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BRAIN–COMPUTER INTERFACE

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3.1. INTRODUCTION

Human–computer interfaces (HCIs) have become ubiquitous. Interfaces such as keyboards and mouses are used daily while interacting with computing devices (Ebrahimi et al., 2003). There is a developing need, however, for HCIs that can be used in situations where these typical interfaces are not viable. Direct brain–computer interfaces (BCI) is a developing field that has been adding this new dimension of functionality to HCI. BCI has created a novel communication channel, especially for those users who are unable to generate necessary muscular movements to use typical HCI devices.

3.1.1. WHAT IS BCI

Brain–computer interface is a method of communication based on neural activity generated by the brain and is independent of its normal output pathways of peripheral nerves and muscles. The neural activity used in BCI can be recorded using invasive or noninvasive techniques. The goal of BCI is not to determine a person's intent by eavesdropping on brain activity, but rather to provide a new channel of output for the brain that requires voluntary adaptive control by the user (Wolpaw et al., 2000b).

The potential of BCI systems for helping handicapped people is obvious. There are several computer interfaces designed for disabled people (Wickelgren, 2003). Most of these systems, however, require some sort of reliable muscular control such as neck, head, eyes, or other facial muscles. It is important to note that although requiring only neural activity, BCI utilizes neural activity generated voluntarily by the user. Interfaces based on involuntary neural activity, such as those generated during an epileptic seizure, utilize many of the same components and principles as BCI, but are not included in this field. BCI systems, therefore, are especially useful for severely disabled, or locked-in, individuals with no

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reliable muscular control to interact with their surroundings. The focus of this chapter is on the basics of the technology involved and the methods used in BCI.

3.1.2. HISTORY OF BCI

Following the work of Hans Berger in 1929 on a device that later came to be known as electroencephalogram (EEG), which could record electrical potentials generated by brain activity, there was speculation that perhaps devices could be controlled by using these signals. For a long time, however, this remained a speculation.

As reviewed by Wolpaw and colleagues (2000b), 40 years later, in the 1970s, researchers were able to develop primitive control systems based on electrical activity recorded from the head. The Pentagon's Advanced Research Projects Agency (DARPA), the same agency involved in developing the first versions of the Internet, funded research focused on developing bionic devices that would aid soldiers. Early research, conducted by George Lawrence and coworkers, focused on developing techniques to improve the performance of soldiers in tasks that had high mental loads. His research produced a lot of insight on methods of autoregulation and cognitive biofeedback, but did not produce any usable devices.

DARPA expanded its focus toward a more general field of biocybernetics. The goal was to explore the possibility of controlling devices through the real-time computerized processing of any biological signal. Jacques Vidal from UCLA's Brain–Computer Interface Laboratory provided evidence that single-trial visual-evoked potentials could be used as a communication channel effective enough to control a cursor through a two-dimensional maze (Vidal, 1977).

Work by Vidal and other groups proved that signals from brain activity could be used to effectively communicate a user's intent. It also created a clear-cut separation between those systems utilizing EEG activity and those that used EMG (electromyogram) activity generated from scalp or facial muscular movements. Future work expanded BCI systems to use neural activity signals recorded not only by EEG but also by other imaging techniques.

Current BCI-based tools can aid users in communication, daily living activities, environmental control, movement, and exercise, with limited success and mostly in research settings. A more detailed evolution of BCI systems is detailed later in this chapter. The primary users of BCI systems are individuals with mild to severe muscular handicaps. BCI systems have also been developed for users with certain mental handicaps such as autism. Basic and applied research is being conducted with humans and animals for using BCIs in numerous clinical and other applications for handicapped and nonhandicapped users.

3.2. COMPONENTS OF A BCI SYSTEM

To understand the requirements of basic research in BCI, it is important to put it in the context of the entire BCI system. The recent work of Mason and Birch (2003), which is adapted in this section, presented a general functional model for BCI systems upon which a universal vocabulary could be developed and different BCI systems could be compared in a unified framework.
The goal of a BCI system is to allow the user to interact with the device. This interaction is enabled through a variety of intermediary functional components, control signals, and feedback loops as detailed in Figure 3.1. Intermediary functional components perform specific functions in converting intent into action. By definition, this means that the user and the device are also integral parts of a BCI system. Interaction is also made possible through feedback loops that serve to inform each component in the system of the state of one or more components.

3.2.1. FUNCTIONAL COMPONENTS

Any BCI system is subject to the conditions in which it operates. The operating environment is the physical location and the surrounding objects at the location(s) in which the system is being used. This includes physical boundaries, temperature, terrain conditions, external noise, etc. Other components in the system must be able to adapt to the changing conditions in the operating environment.

A user is any entity that can relay its intent by intentionally altering its brain state to generate the control signals that are the input for the BCI system. The user’s brain state
A notable experiment has been conducted by Nicolelis and Chapin (2002) on monkeys to control a robot arm in real time by electrical discharge recorded by microwires that lay beside a single motor neuron. Various motor-control parameters, including the direction of hand movement, gripping force, hand velocity, acceleration, three-dimensional position, etc., were derived from the parallel streams of neuronal activity by mathematic models. In this system, monkeys learn to produce complex hand movements in response to arbitrary sensory cues. The monkeys could exploit visual feedback to judge for themselves how well the robot could mimic their hand movements. Refer to Figure 3.3 for a detailed description (Nicolelis, 2003).

A less invasive approach that has been well applied to epileptic patients for surgical planning is patching subdural electrode array over cortex to record electrocorticogram (ECoG) signals. Subdural electrodes are closer to neuronal structures in superficial cortical layers than electroencephalogram (EEG) electrodes placed on the scalp. It is estimated that scalp electrodes represent the spatially averaged electrical activity over a cortical area of at least several square centimeters. Several closely spaced subdural electrodes can be placed over an area of this size such that each of these electrodes measures the spatially averaged bioelectrical activity of an area very likely much smaller than several square centimeters. The advantages of subdural recordings include recording from smaller sources of “synchronized activity,” higher signal-to-noise ratio than that of scalp recordings, and increased ability to record and study gamma activity above 30 Hz. Gamma activity is generated by rapidly oscillating cell assemblies composed of a small number of neurons. Consequently, gamma activity is characterized by small amplitude fluctuations that are not easily recorded with scalp electrodes (Pfurtscheller et al., 2003).

Levine and coworkers (2000) have implemented a “direct brain interface” that accepts voluntary commands directly from recording ECoG signal in epileptic patients. The subjects
FIGURE 3.3. Experimental design used to test a closed-loop control brain–machine interface for motor control in macaque monkeys. Chronically implanted microwire arrays are used to sample the extracellular activity of populations of neurons in several cortical motor regions. Linear and nonlinear real-time models are used to extract various motor-control signals from raw brain activity. The outputs of these models are used to control the movements of a robot arm. For instance, while one model might provide a velocity signal to move the robot arm, another model, running in parallel, might extract a force signal that can be used to allow a robot gripper to hold an object during an arm movement. Artificial visual and tactile feedback signals are used to inform the animal about the performance of a robot arm controlled by brain-derived signals. Visual feedback is provided by using a moving cursor on a video screen to inform the animal about the position of the robot arm in space. Artificial tactile and proprioceptive feedback is delivered by a series of small vibromechanical elements attached to the animal’s arm. This haptic display is used to inform the animal about the performance of the robot arm gripper (whether the gripper has encountered an object in space, or whether the gripper is applying enough force to hold a particular object). ANN, artificial neural network; LAN, local area network. (From Nicolelis, 2003, with permission, © 2003, Nature)

were instructed to make different movements of the face, tongue, hand, and foot in either a prompt-paced or a self-paced manner. Half of the ECoG recoding was used to produce an averaged ECoG segment (as “ERP templates”) and the cross-correlation of templates with the continuous ECoG was used to detect ERPs that correspond to specific movements. The cortical locations of the subdural electrodes were based solely on clinical considerations relating to epilepsy surgery (as opposed to research needs). The accuracy of ERP detection for the five best subjects has hit more than 90%. In another experiment of self-paced movement study using ECoG (Pfurtscheller et al., 2003), it was concluded that self-paced movement is accompanied not only by a relatively widespread mu and beta ERD, but also by a more focused gamma ERS in the 60–90 Hz frequency band.
In a different system, individual electrodes in the Utah electrode (Maynard et al., 1997) are tapered to a tip, with diameters <90 μm at their base, and they penetrate only 1–2 mm into the brain. Invasive techniques cause significant amount of discomfort and risk to the patient. Researchers use them in human subjects only if it will provide considerable improvement in functionality over available noninvasive methods. A majority of the initial research, therefore, is conducted in animals, especially monkeys and rats, and is also called the brain–machine interface (BMI) (Nicolelis, 2001). Research in these animals has led to the rapid development of microelectronics that enables recording electrophysiological activities from a small group of neurons or even a single neuron. Present technology allows reliable simultaneous sampling of 50–200 neurons, distributed across multiple cortical areas of small primates, for a period of a few years (Wessberg et al., 2000).

