Brain–Computer Interfaces

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Bin He, Han Yuan, Jianjun Meng, and Shangkai Gao

Abstract

Brain–computer interfaces (BCIs) have emerged as a novel technology that bridges the brain with external devices. BCIs have been developed to decode human's intention, leading to direct brain control of a computer or device without going through the neuromuscular pathway. Bidirectional brain–computer interfaces not only allow brain control but also open the door for modulating the central nervous system through neural interfacing. We review the concepts, principles, and various building blocks of BCIs, from signal acquisition, signal processing, feature extraction, feature translation, to device control, and various applications. The performance assessment and challenges of BCIs are also discussed. Examples of noninvasive BCIs are discussed to aid readers for an in-depth understanding of the noninvasive BCI technology, although this chapter is aimed at providing a general introduction to brain–computer interfaces.

Keywords

Brain–computer interface · Brain–machine interface · BCI · BMI · Neural interface · Mind control · Neuroprosthesis · Neurorobotics · EEG

4.1 Introduction

Brain–computer interfaces are a new technology that could help to restore useful function to people severely disabled by a wide variety of devastating neuromuscular disorders and to enhance functions in healthy individuals. The first demonstrations of brain–computer interface (BCI) technology occurred in the 1960s when Grey Walter used the scalp-recorded electroencephalogram (EEG) to control a slide projector in 1964 [1] and when Eberhard Fetz taught monkeys to control a meter needle (and thereby earn food rewards) by changing the firing rate of a single cortical neuron [2]. In the 1970s, Jacques Vidal developed a system that used the scalp-recorded visual evoked potential (VEP) to determine the eye gaze direction (i.e., the visual fixation point) in humans

B. He (✉)
Department of Biomedical Engineering, Carnegie Mellon University, Pittsburgh, PA, USA
e-mail: bhe1@andrew.cmu.edu

H. Yuan
Stephenson School of Biomedical Engineering, University of Oklahoma, Norman, OK, USA
e-mail: hanyuan@ou.edu

J. Meng
School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China
e-mail: mengjianjunxs008@sjtu.edu.cn

S. Gao
Department of Biomedical Engineering, Tsinghua University, Beijing, China
e-mail: gsk-dea@tsinghua.edu.cn

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and thus to determine the direction in which a person wanted to move a computer cursor [3, 4]. At that time, Vidal coined the term *brain–computer interface*. Since then and into the early 1990s, BCI research studies continued to appear only every few years. In 1980, Elbert et al. showed that people could learn to control slow cortical potentials (SCPs) in scalp-recorded EEG activity and could use that control to adjust the vertical position of a rocket image moving across a TV screen [5]. In 1988, Farwell and Donchin [6] reported that people could use scalp-recorded P300 event-related potentials (ERPs) to spell words on a computer screen. Wolpaw and his colleagues trained people to control the amplitude of *mu* and *beta* rhythms (i.e., sensorimotor rhythms) in the EEG and showed that the subjects could use this control to move a computer cursor [7].

The pace and breadth of BCI research began to increase rapidly in the mid-1990s, and this growth has continued almost exponentially into the present. The work over the past 20 years has included a broad range of studies in all the areas relevant to BCI research and development, including basic and applied neuroscience, biomedical engineering, materials science, electrical engineering, signal processing, machine learning, computer science, assistive technology, clinical rehabilitation, and human factors engineering [8–10].

The central goal of BCI research and development is the realization of powerful new assistive communication and control technology for people severely disabled by neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), stroke, spinal cord injury, cerebral palsy, multiple sclerosis, and muscular dystrophies. This emphasis has been encouraged and strengthened by increased societal appreciation of the needs of people with severe disabilities, as well as by greater realization of their ability to live enjoyable and productive lives if they can be provided with effective assistive technology. In addition, in recent years a number of investigators have begun to explore possibilities for developing BCIs for the general population. These include systems for enhancing or supplementing human performance in demanding tasks such as image analysis or continuous attention, as well as systems for expanding or enhancing media access, computer gaming, or artistic expression. Furthermore, BCI technology has recently begun to be explored as a means to assist in the rehabilitation of people disabled by stroke and other acute events. This chapter provides an introduction to the underlying concepts and principles as well as the applications of BCIs.

4.2 BCI Definition and Structure

4.2.1 What Is a BCI?

According to present understanding, the role of the central nervous system (CNS) is to respond to occurrences in the environment or in the body by producing appropriate outputs. The natural outputs of the CNS are either neuromuscular or hormonal. Correspondingly, the natural inputs of the CNS are from different sensory organs, peripheral nerves, internal hormones, etc. A brain–computer interface (BCI), which could interact with the CNS bidirectionally, gives the CNS new output that is not neuromuscular or hormonal or provides new inputs to the CNS, which could be direct stimulations to the CNS by injecting physical energy, such as deep brain stimulation (DBS), transcranial electrical stimulation (TES), transcranial magnetic stimulation (TMS), transcranial focused ultrasound (tFUS), or other forms of brain signal modulation. *A BCI is a system that measures CNS activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output; it can also be considered as a system to influence CNS activity and behavioral performance by injecting physical energy such as TES, TMS, tFUS, or direct brain signal modulation and thereby changes the ongoing interactions between the CNS and its external or internal environment.*

To understand this definition, one needs to understand each of its key terms, starting with *CNS*. The CNS is composed of the brain and the spinal cord and is differentiated from the peripheral nervous system (PNS), which is composed of the peripheral nerves and ganglia and the sensory receptors. The unique features of CNS structures are their location within the meningeal coverings (i.e., meninges), their distinctive cell types and histology, and their role in integrating the numerous different sensory inputs to produce effective motor outputs. In contrast, the PNS is not inside the meninges, does not have the unique CNS histology, and serves primarily to bring sensory inputs to the CNS and to carry motor outputs from it.

