–machine interaction, rehabilitation, and entertainment are all important
<table>
<thead>
<tr>
<th>Application Type</th>
<th>Visual</th>
<th>Auditory</th>
<th>Tactile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hierarchical design—LCD (Cecotti 2010)</td>
<td></td>
<td>Braille (Severens et al. 2010)</td>
</tr>
<tr>
<td></td>
<td>Online chatting—LCD (Wang et al. 2011)</td>
<td></td>
<td>Solenoid stimulator (Choi et al. 2015)</td>
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<tr>
<td></td>
<td>Qwerty keyboard—LED (Hwang et al. 2012)</td>
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</tr>
<tr>
<td>Control HMI</td>
<td>Flight simulator—computer display (Müller-Putz et al. 2005)</td>
<td>GUI (Middleton et al. 2006)</td>
<td>Wheelchair (Kim &amp; Lee 2014)</td>
</tr>
<tr>
<td></td>
<td>Remote control car (Gonzalez-Mendoza et al. 2015)</td>
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<td></td>
<td>Robot (Nam et al. 2015)</td>
<td></td>
<td></td>
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<tr>
<td>Regain functionality</td>
<td>Prosthesis—LED (Muller-Putz &amp; Pfurtscheller 2008)</td>
<td>Schizophrenia (Hong et al. 2004)</td>
<td>(Colon et al. 2012; Muller-Putz et al. 2006; Severens et al. 2013)</td>
</tr>
<tr>
<td>Entertainment</td>
<td>FES—LCD (Yao et al. 2012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Exoskeleton—LED (McDaid et al. 2013)</td>
<td></td>
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</tr>
<tr>
<td>Art</td>
<td>Two-class—checker (Lalor et al. 2005)</td>
<td>Attention—Tetris (Roth et al. 2013)</td>
<td></td>
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<tr>
<td></td>
<td>Four-direction—maze (Chumerin et al. 2012)</td>
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<td></td>
<td>Three-direction—VR (Faller et al. 2010)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Two-class—eye-closed (Lim et al. 2013)</td>
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</tr>
<tr>
<td></td>
<td>Sketch (Todd et al. 2012)</td>
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</table>
focuses of SSVEP-based BCIs. Research has been promising for SSVEP, SSAEP, and SSSEP systems for human–machine interactions.

In the field of rehabilitation, SSVEP BCIs have led to greater patient involvement in their therapeutic exercises (e.g., McDaid et al. 2013; Yao et al. 2012). Not only does patient involvement lead to more attentive participation, but it also helps the patient feel more in control of the process. Games developed using SSVEP-based BCI technology have also been used for rehabilitation purposes to keep the patient engaged in the process. From an entertainment perspective, SSVEP-based BCI applications are quite popular, with navigation games currently cornering the research market (e.g., spacecraft control, maze, etc.). Even able-bodied users can appreciate a BCI-driven game environment because of its novelty and uniqueness.

1.5.3 ERD/ERS-BASED BCIS

Table 1.5 gives an overview of many different ERD/ERS-based BCI application resources; comparing control mechanisms and the application objectives.

1.5.3.1 Communication

Seeking to overcome the time-related decline in P300 potentials and reduce visual fatigue caused by staring at high-contrast, blinking stimuli for too long, Yue et al. (2011) among others (e.g., Perdikis et al. 2014) have developed motor imagery–based BCI speller applications. Motor imagery communication BCIs could also be useful for individuals with reduced eye movement ability and decreased vision, as prolonged eye gaze or movement is not required to control the application.

1.5.3.2 Control

BCI for control of machines using motor imagery has led researchers to test the controlled movements of a humanoid robot (Prataksita et al. 2014), a driving simulator (Bi et al. 2014), and a mouse within a web browser (Yu et al. 2012). All of these laying the bases for future research into more complex systems that continue to provide disabled users with more independence and autonomy.