The advantage of these types of invasive techniques is the high spatial and temporal resolution that can be achieved, as recordings can be made from individual neurons at very high sampling rates. Intracranially recorded signals could obtain more information and allow quicker responses, which might lead to decreased requirements of training and attention (Sanchez et al., 2004). Several issues, however, have to be considered (Lauer et al., 2000). First, the long-term stability of the signal over days and years is hard to achieve. The user should be able to consistently generate the control signal reliably without the need for frequent retuning. Second is the issue of cortical plasticity following a spinal cord injury. It has been hypothesized that the motor cortex undergoes reorganization after a spinal cord injury, but the degree is unknown (Brouwer and Hopkins-Rosseel, 1997). Finally, if a neuroprosthesis that requires a stimulus to the disabled limb is used, this stimulus would also produce a significant artifact on the scalp that might interfere with the signal of interest. In such cases, BMI systems must be able to accurately detect and remove this artifact.

It is also necessary to develop a better understanding of the principles by which neural ensembles encode sensory, motor, and cognitive information (Isaacs et al., 2000; Nicolelis, 2001; Serruya et al., 2002). In the case of motor control, for instance, the areas of the primate brain that are involved are well known and even the physiological properties of individual neurons located in these areas have been studied well (Nicolelis, 2001). Little is known, however, about how the brain makes use of this information from neurons to generate the movements. In the movement control design, therefore, further work is needed to develop a method that can efficiently sample and accurately decode the motor signals generated by neurons so an artificial device can mimic the intended movement.

Classic experiments in primates, for example, have demonstrated that fundamental parameters of motor control emerge by the collective activation of large distributed populations of neurons in the primary motor cortex (M1). To compute a precise direction of arm movement, the brain may have to perform the equivalent of a neuronal “vote” or, in mathematical terms, a vector summation of the activity of these broadly tuned neurons. This implies that to obtain the motor signals required to control an artificial device it is necessary to sample the activity of many neurons simultaneously as well as to design algorithms that are capable of extracting motor control signals from these ensembles. Several well-established models such as linear regression, population vector, and neural network have been successfully applied to deal with large neural data to estimate the hand movement trajectory from the firing rate of motor cortex populations (Wessberg et al., 2000, Taylor et al., 2002, Serruya et al., 2003). But these signals and models are far from providing the full range of motion that the arm can produce (Donoghue, 2002).
As mentioned earlier, experiments with humans thus far have been limited. Currently, only a few severely disabled patients have been implanted with electrodes. In some cases, success has been limited, with some patients able to communicate at a rate of only three letters per minute (Mussa-Ivaldi and Miller, 2003). Further advancements in microelectrodes, however, are required to obtain stable recordings over a long term (i.e. more than 1 year). In addition to the areas mentioned above, additional research focusing on minimizing the number of cells required for simultaneous recordings to obtain a useful signal as well as on providing feedback to the nervous system via electrical stimulation through electrodes is also essential for a potential widespread use of invasive techniques in humans. For a comprehensive review of the BMI and neurorobotic research, see Chapter 4 in this book.

3.3.2. NONINVASIVE TECHNIQUES

There are many methods of measuring brain activity through noninvasive means. Noninvasive techniques reduce risk for users since they do not require surgery or permanent attachment to the device. Techniques such as computerized tomography (CT), positron electron tomography (PET), single-photon emission computed tomography (SPECT), magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and electroencephalography (EEG) have all been used to measure brain activity noninvasively.

EEG, however, is the most prevalent method of signal acquisition for BCI. EEG has a high temporal resolution capable of measuring every thousandth of a second. Modern EEG also has a reasonable spatial resolution as signals from up to 256 electrode sites can be measured at the same time.

Practicality of EEG in a laboratory and in a real-world setting is unsurpassed. The device is portable and the electrodes can be easily placed on the subject's scalp by simply donning a cap. In addition, EEG systems have seen widespread use in numerous fields since its inception. Therefore, the techniques and technology of signal acquisition through this method have been standardized. Finally, and most important, the method is noninvasive (Wolpaw et al., 2000a).

Many EEG-based BCI systems use an electrode placement strategy suggested by the International 10/20 system as detailed in Figure 3.4. For better spatial resolution, it is also common to use a variant of the 10/20 system that fills in the spaces between the electrodes of the 10/20 system with additional electrodes (Malmivuo and Plonsey, 1995).

3.4. FEATURE EXTRACTION AND TRANSLATION

Basic research in BCI is focused on improving methods of feature extraction from the acquired signals and translating them into logical control commands for single-trial and averaged trials. A feature in a signal can be viewed as a reflection of a specific aspect of the physiology and anatomy of the nervous system (Wolpaw et al., 2000b). The goal of feature extraction methods, based on this definition, would be to obtain the specific physiological aspect of the nervous system across a specific time series. The steps involved in feature extraction and translation are detailed in Figure 3.5.
FIGURE 3.4. Placement of electrodes for noninvasive signal acquisition using an electroencephalogram (EEG). This standardized arrangement of electrodes over the scalp is known as the International 10/20 system and ensures ample coverage of all parts of the head. The exact positions for each electrode are at the intersection of the lines calculated from measurements between standard skull landmarks. The letter at each electrode identifies the particular subcranial lobe (FP, prefrontal lobe; F, frontal lobe; T, temporal lobe; C, central lobe; P, parietal lobe; O, occipital lobe). The number or the second letter identifies its hemispherical location (Z, denoting line zero refers to an electrode placed along the cerebrum’s midline; even numbers represent the right hemisphere; odd numbers represent the left hemisphere. The numbers are in ascending order with increasing distance from the midline.). (From Malmivuo and Plonsey, 1995 [web edition at http://butler.cc.tut.fi/~malmivuo/bem/bembook/in/in.htm], with permission).
3.4.1. TYPES OF SIGNALS

3.4.1.1. Spikes and Field Potentials

The brain generates a tremendous amount of neural activity. There are a plethora of signals, also referred to as components, which can be used for BCI. These signals fall into two major classes: spikes and field potentials (Wolpaw, 2003). Spikes reflect the action potentials of individual neurons and thus acquired primarily through microelectrodes implanted by invasive techniques. Field potentials, however, are measures of combined synaptic, neuronal, and axonal activity of groups of neurons and can be measured by EEG or implanted electrodes depending on the spatial resolution required. As previously mentioned, most of the BCI research is focused on using signals from EEG, and thus the most commonly used components are derived from EEG recordings.

3.4.1.2. EEG Frequency Bands

Signals recorded from EEG are split into several bands as shown in Figure 3.6. Delta band ranges from 0.5 to 3 Hz and the theta band covers the 4–7 Hz range. A majority of BCI research focuses on the alpha band (8–13 Hz) and the beta band (14–30 Hz). The beta band is sometimes considered to have an extended range of up to 60 Hz with the gamma band indicating all signals greater than 30 Hz.

3.4.1.3. Components of Interest

Components of particular interest to BCI can be divided into four categories: oscillatory EEG activity, event-related potentials (ERP), slow cortical potentials (SCP), and neuronal potentials.