CNS activity comprises electrophysiological, neurochemical, and metabolic phenomena (such as neuronal action potentials, synaptic potentials, neurotransmitter releases, and oxygen consumption) that occur continually in the CNS. These phenomena can be monitored by measuring electric or magnetic fields, hemoglobin oxygenation, or other parameters employing sensors on the scalp, on the surface of the brain, or within the brain. A BCI records brain signals, extracts particular measures (or features) from them, and converts (or translates) the features into new artificial outputs that act on the environment or on the body itself. Alternatively, a BCI system could also deliver physical energy directly to the brain through transcranial electrical, magnetic, acoustic stimulation or direct-current stimulation to the brain (e.g., DBS or direct cortical stimulation), to modulate the CNS to change the information-processing patterns within the brain and affect human behaviors.

Figure 4.1 illustrates the concepts of bidirectional BCIs, either controlling a device by the brain bypassing the common neuromuscular pathways or modulating and affecting the brain by injecting external physical energy.

A BCI output could *replace* natural output that has been lost to injury or disease. Thus, someone who cannot speak could use a BCI to spell words

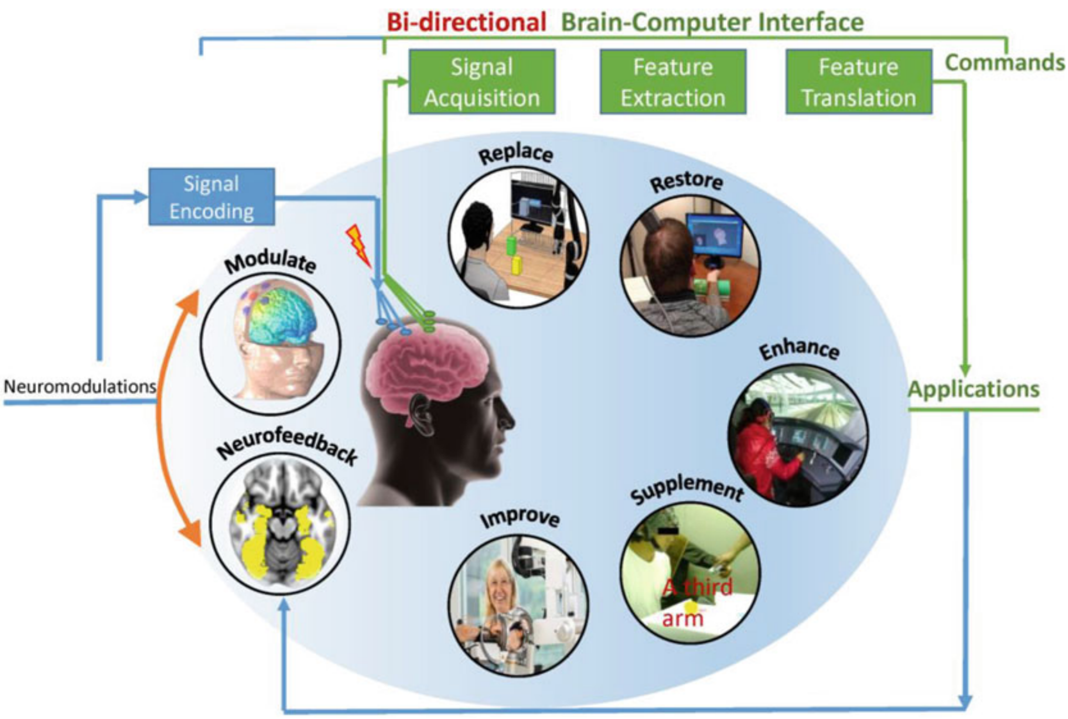

Fig. 4.1 Schematics of bidirectional brain–computer interface (BCI) systems. For a brain-to-device BCI, signals produced by brain activity are recorded from the scalp, from the cortical surface, or from within the brain. These signals are analyzed to extract signal features (e.g., amplitudes of EEG rhythms or firing rates of individual neurons) that correlate with the user's intent. These features are then translated into commands that control application devices that replace, restore, enhance, supplement, or improve natural CNS outputs. For a device-to-brain BCI, neuromodulation can be exerted on the brain through physical energy to modulate the CNS activity

that are then spoken by a speech synthesizer [11] or someone who has lost limb control could use a BCI to operate a powered wheelchair [12] or control a robotic arm [13, 14].

A BCI output could *restore* lost natural output. Thus, someone with a spinal cord injury whose arms and hands are paralyzed could use a BCI to control stimulation of the paralyzed muscles with implanted/attached electrodes so that the muscles move the limbs [15, 16] or someone who has lost bladder function from multiple sclerosis could use a BCI to stimulate the peripheral nerves controlling the bladder so as to produce urination.