<table>
<thead>
<tr>
<th>TABLE 1.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example ERD/ERS-Based BCI Applications</td>
</tr>
</tbody>
</table>
| Communication | • SMR-Speller (Yue et al. 2011)  
• BrainTree (Perdikis et al. 2014)  
• NLP (D’albis et al. 2012)  
• Communication board (Scherer et al. 2015) |
| Control | HMI | • Robot (Prataksita et al. 2014)  
• Simulated vehicle (Bi et al. 2014)  
• 2-D cursor with target selection (Long et al. 2012)  
• BCI mouse (Yu et al. 2012) |
| Rehabilitation | • Virtual hand (Cincotti et al. 2012; Morone et al. 2015; Pichiorri et al. 2015)  
• FES (Mukaino et al. 2014)  
• Robot arm (Onose et al. 2012)  
• Orthosis (Pfurtscheller et al. 2010b)  
• Wheelchair (Choi & Cichocki 2008) |
| Entertainment | • Maze (Bordoloi et al. 2012)  
• Virtual helicopter (Doud et al. 2011)  
• Co-BCI video game (Bonnet et al. 2013)  
• Quadcopter (LaFleur et al. 2013)  
• Continuous control (Coyle et al. 2011) |
Brain–Computer Interface (Jeon et al. 2011; Nam et al. 2011). Neurorehabilitation after a stroke often requires training undamaged part of the brain to perform the tasks that were previously performed by the affected area (Cincotti et al. 2012). Many stroke victims have impaired motor movements and using motor imagery therapies could potentially help rehabilitate motor function (Cincotti et al. 2012; Triponyuwasin & Wongswat 2014). Certain motor imagery therapeutic techniques found that brainwave intensity, or “spectral power,” increases over a short period of time. This is indicative of rebuilding damaged brain cells, training other brain cells to do different work, and greater ability to interact with a motor imagery BCI.

Research into games using motor imagery BCI can give insight into future techniques to improve other systems focused on rehabilitation or control. For example, Bonnet et al. (2013), through creating a collaborative football game, found that users preferred multiuser conditions as they improved fun and motivation. Incorporating those methods or game-like environments into rehabilitation could have a positive effect on patient outcomes.

1.6 SUMMARY

This chapter reviewed the state of the art of BCI as an emerging human–computer interaction technology, including a BCI classification scheme (Section 1.1), different types of the signal recording methods and brain signal patterns for BCI operation (Section 1.2), the most commonly used signal processing techniques and feature extraction techniques (Section 1.3), classification methods used for identifying the user’s intentions (Section 1.4), and various types of BCI applications (Section 1.5).

In the last two decades, the BCI community has witnessed a substantial amount of work done on BCI technologies and many successful BCI applications. However, continuing effort is still needed to further optimize the capabilities, robustness, and usability of BCI systems for human use, including those who suffer from muscular disabilities such as ALS, brainstem stroke, and severe cerebral palsy. That is, more research and development is required to advance BCI technology in the areas of (1) invasive and noninvasive methods to monitor and obtain brain signals, (2) effective signal processing methods that extract signal features (e.g., spatial and temporal filters), (3) innovative algorithms that translate these features into device commands (e.g., linear and nonlinear classifiers), and (4) the development and evaluation of potential applications to enhance the value of brain–computer interfacing technology. Additionally, most BCI technology has strictly focused on supporting individuals with disabilities, and while those efforts continue to be necessary, applications outside of clinical settings, including passive BCI systems, could prove useful and beneficial as well (Zander & Kothe 2011). Finally, the future of BCI research and development, including readily available BCI applications, also depends on close inter- and multidisciplinary collaborations and ongoing communication among neuroscientists, engineers, psychologists, human factors professionals, clinicians, and rehabilitation specialists (Kothe & Makeig 2013; Nam et al. 2015; Schalk et al. 2004).

ACKNOWLEDGMENTS

This work was supported in part by the National Science Foundation (NSF) under grants numbers IIS-1421948 and BCS-1551688. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

REFERENCES


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