FIGURE 3.5. Processing steps required to convert user’s intent, encoded in the raw signal, into device action. Signals captured through invasive or noninvasive methods contain a lot of noise. The first step in feature extraction and translation is to remove noise. This is followed by selection of relevant features through several feature extraction techniques that focus on maximizing the signal-to-noise ratio. Finally, feature translation techniques are used to classify the relevant features into one of the possible states. (From Kelly et al., 2002, with permission)

FIGURE 3.6. Different signal bands present in the EEG signal. The delta band ranges from 0.5 to 3 Hz and the theta band ranges from 4 to 7 Hz. Most BCI systems utilize components in the alpha band (8 to 13 Hz) and the beta band (14 to 30 Hz).
3.4.1.4. Oscillatory EEG Activity

Oscillatory EEG activity is caused by complex network of neurons that create feedback loops. The synchronized firing of the neurons in these feedback loops generates observable oscillations. The frequency of oscillations decreases as the number of synchronized neuronal bodies increases. The underlying membrane properties of neurons and dynamics of synaptic processes, the strength and complexity of connections in the neuronal network, and the influences from other neurotransmitter systems also play a role in determining the oscillations.

Two distinct oscillations of interest are the \textit{Rolandic mu-rhythm}, occurring in the 10–12 Hz range, and the \textit{central beta rhythm}, occurring in the 14–18 Hz range. Both originate in the sensorimotor cortex region of the brain. These oscillations occur continuously during “idling” or rest. During nonidling periods, however, these oscillations are temporarily modified and the change in frequency and amplitude are evident on the EEG. The amplitude of oscillations decreases as the frequency increases because the frequency of the oscillations is negatively correlated with their amplitude (Pfurtscheller and Neuper, 2001).

3.4.1.5. Event-Related Potentials

Event-related potentials (ERPs) are time-locked responses by the brain that occur at a fixed time after a particular external or internal event. These potentials usually occur when subjected to sensory or aural stimulus, mental event, or the omission of a constantly occurring stimulus.

Exogenous ERP components are obligatory responses to physical stimuli and occur due to processing of the external event but independent of the role of the stimuli in the processing of information. The random flash of a bulb, for example, will generate an exogenous component as the brain responds to the sudden flash of light regardless of the context.

Endogenous ERP components occur when an internal event is processed. It is dependent on the role of the stimulus in the task and the relationship between the stimulus and the context in which it occurred. A user trying to spell the letter R in a word, for example, will generate an endogenous ERP component if the letter R is presented since it is the event he or she is looking for. If the user is trying to spell the letter S, however, he or she will not generate an endogenous ERP component if the same letter R is presented since the relationship between the stimulus and the context in which it occurred is no longer valid.

3.4.1.6. Event-Related Synchronization/(De)synchronization

A particular type of ERP is characterized by the occurrence of an event-related desynchronization (ERD) and an event-related synchronization (ERS). Changes in the factors that control the oscillation of neuronal networks, such as sensory stimulation or mental imagery, are responsible for the generation of these event-related potentials. A decrease in the synchronization of neurons causes a decrease of power in specific frequency bands and this phenomenon is defined as an ERD and can be identified by a decrease in signal amplitude. Presence of ERD is very widespread in the alpha band, especially during tasks involving perception, memory, and judgment. Increasing task complexity or attention amplifies the magnitude of the ERD.

ERS, on the other hand, is characterized by an increase of power in specific frequency bands that is generated by an increase in the synchronization of neurons and can be identified
Post-movement beta ERS 14–18 Hz
MuERD 10–12 Hz
Fz
C3
C4
Cz
P3
P4
Oz

FIGURE 3.7. Evidence of event-related desynchronization (ERD) and event-related synchronization (ERS) phenomena before and after movement onset. ERD is the result of a decrease in the synchronization of neurons, which causes a decrease of power in specific frequency bands, and can be identified by a decrease in signal amplitude. ERS is the result of an increase in the synchronization of neurons, which causes an increase of power in specific frequency bands, and can be identified by the increase in signal amplitude. (From Pfurtscheller and Neuper, 2001, with permission, © 2001, IEEE)

by an increase in signal amplitude. ERD and ERS are measured relative to a baseline or reference interval, so the strength of an ERD/ERS is affected by the variance of the rhythms in this interval.

The time-locked property of ERPs is particularly evident for ERD/ERS during imagined or actual motor tasks as shown in Figure 3.7. An ERD in the mu rhythm starts 2.5 s prior to movement onset and peaks after onset of movement before recovering to baseline. A short-lived ERD in the central beta rhythm occurs prior to movement onset and is immediately followed by an ERS that peaks after movement onset. Oscillations and ERS are also found around the 40-Hz gamma band when subjected to visual stimulation owing to binding of sensory information and in motor tasks owing to sensorimotor integration. The high frequency of the gamma band works well to set up rapid coupling or synchronization between spatially separated groups of neurons (Pfurtscheller and Lopes da Silva, 1999).

3.4.1.7. Visual-Evoked Potentials

Another type of ERP commonly used in BCI is the visual-evoked potential (VEP), an EEG component that occurs in response to a visual stimulus. VEPs are dependent on the
user's control of their gaze and thus require coherent muscular control. One frequently used VEP is the *steady-state visual evoked potential* (SSVEP).

SSVEP is an exogenous ERP component. The user visually focuses on one of two objects on a screen that flicker at different frequencies in the alpha and beta bands. The SSVEP component is amplified when the user shifts focus to the other object and then returns to baseline. The user can continue to switch focus between the two objects on the screen to generate changes in the signal (Middendorf et al., 2000).

### 3.4.1.8. P300

The *P300* is an endogenous ERP component and occurs as part of the "oddball paradigm" (Donchin and Coles, 1988; Donchin et al., 2000). In this phenomenon, users are subject to events that can be categorized into two distinct categories. Events in one of the two categories, however, are rarely displayed. The user is presented with a task that cannot be accomplished without categorization into both categories. When an event from the rare category is displayed, it elicits a P300 component, which is a large positive wave that occurs approximately 300 ms after event onset as shown in Figure 3.8. The amplitude of the P300 component is inversely proportional to the rate at which the rare event is presented. This ERP component is a natural response and thus especially useful in cases where either sufficient training time is not available or the user cannot be easily trained (Spencer et al., 2001).

![Figure 3.8](image-url)

**FIGURE 3.8.** P300 ERP component. When the user is randomly flashed objects on a screen, the P300 component occurs when the object the user is looking for is flashed, while any of the other objects do not elicit a similar change in voltage. The amplitude of the P300 component is inversely proportional to the rate at which the object of interest is presented and occurs approximately 300 ms after the object is displayed. It is a natural response and requires no user training. (From Kubler et al., 2001, with permission)
3.4.1.9. Slow Cortical Potential

A completely different type of signal is the slow cortical potential, which is caused by shifts in the depolarization levels of certain dendrites. Negative SCP indicates the sum of synchronized potentials, whereas positive SCP indicates reduction of synchronized potentials from the dendrites. As behavioral and cognitive performance of the user improves, so do the synchronized potentials, resulting in an increase of negativity of SCP. Since this cortical potential occurs anywhere from a 0.5 to 10 s after the onset of an internal event, as shown in Figure 3.9, it is referred to as the slow cortical potential (Birbaumer et al., 1999, 2000; Wolpaw et al., 2000b).

3.4.1.10. Neuronal Potential

Neuronal potential is a voltage spike from individual neurons as shown in Figure 3.10. This potential can be measured for a particular neuron or a group of neurons. The signal is a measure of the average rate, correlation, and temporal pattern of the neuronal firing. The central nervous system presents information on the firing rate of each neuron. Therefore, learning can be measured through changes in the average firing rate of neurons located in the cortical areas associated with the task.

Neuronal potential is extremely useful since it can achieve two-dimensional controls for the BCI by identifying the location of the neurons which are firing and also their rate of firing (Wolpaw, 2003). Research in neuronal potentials has been limited to animals until very recently because of the invasive procedures required to implant the electrodes as well as a lack of electrodes that generate stable recordings over a long period of time. The limited work, however, helps prove that better machine control is achievable by isolating signals with better spatial resolution (Wolpaw et al., 2002; Moxon, 2005).
3.4.2. TRAINING

According to the review by Curran and Stokes (2003) and other research (Kostov and Polak, 2000; Laubach et al., 2000), which is adapted here, the effectiveness of BCI is dependent on the capacity of the user to willingly and consistently control their EEG activity. Unlike motor tasks, control of brain activity is harder to achieve since the user can neither identify nor discern the activity. The user can only comprehend their EEG activity through the feedback received from the components in the BCI system.