A BCI output could *enhance* natural CNS output. Thus, someone engaged in a task that needs continuous attention over a long time (e.g., driving a car or performing sentry duty) could employ a BCI to detect the brain activity preceding breaks in attention and then produce an output (such as a sound) that alerts the person and restores attention [17]. By preventing the periodic attentional breaks that normally compromise natural CNS output, the BCI *enhances* the natural output.

A BCI output could *supplement* natural CNS output. Thus, someone controlling cursor position with a standard joystick might employ a BCI to choose items that the cursor reaches [18]. Or a person could use a BCI to control a third (i.e., robotic) arm and hand [19]. In these examples, the BCI *supplements* natural neuromuscular output with another artificial output.

Lastly, a BCI output might possibly *improve* natural CNS output. For example, a person whose arm movements have been compromised by a stroke damaging sensorimotor cortex might employ a BCI that measures signals from the damaged areas and then excites muscles or controls an orthosis that improves arm movement [20]. Because this BCI application enables the production of more normal movements, its continued use might induce activity-dependent CNS plasticity that *improves* the natural CNS output and thus helps to restore more normal arm control.

The first two kinds of BCI application, replacement or restoration of lost natural outputs, are the focus of most present-day BCI research and development. At the same time, the other three types of applications are drawing increasing attention. Furthermore, a BCI *changes the ongoing interactions between the CNS and its external or internal environment*. The CNS interacts constantly with the environment and the body. These interactions comprise its outgoing motor outputs along with its incoming sensory inputs. By monitoring CNS activity and translating it into artificial outputs that act on the environment or the body, BCIs modify both CNS motor outputs and sensory inputs (i.e., feedback). Devices that only monitor brain activity and do not employ it to modify the continuing interactions of the CNS with its environment are not considered BCIs.

In addition to interacting with and controlling the environment by the brain, a BCI might modulate brain signals through direct physical stimulation such as TES, TMS, tFUS, and DBS or through neurofeedback trainings. Conventionally, such device-to-brain interfacing systems are referred to as neuromodulation approaches (see Fig. 4.2 for the illustration of device-to-brain BCI approaches) and will be treated comprehensively in Chaps. 6, 7, and 8 for deep brain stimulation, transcranial magnetic stimulation, and transcranial electrical stimulation. In this chapter, we will mainly focus on brain-to-device interfacing and control.

4.2.2 Alternative or Related Terms

BCIs are also called brain–machine interfaces or BMIs. The choice between these two synonymous terms is essentially a matter of personal preference. One reason for using BCI rather than BMI is that the word “machine” in BMI implies a fixed translation of brain signals into output commands, which does not match the reality that a computer and the brain are essentially partners in the interactive adaptive control that is required for successful BCI, or BMI, function.

The terms *dependent BCI* and *independent BCI* appeared in 2002 [10]. In accord with the definition of a BCI, both employ brain signals to control applications; however, they differ in how they depend on natural CNS output. A dependent BCI employs brain signals that depend on muscle activity. The BCI developed by Vidal [3, 4] used a VEP that depended on gaze direction and therefore on the muscles that controlled gaze. A dependent BCI is basically an alternative way to

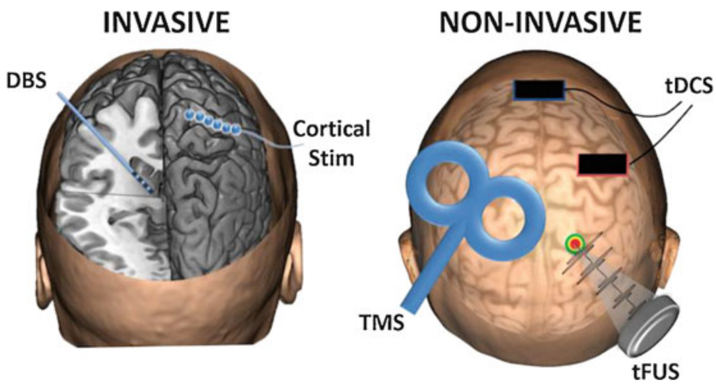

Fig. 4.2 A summary of invasive and noninvasive device-to-brain BCI technologies (also called neuromodulation). Invasive techniques include DBS, in which a lead is implanted into a deep brain structure, and cortical stimulation, in which electrodes are placed on the brain surface. Noninvasive techniques include transcranial magnetic stimulation (TMS), transcranial direct-current stimulation (tDCS) via scalp sponge electrodes, or transcranial focused ultrasound stimulation (tFUS) using pulsed ultrasound from a transducer on the scalp. These neuromodulation approaches impact the brain by injecting physical energy to modulate the neural activation and connectivity within the brain. (From Edelman et al. [35], licensed under CC BY 4.0)

detect messages conveyed by natural CNS outputs. Thus, it does not give the brain a new output independent of natural outputs. Nevertheless, it can still be very useful.

Contrastingly, an *independent BCI* does not depend on natural CNS output; muscle activity is not needed to generate the crucial brain signals. Thus, in BCIs that measure EEG sensorimotor rhythms, the user typically employs mental imagery to modulate sensorimotor rhythms in order to produce the BCI output. For those who are severely disabled by neuromuscular disorders, independent BCIs are likely to be more effective.