The goal of training, therefore, is to have users voluntarily produce detectable EEG signals that can be altered to achieve a specific result. From the definition of BCI, it should be evident that the components produced by the user must be voluntary. Although the user might not be aware of how and when the signals are generated, the signal generation process can only be activated by voluntary actions from the user. BCI systems, however, differ in whether these voluntary signals must be produced through conscious mental activity (e.g., adding numbers) (Birbaumer, 1999) or as an automatic response to the situation that requires minimal conscious effort (e.g., riding a bicycle).

3.4.2.1. Cognitive Tasks

Most training methods require the user to perform specific cognitive tasks. These methods focus on developing the user's ability to generate EEG components through voluntary and conscious mental activity. Motor imagery (MI) tasks have been among the most widely used cognitive tasks. In each trial the user imagines or plans one of several motor movements (i.e. left or right hand movement) based on visual or aural cues. Research has shown that this generates signals from the sensorimotor cortex of the brain and can be detected by EEG (Annett, 1995; Jeannerod, 1995). After several training sessions, the user is able to control the amplitude and frequency of the required component (Babiloni et al., 2000).

Other commonly used cognitive tasks do not involve motor imagery. Rather, they require the user to perform actions such as arithmetic (addition of a series of numbers), visual counting (sequential visualization of numbers), geometric figure rotation (visualization of rotation of a 3D object around an axis), letter composition (nonvocal letter composition), and
baseline (relaxation). Research has shown that these tasks produce discernable components detectable by EEG (Pfurtscheller et al., 1993; Penny and Roberts, 1999; Babiloni et al., 2000; Birbaumer et al., 2000; Penny et al., 2000).

3.4.2.2. Operant Conditioning

In contrast, the operant conditioning approach does not require the user to perform specific cognitive tasks. The focus of this method is on helping the user gain automatic control of the device by thinking about anything. The feedback provided by the system serves to condition the user to continue to produce and control the EEG components that have achieved the desired outcome. With continuous practice, the user is able to gain control of the device without necessarily being aware of the specific EEG components being produced. It is important to note, however, that operant conditioning method often uses motor imagery tasks to initially acclimate users to the concept that brain waves can be controlled.

3.4.2.3. Factors That Affect Training

Both methods of training, cognitive tasks and operant conditioning, are subject to numerous external factors. Some of the most common factors are concentration, distractions, frustration, emotional state, fatigue, motivation, and intentions. It is important to counteract these factors during training by providing ample feedback and varying the duration or frequency of the training sessions.

In addition, the EEG components produced by cognitive tasks are vulnerable to the amount of direction provided to the user. Motor imagery, for example, is subject to issues such as first/third-person perspective, visualization of the action versus retrieving a memory of the action performed earlier, imagination of the task as opposed to a verbal narration, etc. Research has yet to prove whether users can effectively control such fine details to produce significant change in the components they produce.

Because the focus of BCI is to provide a means of communication for the disabled, it is possible that some users have suffered from mentally debilitating diseases that do not allow them control of all areas of the brain. The left hemisphere of the brain, for example, is the center of activity for tasks involving language, numbers, and logic, whereas the right hemisphere is more active during spatial relations and movement imagery. Users need to be paired with the cognitive tasks that best suit their capabilities.

As indicated earlier, it is possible to discern different cognitive tasks based on the EEG components generated when the task is achieved. When using a combination of cognitive tasks during training, overlap of EEG signals can occur if the tasks require similar skills or cortical areas. It is important to choose tasks with contrasting EEG components for easy discrimination.

Another factor to consider during training is the particular EEG component to use. Slow cortical potentials, for example, are a natural response and thus require less training time than for users trying to control their mu rhythm. As mentioned above, choosing contrasting cognitive tasks accelerates training. It is also important to maintain consistent training regimens to ensure subjects retain their ability to control their EEG components.
The tasks used in training a user carry forward into general BCI usage. The method of training, therefore, determines the method of signal acquisition. Neuronal activity generated by cognitive tasks is restricted to certain areas of the brain. This allows signal acquisition to occur over a few electrodes that encompass the specific region. The operant conditioning method, however, can only work on a BCI that uses all or unspecific electrode locations since the mental activity used to control the objective is not defined.

3.4.3. SIGNAL PROCESSING AND FEATURE EXTRACTION TECHNIQUES

The user is able to voluntarily generate detectable signals to convey his or her intent. Signal acquisition methods, however, capture noise generated by other unrelated activity in or out of the brain. Appropriate features need to be extracted by maximizing the signal-to-noise ratio.

The goal of all processing and extraction techniques is to characterize an item by discernable measures whose values are very similar for those in the same category but very different for items in another category. Such characterization is done by choosing relevant features from the numerous choices available. This selection process is necessary, because unrelated features can cause the translation algorithms to have poor generalization, increase the complexity of calculations, and require more training samples to attain a specific level of accuracy.

3.4.3.1. Artifact/Noise Removal

Because signals are often captured across several electrodes over a series of time, existing methods concentrate on either spatial domain processing or temporal domain processing, or both. In addition, research has shown that a lot of noise captured in EEG is generated by non-central nervous system (CNS) activity, especially muscular movements in the facial muscles (Wolpaw et al., 2002). To counteract this noise, another set of techniques focus on non-CNS artifact removal.

To minimize noise in the signal, it is important to understand its sources. Noise can be captured through neural sources when components not related to the target signal are captured. Noise can also be generated by nonneural sources such as muscular movements, particularly of the facial muscles. This type of noise is especially important, because signals generated by muscular movements are overpowering and can be mistaken for the target signal. The problem is further complicated when the frequency or amplitude of the noise and the target signal are similar.

Typically more prominent than EEG signals, non-CNS artifacts are the result of unwanted potentials from eye movements, scalp-recorded EMG activity, and other such nonneural sources. Simple instructions to the user to not use facial muscles or to disregard the trials that contain artifacts can be used, but are not always adequate to remove this noise. Mathematical operations such as linear transformations and component analysis are also used for artifact removal (Makeig et al., 2000; Müller et al., 2000).

3.4.3.2. Characteristics of Feature Extraction Methods

Blum and Langley (1997) create an analogy of feature selection or extraction algorithms as heuristic search techniques that process large amounts of irrelevant data to find and
extract a few relevant features. They further characterized algorithms designed for feature extraction based on four criteria.

The first criterion is the definition of a starting point(s) that will also determine the direction of the search as well as the operators to decide the succeeding states. Algorithms could start with an empty set of features and successively add features based on a scoring function. This method is called forward selection. Another option is to start with all available features and remove certain features based on a scoring function. This method is known as backward elimination. Some algorithms even apply a combination of forward selection followed by backward elimination or vice versa.

The second criterion is the organization of the search. Because it is not efficient to do a comprehensive search of the entire feature space, algorithms use techniques such as greedy selection, stepwise addition and elimination, or best-search to select the next feature that will improve the score over the current set.

The third criterion is the strategy used to evaluate all possible subsets of features. Most algorithms tend to use a scoring function that reflects a feature’s ability to discriminate among the different classes. Many algorithms score features on the basis of information theory or contribution to the classification accuracy.

The fourth criterion is the terminating condition for the search. Some feature extraction algorithms stop when successive iterations fail to improve the score of the feature set above a certain threshold. Others continue to search as long as there is no decrease in the score or accuracy of the feature set. Another option used is to sort each of the features on the basis of some scoring function and selecting a breakpoint at which all features above this point are automatically selected.

3.4.3.3. Types of Feature Extraction Methods

Also discussed by Blum and Langley (1997), feature extraction techniques can be divided into three categories (Yom-Tov & Inbar, 2002). The first category is called embedded algorithms, wherein the feature selection is a part of the translation, also called classification, method. The feature selection procedure adds or removes features to counter prediction errors as new training data is introduced. Embedded algorithms, however, are of little use when there is a high level of interactions between relevant features.

The second category is called filter algorithms, which select specific features prior to, and independent of, the translation process. They work by removing irrelevant features (those providing redundant data or contaminated by noise) prior to training the translation technique. One way of filtering involves calculating each feature’s correlation with the target function and then selection of a fixed number of features with the highest scores. Another filtering method involves the derivation of higher-order features based on features from the raw data and sorting these higher-order features on the basis of the amount of variance they explain and selecting a fixed number of highest scoring features.

The final category is called wrapper algorithms, which select features by utilizing the translation algorithms to rate the viability or quality of a feature set. Rather than selecting a feature set on the basis of the results of the classification, these algorithms utilize the translation algorithm as a subroutine to estimate the accuracy of a particular subset of features. This type of algorithm is unique to a translation algorithm and particularly useful with limited training data.
In certain occasions, existing signals are not enough for high accuracy feature extraction. Some methods introduce more signals to capture additional information about the state of the brain, for example, by using 56 electrodes where only 2 were previously used. This increased spatial data can be processed to derive common spatial patterns. This is achieved by projecting the high-dimensional spatiotemporal signal onto spatial filters that are designed such that the most discriminative information is inherent in the variances of the resulting signals (Ramoser et al., 2000).

3.4.3.4. Spatial and Temporal Domain Processing

Spatial filtering techniques are useful for extracting features with a specific spatial distribution (McFarland et al., 1997; Muller-Gerking et al., 1999). In BCI systems that utilize mu or alpha rhythms, the selection of spatial filters can greatly affect the signal-to-noise ratio. A high-pass spatial filter such as the bipolar derivation calculates the first spatial derivative and emphasizes the difference in the voltage gradient in a particular direction. The surface Laplacian (Hjorth, 1975; Perrin et al., 1987; He and Cohen, 1992; Le et al., 1992; Nunez et al., 1994; Babiloni et al., 1996; He, 1999; He et al., 2001) also acts as a high-pass filter and can be approximated by subtracting the average of the signal at four surrounding nodes from the signal at the node of interest (Hjorth, 1975). It is the second derivative of the spatial voltage distribution and as the distance to the surrounding nodes increases, its sensitivity to higher spatial frequencies decreases, whereas a decreasing distance from the surrounding nodes increases its sensitivity to higher spatial frequencies (Wolpaw et al., 2002).

Temporal domain processing techniques are also useful in maximizing the signal-to-noise ratio. These methods work by analyzing the signal across a period of time. Some temporal domain-processing methods such as Fourier analysis require significantly long signal segments, whereas others such as band-pass filtering or autoregressive analysis can work on shorter time segments. Though all temporal domain-processing methods work well during offline BCI analysis, some of them are not as useful as spatial domain-processing methods during online analysis because of the quick responses required (Wolpaw et al., 2002).

3.4.3.5. Extracting ERD/ERS Features

ERD/ERS components can serve as an ideal example of how to extract relevant features from a raw EEG signal, and several procedures exist to calculate these ERP components, which have been covered in detail by Kalcher and Pfurtscheller (1995) and Pfurtscheller and Lopes da Silva (1999) and shown in Figure 3.11. Since EEG signals are recorded from multiple channels that are referenced to a common electrode, the raw data is reference-dependent and must be dereferenced or, in other words, converted into reference-free data. This can be done through using methods such as common average reference, surface Laplacian, or local average reference.

Computation of the time course of ERD/ERS can be done using the classical ERD method, also known as the power method, and requires the following steps. (1) The raw EEG signal from each trial, where \( x(i,j) \) is the \( j \)th sample of the \( i \)th trial, needs to be bandpass filtered \( \left( x_f(i,j) \right) \). (2) The amplitude samples need to be squared to obtain power
FIGURE 3.11. Techniques required to extract ERD and ERS from raw EEG signal. First, the raw EEG signal from each trial is bandpass filtered. Second, the amplitude samples are squared to obtain the power samples. Third, the power samples are averaged across all trials. Finally, variability is reduced and the graph is smoothed by averaging over time samples. (From Pfurtscheller and Lopes da Silva, 1999, with permission from Elsevier)

samples \((x^2_{i,j})\). (3) The power samples need to be averaged across all the trials. (4) The variability must be reduced by averaging over time samples. This calculation of the instantaneous power is summarized in Eq. (3.1).

\[
\tilde{P}_{ij} = \frac{1}{N} \sum_{i=1}^{N} x^2_{ij}
\]  

(3.1)

Though ERD is known to occur in the alpha band and ERS is known to occur in the beta band, the range of frequencies to use for bandpass filtering needs to be more accurate. This range can be calculated by comparing two short-term power spectra to detect the most reactive frequency band or utilizing the continuous wavelet transform method or using the mean peak center of gravity frequency as the basis to adjust frequency bands individually.

The signal processing method to compute the time course of ERD/ERS described above produces a time course of phase-locked and non-phase-locked power changes and
band power values. To discern between phase-locked and non-phase-locked power changes, the same procedure can be followed when substituting step 2 with a calculation of point-to-point intertrial variance \( IV(j) \) prior to averaging over time, thus replacing Eq. (3.1) with Eq. (3.2).

\[
IV(j) = \frac{1}{N-1} \sum_{i=1}^{N} (x_f(i, j) - \bar{x}_f(j))^2
\]

This variant procedure is useful in cases with lower frequency components where the non-phase-locked ERD, characterized by a decrease in power, can be hidden by a phase-locked increase in power caused by a different ERP.

ERD/ERS is typically expressed as a percentage of change in power compared to baseline power measures taken prior to onset of event. These values can be calculated by taking the ratio of the difference between the power or intertrial variance at each sample point or an average of sample points within the frequency band of interest during the period after event onset (\( A \)) in the \( j \)th channel and the baseline power or intertrial variance prior to the event averaged over \( k \) samples (\( R \)) (Eqs. (3.3) and (3.4)).

\[
ERD\% = \left[ \frac{(A(j) - R)}{R} \right] \times 100
\]

\[
R = \frac{1}{k} \sum_{j=0}^{n} A(j)
\]

As the number of extraction methods created or adapted for BCI increases, it is difficult to compare their relative effectiveness in isolating the required features. An \( r^2 \) measure has been used as the scoring method. The \( r^2 \) score is a measure of the proportion of the total variance in the features generated by the method that is accounted for by the user’s intent.

### 3.4.4. TRANSLATION TECHNIQUES

Translation techniques are algorithms developed with the goal of converting the input features (independent variable) into device control commands (dependent variable) (Wolpaw et al., 2002). Translation techniques used widely in other areas of signal processing are adapted to BCI.

Discussed by Wolpaw et al. (2002), effective BCI techniques have three levels of adaptation. First, the technique must be able to adapt to the uniqueness of each user’s signal features. Second, the technique must be able to reduce the impact of spontaneous variations that occur during regular use by making periodic online adjustments. Finally, the technique must be able to accommodate and engage the adaptive ability of the brain through increasing levels of feedback to encourage stronger feature signal generation.

Wolpaw and coworkers suggested that the success of a translation technique is determined by three criteria. The first criterion is the appropriateness of the selection of features. In other words, from all the features extracted, how well is the translation technique able to select those features that accurately convey the user’s intent. The second criterion is the level at which the technique can assist the user’s control of signal features through its adaptive
capacity. The final criterion is the effectiveness of the method in translating command into logical control.

There are numerous types of feature translation algorithms. Some utilize simple characteristics such as amplitude or frequency. Others utilize single features while advanced algorithms utilize a combination of spatial and temporal features produced by one or more physiological processes (Bianchi and Babiloni, 2003). Algorithms currently in use include, but are not limited to, linear classifiers (Babiloni et al., 2001; Wang and He, 2004), Fisher discriminant (Blankertz et al., 2002) CSSD and Fisher discriminant (Wang et al., 2004), Mahalanobis distance based classifiers (Cincotti et al., 2002), neural networks (NN) (Penny and Roberts, 1998; Peters et al., 1998; Robert et al., 2002; Deng and He, 2003), support vector machines (SVM) (Vallabhaneni and He, 2004), and hidden Markov models (HMM) (Obermaier et al., 2001).

3.4.5. EXTRACTION AND TRANSLATION IN ACTION: A CASE STUDY ON CLASSIFICATION OF MOTOR IMAGERY TASKS

Some BCI systems are based on classification of motor imagery tasks through recognition of mental states. In this study, a common data set of EEG recordings, made available by Dr. Osman (Osman and Robert, 2001; Sajda et al., 2003) from University of Pennsylvania (http://liinc.bme.columbia.edu/competition.htm), is used to investigate three (Methods A, B, and C) different combinations of feature extraction and translation techniques offline.