The recent term *hybrid BCI* is used in two ways [21]. It can be applied to a BCI that employs two different types of brain signals (e.g., VEPs and sensorimotor rhythms) to produce its outputs, or it can be applied to a system that combines a BCI output and a natural muscle-based output. In this second usage, the BCI output supplements a natural CNS output (as Fig. 4.1 illustrates).

4.2.3 The Components of a BCI

A BCI detects and measures features of brain signals that reveal the user's intentions and translates these features in real time into commands that achieve the user's intent or affect the user's brain state (Fig. 4.1). In order to do this, a BCI system has four components: 1) signal acquisition, 2) feature extraction, 3) feature translation, and 4) device output commands or neurofeedback training paradigm. Note that, besides these four traditional BCI components, a direct physical energy might be injected to interact with or affect the CNS (also an approach called neuromodulation). A BCI also has an operating protocol that specifies how the onset and timing of operation or physical energy injection is controlled; how the feature translation process is parameterized, the nature of the commands that the BCI produces, the neurofeedback training that the BCI induces; and how errors in translation are handled. A successful operating protocol enables the BCI system to be flexible and to serve the particular needs of each of its users.

The signal acquisition component measures brain signals using a particular kind of sensor (e.g., scalp or intracranial electrodes for electrophysiological activity, functional magnetic resonance imaging for metabolic activity, etc.). It amplifies the signals to enable subsequent processing, and it may also filter them to remove noise such as 60-Hz (or 50-Hz) power line interference. The amplified signals are digitized and transmitted to a computer.

The feature extraction component analyzes the digitized signals to isolate signal features (e.g., power in specific EEG frequency bands or firing rates of individual cortical neurons) and expresses them in a compact form suitable for translation into output commands. Effective features need to have strong correlations with the user's intent. Since much of the most relevant (i.e., most strongly correlated) brain activity is transient or oscillatory, the signal features most commonly extracted by present-day BCIs are EEG or electrocorticogram (ECoG) response amplitudes, power in particular EEG or ECoG frequency bands, or firing rates of single cortical neurons. To ensure the accurate measurement of the chosen signal features, artifacts such as electromyogram (EMG) from cranial muscles need to be avoided or eliminated.

The signal features are provided to the feature translation algorithm, which converts them into commands for the output device, that is, into commands that achieve the user's intent. Thus, a decrease in power in a specific EEG frequency band might be translated into an upward displacement of a computer cursor, or a particular evoked potential measure might be translated into the selection of a letter to be added to a document being composed. The translation algorithm should be able to accommodate and adapt to spontaneous or learned changes in the user's signal features in order to ensure that the user's possible range of feature values covers the full range of device control and also to make control as effective and efficient as possible.

The commands that the feature translation algorithm produces are the output of the BCI or the input of the brain, which has to be modulated internally [17]. They go to the application and there produce functions such as letter selection [17], cursor control [18], robotic arm operation [13, 14], wheelchair movement [12], etc. The operation of the device provides feedback for the user and thereby closes the control loop.

4.2.4 The Unique Challenge of BCI Research and Development

As noted earlier, the natural CNS function is to produce muscular and hormonal outputs that act on the outside world or the body. BCIs give the CNS entirely new artificial outputs derived from brain signals. In essence, they ask the CNS, which has evolved to produce muscular and hormonal outputs, to produce entirely new kinds of outputs. Thus, for example, the sensorimotor cortical areas, which normally act in combination with subcortical and spinal areas to control muscles, are now required instead to control specific brain signals (such as neuronal firing patterns or EEG rhythms). The fundamental implications of this requirement become evident when BCI use is considered in terms of two basic principles that govern how the CNS produces its natural outputs.

First, the task of producing natural outputs is distributed throughout the CNS, from the cerebral cortex to the spinal cord. No one area is entirely responsible for a natural output. Actions such as speaking, walking, or playing the piano are produced by the integrated activity of cortical areas, basal ganglia, thalamic nuclei, cerebellum, brain stem nuclei, and spinal cord interneurons and motoneurons. Thus, while the cortex usually initiates walking and monitors its course, the rhythmic rapid sensorimotor interactions that underlie effective walking are handled primarily by circuits in the spinal cord [22]. The final result of this highly distributed CNS activity is the proper excitation of the spinal (or brain stem) motoneurons that activate muscles and thereby produce actions. In addition, while activity in the different CNS areas that are participating generally correlates with the action, the activity in a particular area may vary considerably from one performance of the action to the next. At the same time, the coordinated activity in the many areas involved ensures that the action itself is stable.

Second, natural CNS outputs (such as speaking, walking, or playing a musical instrument) are acquired initially and maintained in the long term by adaptive changes in the many CNS areas that contribute to them. Throughout life, CNS neurons and synapses change continually to master new skills and to maintain those already learned [23, 24]. Referred to as activity-dependent plasticity, this continuing change underlies the acquisition and preservation of both common skills (e.g., walking and talking) and special skills (e.g., athletics, singing); and it is guided by its results. For example, as muscle strength and body size and weight change during life, CNS areas change appropriately to maintain these skills. In addition, the basic CNS features (i.e., its anatomy, physiology, and plasticity mechanisms) that support this ongoing adaptation are the results of evolution shaped by the need to produce appropriate muscle-based actions.