3.4.5.1. Experiment Setup

Subjects were seated in front of a display screen and instructed to wear an EEG cap with 59 electrodes placed according to the International 10/20 system. The subjects were then trained to synchronize an indicated response base within 100 ms of a timed cue.

Each subject was put through several trials, with each trial epoch lasting 6 s as shown in Figure 3.12. Every trial started out with a blank screen displayed for 2 s. This was immediately followed up with a fixation point displayed for 500 ms to indicate that the trial has begun. This was replaced by either an E or an I for 250 m to instruct the subject.

![FIGURE 3.12](image-url) Onset of cues during one trial epoch. Subjects were seated in front of a monitor. For each trial, the display changed based on the timing sequence indicated above.
whether to perform an explicit or imagined hand movement when cued. The fixation point was returned to the screen for another 1 s.

This fixation point was followed by the display of L, R, B, or N for 250 ms to instruct the subject to employ the left, right, both, or no index finger when movement is cued. An X was displayed for 50 ms to cue the subject to perform the instructed action and was preceded by the fixation point for 1 s and was also followed up with the fixation point for 950 ms.

3.4.5.2. Data Preparation

For each trial, EEG data was recorded from all 59 electrodes. A final data set was created with 180 trials from each subject that contained only the imagined left or right finger movements. Half of these trials were labeled as left or right to use for training purposes.

All three methods redefined the 0th second to be when the L/R cue was displayed. All time data was referenced to this point. Method A used data from 1.75 s before to 2.25 s after the 0th second from only 9 centroparietal electrodes (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4). Method B used data from 0.10 s before to 2 s after the 0th second from FC3, FC1, C3, C1, FC2, FC4, C3, and C4. Method C used data channel combinations—2-pair (C1/2, C3/4) and 4-pair (FC1/2 and FC3/4).

3.4.5.3. Feature Extraction

For all three methods, the first step in data processing utilized spatial filters, a very popular method in BCI, for accentuating localized activity and reducing diffused activity. Particularly, the surface Laplacian method was used. As previously described, it is the second spatial derivative of the instantaneous voltage distribution. With the assumption that distance between every adjacent channel is approximately equal, the surface Laplacian (Eq. 3.5) can be estimated by the difference between the potential $V_j$, at the $j$th channel of interest and the average value of the set of surrounding channels $S_j$ (Hjorth, 1975).

$$V_j^{Lap} = V_j - \frac{1}{4} \sum_{k \in S_j} V_k$$  \hspace{1cm} (3.5)

Spline algorithms have been developed for computing the surface Laplacian from the recorded potentials (Perrin et al., 1987; Nunez et al., 1994; Babiloni et al., 1996, 1998; He, 1999; He et al., 2001), whereas the finite difference algorithm (Hjorth, 1975) was adopted because of the computational efficiency.

Because motor imagery tasks are known to cause an ERD/ERS phenomenon in the mu and beta rhythms, the appropriate frequency ranges were isolated. Methods A and B focused only on the standard mu-rhythm-associated components. Therefore, they used a fifth-order Butterworth bandpass filter with appropriate filter coefficients to extract components in the 8–13 Hz frequency range as shown in Figure 3.13.

Method C, however, recognized that ERD/ERS calculation requires an exact frequency band based on analysis of the signals (Wang and He, 2004). So this method followed a more precise technique to determine the most optimal frequency bands for each subject as they are affected by individual differences. For each trial, the frequency range from 5 to 25 Hz
FIGURE 3.13. Results of concurrent steps of feature extraction on raw EEG signal in Methods A and B. It is difficult to detect a coherent component in the raw EEG signal depicted in the top frame as it is filled with noise. The second frame shows the signal after being processed through a surface Laplacian filter to get the spatial signal distribution. The signal is then bandpass filtered for 8–13 Hz, as shown in the third frame, to isolate the mu-rhythm ERD features noticeable around 0.5 s.

(coversing mu and beta bands) was isolated and then divided into twenty bins, each with a 2 Hz bandwidth and a 50% frequency overlap with adjacent bins.

This collection of narrow bandpass filters decomposed the EEG signals into different frequency components, resulting in a rhythmical component of EEG, i.e., a temporal signal with amplitude variations that modulated the rapid oscillations. These can be approximately expressed as (Eq. 3.6).

\[ x(t) = a(t) \cos(2\pi f_0 t + \varphi(t)) \]  

where the enveloped portion, \( a(t) \), should include the time-locked features. In order to extract \( a(t) \), we can first calculate the Hilbert transform of the \( x(t) \) using Eq. (3.7).

\[ x_h(t) = a(t) \sin(2\pi f_0 t + \varphi(t)) \]  

Eq. (3.8) can then be derived by combining Eqs. (3.6) and (3.7) (Papoulis, 1977).

\[ z(t) = x(t) + j x_h(t) = a(t) \exp(2\pi f_0 t + \varphi(t)) \]  

where \( z(t) \) is termed the analytical signal. Thus \( a(t) \) can be approximated using Eq. (3.9).

\[ a(t) = |z(t)| = \sqrt{x^2(t) + x_h^2(t)} \]  

The ERD/ERS phenomenon was then isolated through a grand average approach over all the envelopes because each envelope contains the relevant information for instantaneous power estimations for that particular narrow frequency band. In addition, the nonstationary
FIGURE 3.14. Results of concurrent steps of feature extraction on raw EEG signal in Method C. It is difficult to detect a coherent component in the raw EEG signal depicted in the top frame as it is filled with noise. The second frame shows the signal after being processed through a surface Laplacian filter to get the spatial signal distribution. The signal is then bandpass filtered, as shown in the third frame, to isolate the frequencies of interest. The features become evident in the fourth frame as they are extracted by utilizing a grand averaging method over a fixed bin or window size.

nature of the EEG signal would alter the dynamic region of the signal amplitude, and since spatial noise is amplified owing to the surface Laplacian filter, amplitude is normalized to counter these effects. Figure 3.14 shows the affect of each processing step on the raw EEG signal.

Returning to Method A, feature selection was done by extracting the amplitude values with a resolution of 1 Hz for the 8–13 Hz frequency range from a standard power spectral density (PSD) calculation. PSD, derived using the Welch’s averaged modified periodogram method, describes how the power (or variance) of a time series is distributed with frequency and is obtained by the fast Fourier transform (FFT) of the autocorrelation function (ACF) of the time series.

The PSD calculations derived six features, 1 for each 1 Hz division, from each of the nine electrodes and a total of 54 features for each trial. Concurrently plotting the features from each channel, C3, C4, and Fz were chosen as the features from these channels, which exhibited prominent differences between trials labeled left and right (Deng and He, 2003).

Following the Butterworth filter, in Method B (Vallabhaneni and He, 2004), the data is squared, as recommended in the classic ERD calculation method, and feature extraction is performed using spatiotemporal principal components analysis (PCA). PCA is commonly used in data analysis for extracting the most significant parts of any data without changing the meaning of the data itself. This process reduces the dimensionality of a given data set to the few principal components that explain the majority of the variance in the data.
FIGURE 3.15. Representation of the three-layer supervised artificial neural network. PSD values from 90 trials (45 left and 45 right) from the three channels of interest were used for training and fed into the first layer with 18 neurons (one for each feature), which were mapped to a hidden layer with 3 neurons and the final output layer with 1 neuron with 2 possible values (0 for left, 1 for right). A separate set of 90 trials were used for testing the prediction accuracy of the neural network. (From Deng and He, 2003, with permission, © 2003, IEEE)

The steps involved in PCA are the following:

1. Center the data matrix by subtracting the mean from each dimension.
2. Calculate the covariance matrix of the centered data.
3. Calculate the eigenvectors and eigenvalues of the covariance matrix.
4. Select the eigenvectors with the highest \( n \) corresponding to the eigenvalues as they are the principal components of the data set.
5. Final data set = [principal components]\(^T\) \( \times \) [centered data]\(^T\)

Spatiotemporal PCA involves, for each trial, performing the standard PCA along the spatial dimensions or channels to find spatial factors that explain the spatial variance and indicate interchannel signal correlation and patterns. This is followed by performing PCA along the time series to identify temporal features. Principal components were chosen based on a scree test threshold of 95, which means that the sum of the percentage of variance in the data explained by the chosen principal components was at least 95%. The final dimensions of the feature space, therefore, varied for each subject.

3.4.5.4. Feature Translation

All three methods utilized different supervised learning methods as feature translation techniques. Method A used a three-layer supervised artificial neural network (ANN) as shown in Figure 3.15 (Deng and He, 2003). This method requires a desired output to learn and creates a model that correctly maps the input to the output so that trials with unknown output can be predicted.

The input layer with 18 neurons (i.e. one neuron for each of the six features from the three channels of interest) was followed by the hidden layer with three neurons and the output layer with one neuron that had two possible values of 0 (left) and 1(right). Ninety trials were used to train the ANN, of which 45 were left-hand trials and 45 were right-hand trials. A separate set of 90 trials was used to test the prediction accuracy of the ANN.

Feature translation in Method B was performed using a linear kernel-based SVM provided by OSU SVM Classifier Matlab Toolbox (http://www.eleceng.ohio-state.edu/~maj/osu_svm/). SVMs, as a kernel-based statistical learning method, perform especially well in a high dimensional feature space as they efficiently avoid overfitting of the data. SVMs are also supervised learning methods that use knowledge from training data to classify unknown trials with similar features. It should theoretically be possible to find a
hyperplane across an input space that completely separates the trials in the right and left classes. In such cases, a kernel-based method would be unnecessary. This data set, however, is not perfectly separable across the input space, and such data sets are rare. The only possible way to generate a separating hyperplane is by mapping the data onto a higher dimensional feature space as defined by the kernel. As the dimensionality increases, it should be possible to create a feature space that can completely separate the two classes in any data set. The risk of artificially projecting the data onto a high dimensional feature space, however, is to subject the SVM to the possibility of finding trivial solutions that overfit the data.

If there are $n$ trials for each subject, let each of the $m$ dimensions in the final data matrix be a feature vector in an $m$-dimensional input space. The kernel, $K(X,Y)$, that is used to measure the similarity between the two trials $X$ and $Y$ is the dot product of their input spaces, as shown in Eq (3.10).

$$K(X,Y) = X \cdot Y$$  \hspace{1cm} (3.10)

A collection of support vectors are generated using this kernel function. These support vectors are used in the classification decision.

In a two-class problem, a linear SVM has the decision function, as shown in Eq (3.11), where $w$ is a weight vector, $b$ is a constant bias, and $x$ is a particular support vector.

$$f(x) = wx + b$$  \hspace{1cm} (3.11)

Both $w$ and $b$ are automatically chosen to maximize the margin between the decision hyperplane and the class. The class of a particular trial is determined by the sign of $f$.

Prior to translation, Method C used PCA to reduce the dimensionality of the feature set and increase computational efficiency. Feature vectors projecting onto the largest three principal components were retained for translation.

For translation, Method C used a Bayesian linear classifier as the basic technique. This method maximizes the ratio of interclass variance to the intraclass variance in any particular data, thereby guaranteeing maximal margin of separation.

A discrete linear classifier, with discriminant function denoted as $h_{ij}$, was created for each of the frequency bands, $i$, in each channel, $j$, in training stage. The accuracy values $a_{i,j}$ of each of these classifiers reflected the adaptation of every frequency band and channel. A normalized frequency weight, $w_{i,j}$, is defined by

$$w_{i,j} = \begin{cases} (2a_{i,j} - 1)^m, & a_{i,j} > 0.5 \\ 0, & a_{i,j} \leq 0.5 \end{cases} \hspace{1cm} (3.12)$$

where $m$ is the control parameter used to further emphasize those bands with larger accuracy values.

On the basis of the frequency weights, classification of the trial at each channel could be made using the channel discriminant function,

$$g_j(v) = \sum_{i=1}^{m} w_{i,j} \operatorname{sgn}(h_{i,j}(v))$$  \hspace{1cm} (3.13)
TABLE 3.1. Classification Accuracies for Methods A, B, and C for Three Subjects

<table>
<thead>
<tr>
<th></th>
<th>Method A (%)</th>
<th>Method B (%)</th>
<th>Method C (%)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training</td>
<td>Testing</td>
<td>Training</td>
<td>Testing</td>
<td></td>
</tr>
<tr>
<td>Subject 1</td>
<td>90.0</td>
<td>70.0</td>
<td>n/a</td>
<td>74.4</td>
<td>83.0</td>
</tr>
<tr>
<td>Subject 2</td>
<td>85.6</td>
<td>64.4</td>
<td>n/a</td>
<td>91.1</td>
<td>93.0</td>
</tr>
<tr>
<td>Subject 3</td>
<td>84.4</td>
<td>82.2</td>
<td>n/a</td>
<td>82.8</td>
<td>88.6</td>
</tr>
<tr>
<td>Average</td>
<td>86.7</td>
<td>72.2</td>
<td>n/a</td>
<td>82.8</td>
<td>88.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>2 pairs</th>
<th>4 pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>83.0</td>
<td>89.0</td>
</tr>
<tr>
<td>Testing</td>
<td>70.0</td>
<td>70.6</td>
</tr>
<tr>
<td>Training</td>
<td>88.6</td>
<td>95.0</td>
</tr>
<tr>
<td>Testing</td>
<td>82.2</td>
<td>92.2</td>
</tr>
<tr>
<td>Training</td>
<td>88.2</td>
<td>92.9</td>
</tr>
<tr>
<td>Testing</td>
<td>79.6</td>
<td>84.5</td>
</tr>
</tbody>
</table>

The correct classification accuracy for the $j$th channel of all frequency bands was obtained using this method. So the decision for $v$ was made according to the sign of $g_j(v)$, and its absolute value measures the likelihood of this decision. The logical way of synthesizing all the channels is by summarizing the likelihood together as the final discriminant function, i.e.

$$q(v) = \sum_{j=1}^{M} g_j(v)$$  \hspace{1cm} (3.14)

Therefore, the final classification decision was made by synthesizing all frequency bins and channels according to their classification contribution as rated by training.

3.4.5.5. Results

All three feature extraction and translation methods were tested on identical data sets from three different subjects using $n$-fold cross-validation. The classification accuracy of all the methods, as detailed in Table 3.1, is promising. These methods may be further applied in an online feature extraction and translation method to measure their performance in a real-time environment.

It is evident from the methods described above and the resulting accuracies that it is possible to achieve high classification rates using different methods for a small set of subjects. It is important to note that signal variation does exist between subjects on a consistent basis across the three methods. This is because of signal variations in each subject and also their individual capacity to train and produce the required signal components. The adaptive capabilities of the extraction and translation algorithms must allow to accommodate such differences in users for successful application. Note also that Method C was demonstrated to provide good performance for a larger set of subjects (Wang and He, 2004).

3.5. TYPICAL BCI SYSTEMS

With the growing combinations of signals, feature extraction, and translation techniques, the number of different BCI systems is rapidly growing. Basic research is typically
started on offline BCI systems, where signal acquisition is followed by feature extraction and translation as a separate step. This type of BCI allows researchers to refine and test extraction and translation algorithms before utilizing them in applied research. Ultimately, however, a BCI technique needs to be tested online for assessing its performance.

Another important categorization of BCI systems is external versus internal. External BCI systems, also known as exogenous BCI systems, classify on the basis of a fixed temporal context to an external stimulus not under the user’s control. These systems utilize components evoked by external stimuli such as VEP. These BCI systems do not require extensive training but do require a controlled environment and stimulus. Internal BCI systems, also known as endogenous BCI systems, on the other hand, classify based on a fixed temporal context to a timed event or internal stimulus. These systems utilize components evoked by tasks such as motor imagery and do require significant user training (Wolpaw et al., 2002).

In addition, BCI systems vary in the use of specific or unspecific signal acquisition methods. Specific BCI systems use signals recorded at well-chosen positions where effect is expected such as with specified cognitive tasks. Unspecific BCI systems, meanwhile, use signals recorded from electrodes all over the brain such as with operant condition method.

Over the past 20 years, researchers have created models of several working BCI systems. One such BCI system was developed by Farwell and Donchin. They created a BCI that could be used to type out words by selecting letters, words, and commands from a display. The system used an externally paced method to flash letters randomly on a 6 x 6 matrix on a screen while the user thought about the next letter he or she wanted. When the expected letter flashed on the screen, the user would generate a detectable P300.