Given these two principles that numerous CNS areas participate in natural outputs and that adaptive plasticity occurs continually in all these areas, BCI use presents a unique challenge for the CNS, which has evolved and is continually adapting to optimize its natural outputs. In contrast to natural CNS outputs, which are produced by spinal motoneurons and the muscles they control, BCI-based CNS outputs are produced by signals reflecting activity in another CNS area, such as the motor cortex. Activity in the motor cortex is normally one of the multiple contributors to natural CNS output. But when its signals control a BCI, this activity becomes the CNS output. In sum, the cortex is given the role normally performed by spinal motoneurons; that is, it produces the final product, the output, of the CNS. How well the cortex performs this new unnatural role depends on how effectively the multiple CNS areas that normally combine to control spinal motoneurons (which are downstream in natural CNS function) can instead adapt to control the relevant cortical neurons and synapses (which are largely upstream in natural CNS function).

The available evidence indicates that the adaptations needed to control activity in the CNS areas that produce the signals used by BCIs are possible but as yet very imperfect. As a rule, BCI outputs are much less smooth, rapid, and accurate than natural muscle-based CNS outputs, and their moment-to-moment and day-to-day variability is disturbingly high. These problems (especially poor reliability) and the different approaches to solving them represent major challenges in BCI research.

4.2.5 BCI Operation Depends on the Interaction of Two Adaptive Controllers and the User Interface

Muscle-based CNS outputs are optimized to serve the goals of the organism, and the adaptation responsible for this optimization takes place mainly in the CNS. In contrast, BCI outputs can be optimized by adaptations in the CNS and/or in the BCI itself. Thus, a BCI may adapt to the amplitudes, frequencies, and other basic characteristics of the user's brain signals; it may adapt to improve the fidelity with which its output commands match the user's intentions; and it may adapt to improve the effectiveness of CNS adaptations and perhaps to guide the CNS adaptive processes.

In sum, a BCI introduces a second adaptive controller that can also change to ensure that the user's goals are achieved. Thus, BCI usage requires successful interaction between two adaptive controllers, the user's CNS and the BCI. The management of the complex interactions between the concurrent adaptations of CNS and BCI is one of the most difficult problems in BCI research. In the past two decades, a majority of studies have focused on either training subjects' brain while fixating the decoding algorithm after each session's calibration or adapting the machine learning algorithm in real time within each session while minimizing subjects' learning effort [25]. Until recently, studies of both invasive and noninvasive BCI [26, 27] showed a piece of converged evidence that subjects' learning curve probably benefits most from collaboration, adapting both controllers, that is, the brain and the decoder algorithm. Theoretical analysis also indicates that adaptation of the BCI system should be at an appropriate rate, not too slow nor too frequent [28]. Studies showed day-to-day variability in performance using daily retrained decoder and nonstable neural ensembles when tracking subjects' performance from weeks to months [26]. Orsborn et al. showed that beneficial neuroplasticity could occur alongside mild and gradual decoder adaptation, yielding performance improvements, skill retention, and resistance to interference from native motor networks [26]. Similarly, in their study, Perdikis and colleagues only recalibrated the decoder of participants twice during the training periods in multiple months. Sufficient time was provided to the subject to adapt their brain rhythms to the fixed decoder. Besides the two controllers, Perdikis et al. even argue for and evaluate the importance of the application interface, which is one of the three pillars of a successful BCI system besides the subject and the machine learning algorithm. The effect of application interface on BCI performance was rarely investigated previously. Some of the previous studies might assume that using more attractive or more natural application interface would cause better engagement of participants [14, 29–31], which implicitly showed a similar idea along this line [32]. Future investigations should consider the application interface as an important factor to the BCI performance. Various application interfaces including control of physical apparatus [14, 33], immersion of virtual reality [34], or switching the stereotype of center-out trial-based task to continuous tracking task [13] should be further explored.

4.2.6 Choosing Signals and Brain Areas for BCIs

Brain signals acquired by a number of different electrophysiological and metabolic methods can be used as BCI inputs for brain-to-device control. These signals differ in topographical resolution, frequency content, area of origin, and technical needs. The major electrophysiological methods as applied to BCIs are illustrated in Fig. 4.3. They range from EEG with its centimeter resolution, to ECoG with its few millimeter resolution, to neuronal action potentials with their tens-of-microns resolution. Each of these electrophysiological methods has been used by BCIs and deserves continued evaluation, as do the metabolic methods such as functional magnetic resonance imaging (fMRI) and functional near-infrared imaging (fNIRs). Each has distinctive advantages and disadvantages, while electrophysiological signals have gained wide adoption due to its high temporal resolution and portability.