Because the system focused on detecting only P300s, signal acquisition was done at specific electrodes. Feature extraction generated 36 feature vectors, one for each square on the screen. As the P300 is time-locked to the stimulus, when a particular row or column was flashed, a 600-ms window of signal was added to each of the corresponding feature vectors. The translation was done by continuously ranking all the features using various methods. The letter, word, or command corresponding to the highest-ranked feature vector was classified as the user’s intent (Farwell and Donchin, 1988).

Kerin and Aunon developed a BCI system that allowed users with severe physical disabilities to communicate with their surroundings by spelling specific codewords that were predefined commands. Depending on the cognitive task performed by the user, the system could detect differences in lateralized spectral power levels. Because the cognitive tasks were not defined, EEG signals were collected from electrodes covering the parietal and occipital regions. Feature extraction involved generating two feature vectors using fast Fourier transform (FFT) and auto-regressive (AR) spectral estimation methods and then running them through a bandpass filter in four frequency bands. A third vector was generated using AR coefficients of the signals in the four frequency bands. The Bayesian quadratic classifier performed feature translation based on the power or AR coefficients of the features (Kerin and Aunon, 1990).

Wolpaw and coworkers developed a BCI system that allowed users to control prosthetic devices by moving a cursor up or down on the screen to select one of two icons. His team also used internally paced events. The EEG was recorded at specific position as the user actively controlled the power of their mu rhythm. EEG signals were collected from specific
bipolar electrode locations around C3 (refer to Figure 3.4). The EEG power spectrum was calculated using FFT with a 3-Hz resolution to generate the feature vector. A power value centered at 9 Hz was used as the amplitude of the mu rhythm. Feature translation was done using linear discriminant analysis on the basis of the power of the mu rhythm divided into five possible levels. Each of the five levels defined a direction and magnitude for the cursor, which eventually helped the cursor reach its targets on the top and bottom of the screen (Wolpaw et al., 1991).

Like Farwell and Donchin’s system, Sutter also presented a BCI system for locked-in individuals to communicate by selecting letters, words, and commands from a screen. This BCI, however, used SSVEP generated by flashing alternating symbols on a display rather than a P300 component. Signal acquisition for most users was done by EEG, through electrodes over the occipital cortex. In one user, however, an intracranial electrode array was utilized. Since SSVEP is time-locked to the change in stimulus, the feature vector was the averaged EEG signal for a specific period after stimulus onset. These feature vectors were overlaid onto 64 template responses, corresponding to a particular letter, word, or command, and the user’s intent was classified on the basis of a predefined threshold between the calculated feature vector and the template (Sutter, 1992).

Pfurtscheller and coworkers developed a BCI system that used mu rhythm EEG recordings measured over the sensorimotor cortex. This BCI, however, used ERD in the mu rhythm rather than the amplitude used by Wolpaw and coworkers. The raw EEG signals were filtered to the alpha band (8–12 Hz) and then squared to estimate the instantaneous mu power. Five consecutive mu power estimates during ERD were combined to create a five-dimensional feature vector that was classified using one-nearest-neighbor (1-NN) classifier with reference vectors generated using the learning vector quantization (LVQ) method (Birch and Mason, 2000). LVQ is a type of vector quantization method where the high-dimensional input space is divided into different regions, with each region having a reference vector and a class label attached. During feature translation, an unknown input vector is classified using the 1-NN classifier, where it is assigned to the class label of the reference vector to which it is closest (Pfurtscheller et al., 1993).

A few more BCI systems, along with revisions to existing systems were also presented. Pfurtscheller and coworkers introduced the concept of using signals from the sensorimotor cortex generated from imagined motor movements (Pfurtscheller et al., 1994, 1997). Wolpaw and McFarland revised the cursor-based BCI system with predefined directional movements to utilize recordings from multiple channels and allow simultaneous two-dimensional cursor control by using the sum of the feature vector power levels as a magnitude of vertical movement and the difference of the power levels as a magnitude of horizontal movement. This allowed the user to select from four icons, one at each corner of the screen (Wolpaw and McFarland, 1994).

Birbaumer and coworkers introduced a BCI system that utilized SCPs. This system also enabled users to create text messages by selecting letters from a virtual keyboard displayed on a screen. The EEG signals were recorded from electrodes over the frontal cortex. The feature vector was represented by the amplitude of the SCP waveform averaged over a predefined sliding window. Feature translation was done using a linear classification with a heuristic threshold customized to the user. The feature vectors were classified into two states, move up or move down, which moved a cursor up or down on the screen (Birbaumer et al., 1999).
Kennedy and coworkers created a new version of the spelling device that used the firing rate of particular neural groups. The user would make selections by actively controlling the firing rate of neurons through imagined movements, which was recorded by two electrodes implanted within the area of the primary motor cortex that controlled hand movements. The user was presented with a cursor on a screen with a dynamic matrix of letters, words, or commands. The feature vector was a reflection of the firing rate recorded by both electrodes. Increasing neuronal firing rate resulted in increasing output levels, which defined the horizontal and vertical cursor speed. A particular cell could be selected on the basis of a dwell time threshold, a predefined amount of time that the user would leave the cursor on the cell to indicate that it was their choice (Kennedy et al., 2000).

The systems described above are only a small sampling of the work that has been done in BCI. It is difficult to objectively compare the wide array of BCI systems that utilize a variety of signals and are aimed at different applications. The goal of every BCI system, however, is to communicate the user's intent accurately. As the number of possible choices increases, accuracy alone becomes a weak scoring methodology. For communication systems the traditional unit of measure is the amount of information transferred for a unit of time. For BCI systems, therefore, the performance measure can be indicated by bits per trial and bits per minute. This provides a tangible measure for making intrasystem and intersystem performance comparisons.

The bit rate for a BCI system can be calculated easily. Let there be $N$ possible choices for each trial, where each choice has the same probability of being the desired choice. If the probability, $P$, that the desired choice will be selected is constant and the probability of each of the undesired choices being selected is equal, then the bit rate per trial, $B$, can be defined by Eq. (3.15) (Wolpaw et al., 2000b).

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2[(1 - P)/(N - 1)] \quad (3.15)$$

As the number of possible choices increases, an equivalent bit rate can be achieved even with a lower accuracy when compared to systems with smaller number of possible choices as shown in Figure 3.16. It is also important to note that for any BCI, the relationship between accuracy and rate of information transfer is not linear. Increasing the accuracy, for example, from 80 to 90% in a two-choice system nearly doubles the information transfer rate.

3.6. BCI DEVELOPMENT

Basic and applied research in BCI has advanced rapidly, especially over the past 20 years. There are dozens of active research groups around the world involved in the development of BCI technology. Though BCI has emerged from theory to reality with systems now being introduced into commercial applications, the field still holds tremendous untapped potential.

Considering the current rate of development, advancing the proliferation of BCI technology requires an increase in the number of people and funding involved. BCI requires increasing cooperation between various fields such as computer science, neuroscience, engineering, psychology, medical imaging, etc. Establishing multidisciplinary research teams is essential.
Factors such as insurance coverage, for example, can aid in faster commercial applications of BCI devices. If users can be reimbursed for the expenses incurred in operating the BCI device, they would be more willing to utilize them. Increasing interest from the industry would not only standardize manufacturing and lower the unit cost, but also increase research funding. This would require a larger target audience and development of BCI technology for applications beyond assistance of patients with disabilities.

Future work in BCI technology should focus on basic and applied research. New usable features are required for more precise and faster user control. New algorithms are required for feature extraction and translation. Advancements in signal acquisition methods such as invasive techniques also potentially hold great promise in increasing spatial and temporal resolution. Novel applications of EEG inverse solutions, which convert the smeared scalp EEG onto source signals in the brain or over the brain surface (Mosher et al., 1992; Babiloni et al., 1997; He et al., 2001, 2002a, 2002b; He and Lian, 2002, 2004), promise to overcome the limitations of scalp EEG and may lead to high resolution noninvasive BCI (Qin et al., 2004). Better and easier training methods to make BCI devices easier to use will make BCI
systems usable by extremely locked-in users. Finally, increasing awareness of the potential of BCI technology will be essential in generating public interest and channeling government funding.

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