The role of neuronal action potentials (spikes) as basic units of communication between neurons suggests that spikes recorded from many neurons could provide multiple degrees of freedom and might therefore be the optimum signals for BCIs to employ. In addition, the clear relationships between cortical neuronal activity and normal motor control provide logical starting points for

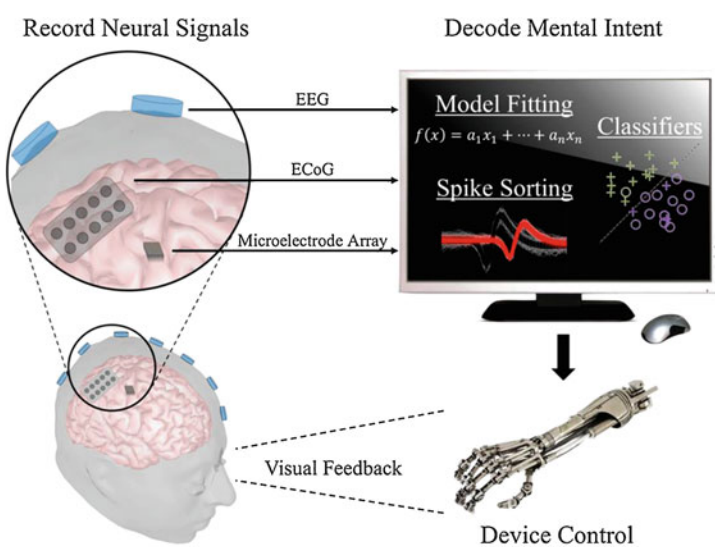

Fig. 4.3 Schematic of a brain-to-device brain–computer interface. Signals are acquired from the brain through the use of internal or external stimuli. A computer then decodes these signals to interpret the user's goal and translates the result into an action of the output device. Subjects can often observe such effects and modulate their brain signals to accomplish the desired task. (From Edelman et al. [35], licensed under CC BY 4.0)

BCI-based control of applications such as robotic arms. On the other hand, the importance of CNS adaptation for all BCIs and the evidence that appropriate training can elicit multiple degrees of freedom from even EEG signals suggest that the difference between the BCI performance possible with single neurons and that possible with EEG or ECoG may not be nearly as large as the difference in their respective topographical resolutions.

The most important point is that questions about signal selection are empirical questions that can be answered only by experimental evidence, not by a priori assumptions about the fundamental superiority of one kind of signal or another. For BCI usage, the crucial issue is which signals can best indicate the user's intent and serve the purpose of applications, that is, which signals are the best language for communicating to the BCI the output that the user wants, to achieve the purpose such a BCI is aimed at.

The choice of the optimum brain areas from which to obtain the signals is also an empirical question at the time. The work to date has focused largely on signals from sensorimotor auditory, and visual areas of cortex. The BCI capacities of signals from other cortical or subcortical areas are just beginning to be investigated. This is an important aspect of BCI research, particularly because the sensorimotor cortices of many possible BCI users have been compromised by disease or injury, and/or their vision may be impaired. Different brain areas may differ in their adaptive capabilities and in other factors that could affect their capacity to function as the sources of BCI output commands. For example, reconstructing speech from the neural responses recorded from the human auditory cortex opens up the possibility of a speech BCI to restore speech in severely paralyzed patients [36, 37]. This new speech BCI is different from the conventional P300 speller or SSVEP-based virtual keyboard which translates users' visual attention into characters, words, and sentences via special visual stimulus pattern [38–40]. These conventional BCI spellers mainly decode brain signals from the visual occipital cortex. However, the nascent field of speech BCI directly decodes the brain signals from the speech production areas in the temporal lobe [37]. Due to the unique characteristics and complexity of producing human languages, it is not possible to do the experiments in animal models. ECoG, which is vastly used in the clinical setting, has a high temporal and spatial resolution. The most common type of intractable epilepsy is usually caused by the pathological change of temporal lobe; however, a good number of these patients with focal epilepsy in the temporal lobe still preserve intact speech ability. Thus, ECoG-based speech BCI could be developed and validated in this population [41]. The advancement of speech BCI may benefit patients undergoing ECoG recordings who cannot speak due to, for example, brain stem stroke and cerebral palsy [42]. Recent advancement of deep learning neural network and its application in speech decoding produce significant progress in decoding the fluent speech directly from the brain signals [11, 36, 41]. The quick development of speech BCI may be a vital option in clinical treatment for those who have language disabilities.

4.3 Signal Acquisition

As discussed earlier, translation of intent into action is dependent on the expression of the intent in the form of a measurable signal. Proper acquisition of this signal is important for the functioning of any BCI. The goal of signal acquisition methods is to detect the voluntary neural activity generated by the user, whether the signals are acquired invasively or noninvasively. Each method of signal acquisition is associated with an inherent spatial and temporal signal resolution. The choice of the appropriate method to use in a particular circumstance depends on striking a balance between the feasibility of acquiring the signal in the operating environment and the resolution required for proper translation.

4.3.1 Invasive Techniques

The invasive acquisition of brain signals for use in BCIs is primarily accomplished by electrophysiologic recordings from electrodes that are neurosurgically implanting either inside the user's brain or over the surface of the brain. The motor cortex has been the preferred site for implanting electrodes since it is more easily accessible and has large pyramidal cells, which produce measurable signals that can be generated through simple tasks such as actual or imaginary motor movements. Other brain areas such as the supplementary motor cortex, parietal cortex, and subcortical motor areas can also serve as candidate sites for electrode implantation. Information from complementary imaging techniques such as fMRI can help determine potential target areas for a specific subject [43]. fMRI measurement of the blood-oxygenation level dependent (BOLD) response has facilitated the determination of cortical areas useful for the recording of brain activity and has also been shown to provide reliable BCI control across several cortical areas using different cognitive tasks.

4.3.1.1 Intracortical

With chronic recording using implanted microelectrode arrays, the key factors for successful recording are the spatial/temporal resolution of the desired signal, the number and placement of electrodes, and the functional lifetime of the device. A growing number of electrode technologies have been developed to meet these requirements. Significant advancement has been witnessed in intracortical BCIs research over the past two decades, demonstrating brain-controlled robotic arms in nonhuman primates [44, 45] and human subjects [46, 47]. For a comprehensive coverage of intracortical BCIs, see Chapter 5 in this book.

4.3.1.2 Cortical Surface

A less-invasive approach, though still requiring surgical implantation of the recording device, is ECoG. This technique, in which an electrode array is implanted subdurally over cortex, has been used mainly in preparation for surgery in people with epilepsy. As is the case for EEG recording, this technique takes advantage of the fact that most large cortical neurons are orientated perpendicular to the cortical surface and that locally synchronized activity within a cortical column can sum to yield a detectable signal. Subdural electrodes are closer to neuronal structures in superficial cortical layers than EEG electrodes placed on the scalp, and therefore, the signals that they record have higher amplitude (as well as a broader frequency bandwidth). Whereas scalp electrode recordings represent synchronized activity from a large number of neurons and synapses over extended regions of cortex [48], subdural recordings are sensitive to smaller sources of synchronized neuronal activity. Subdural recordings also have a higher signal-to-noise ratio than scalp recordings and have increased ability to record and study gamma activity (i.e., activity >30 Hz). Since gamma activity has been shown to be well correlated with the surrounding single-unit activity recorded by penetrating microelectrodes [49], ECoG can yield an effective representation of the underlying cortical electrical activity with less invasiveness and more stability than penetrating microelectrodes, albeit still invasive.

The standard clinical electrodes used for ECoG monitoring in epilepsy patients typically have diameters on the order of a few millimeters. Although finer than scalp electrodes, this dimension is still much larger than that of a typical cortical column. Therefore, most studies involving subdural ECoG use gross motor movements to determine tuning parameters. It was shown that overt movements as well as motor imageries are accompanied not only by relatively widespread mu and beta event-related desynchronization (ERD), but also by a more focused event-related synchronization (ERS) in the gamma frequency band [50]. In the first closed-loop ECoG-based BCI, study subjects quickly learned to modulate high-frequency gamma rhythms in motor cortical areas and in Broca's speech area to control a one-dimensional computer cursor in real time. Subsequent studies achieved two-dimensional control of a computer cursor using the upper arm region of motor cortex for one dimension and the hand region of motor cortex for the other dimension [51]. Other investigators explored distinctly human traits such as speech and language processing that cannot be analyzed in an animal model and have had success using gamma activity from a speech network to control a cursor in one dimension [52]. The subjects used self-selected imagery to modulate gamma-band activity at one or more specific electrodes. This represents a new approach in ECoG-based BCIs.

4.3.2 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 EEG, magnetoencephalography (MEG), fMRI, and fNIRS have been used in noninvasive BCIs.

4.3.2.1 EEG

EEG is the most prevalent method of signal acquisition for BCIs. EEG recording has high temporal resolution: it is capable of measuring changes in brain activity that occur within a few milliseconds. The spatial resolution of EEG is not as good as that of implanted methods, but signals from up to 256 electrodes can be measured at the same time [53]. EEG is easy to set up, portable, and inexpensive and has a rich literature of past performance. The practicality of EEG in the laboratory and the real-world setting is unsurpassed. EEG recording equipment is portable, and the electrodes can be easily placed on the subject's scalp by simply donning a cap. In addition, since EEG systems have been widely used in numerous fields since their inception more than 90 years ago, the methods and technology of signal acquisition with this modality have been standardized. Finally, and most important, the method is noninvasive.

Many EEG-based BCI systems use an electrode placement strategy based on the International 10/20 system as detailed in Fig. 4.4. 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. Nevertheless, EEG-based BCI control with several degrees of freedom can be achieved with just a few electrodes [18, 29].

Over the past few decades, EEG-based BCIs have been widely investigated in healthy human subjects, as well as in people with amyotrophic lateral sclerosis (ALS) and in those with severe CNS damage from spinal cord injuries and stroke, resulting in substantial deficits in communication and motor function.

Compared with invasive BCIs, EEG-based BCI methods have the advantage of no surgical risk, signal stability, and low cost. However, since EEG represents scalp manifestation of brain electrical activity from a distance, it has a lower signal-to-noise ratio than many invasive methods. The spatial resolution of EEG is also reduced by the volume-conduction effect [48]. Many noninvasive BCIs are based on classification of different mental states rather than decoding kinematic parameters as is typically done in invasive BCIs. Various mental strategies exploiting motor, sensory, and cognitive activity detectable by EEG have been used to build communication systems. In these systems, typically one mental state corresponds to one direction of control and four independent mental states are generally required for full two-dimensional control. Therefore, a substantial period of training is typically required for users to develop the skill to maintain and manipulate various mental states to enable the control. This can be quite demanding for users, especially disabled users. Other investigators attempted to directly decode the kinematic information related to movement or motor imagery and have reported success in revealing information about the (imagined) movement direction and speed from the spatiotemporal profiles of EEG signals [54–56]. In a closed-loop experiment by Bradberry et al. [57] using the direct decoding of kinematic information, subjects were able to attain two-dimensional control after a short training (∼40 minutes).

It will also be important to develop better understanding of the mechanisms of information encoding in EEG signals. It has been demonstrated that detailed kinematic information, not simply gross mental states, is represented in the

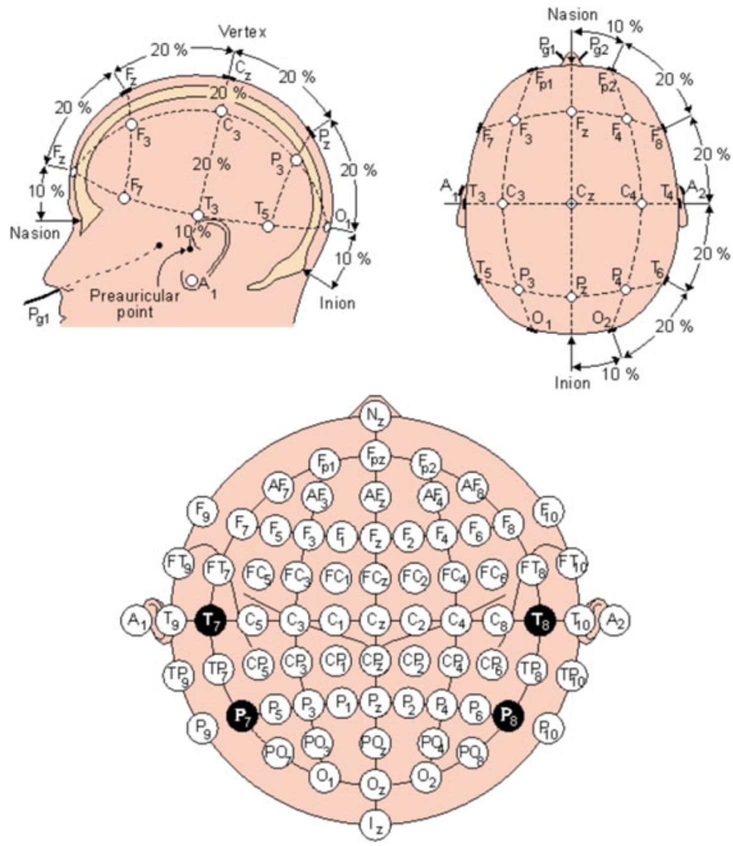

Fig. 4.4 Placement of electrodes for noninvasive signal acquisition using EEG. This standardized arrangement of electrodes over the scalp is known as the International 10/20 system and ensures ample coverage over all parts of the head. The exact positions for the electrodes are at the intersections of the lines calculated from measurements between standard skull landmarks. The letter at each electrode identifies the particular sub-cranial lobe (FP: Prefrontal lobe; F: Frontal lobe; T: Temporal lobe; C: Central lobe; P: Parietal lobe; O: Occipital lobe). The number or second letter identifies its hemispherical location (Z: denotes line zero and 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 [197], http://www.bem.fi/book/, with permission)

distributed EEG signals [54–56]. Interestingly, brain signals recorded on the scalp surface and those recorded intracranially reveal similar encoding models [58], suggesting that knowledge gleaned from invasive BCIs could be transferred to the understanding of EEG-based BCI signals. This might further advance noninvasive BCI technology and thereby possibly achieve high degrees of control and reduce training requirements.

Source analysis has been widely used to estimate the sources of the brain activity that produces noninvasively recorded signals such as EEG [48]. The rationale behind this approach is the linear relationship between current source strength and the voltage recorded at the scalp. Thus, one may estimate equivalent current density representations in regions of interest from noninvasive EEG or MEG recordings. He and colleagues proposed to use such EEG-based source signals to classify motor imagery states for BCI purposes [59]. Such source imaging–based approach has shown promising results based on motor imagery paradigm [43, 60–63].

The use of source estimation in BCI applications involves increased computational cost due to the need to solve the inverse problem. On the other hand, such source analysis transforms signals from sensor space back to source space and can lead to enhanced performance due to the use of a priori information in the source estimation procedure [13].

4.3.2.2 MEG

MEG measures the magnetic induction produced by electrical activity in neural cell assemblies. The magnetic signal outside of the head is on the order of a few femtoteslas, one part in 10^9 or 10^8 of the earth's geomagnetic field. MEG is commonly recorded using the SQUID (superconducting quantum interference device), in which it is also necessary to provide shielding from external magnetic signals, including the earth's magnetic field. The SQUID MEG recording requires a laboratory setting. A modern MEG system is equipped with an array of up to $\sim$300 gradiometers evenly distributed in a helmet shape with an average distance between sensors of 1$\sim$2 cm. Recently the feasibility of a wearable MEG system was reported for human use [64], although it is a technology that is still under development and currently quite expensive.

MEG has similarities to EEG. MEG and EEG are, respectively, magnetic and electric fields produced by neuronal and synaptic activity. Both methods sense synchronized brain activity. MEG detects only the tangential components of a neural current source, whereas EEG is sensitive to both tangential and radial components. Importantly, like EEG, MEG is also a noninvasive recording technology. Studies using electrophysiological source imaging techniques have located common cortical sources underlying the control provided by the EEG- and MEG-based BCIs [63, 65]. Meanwhile, other investigators reported that kinematic parameters are similarly represented in MEG and EEG recordings, since the key information is embedded in the lower frequency ranges [55]. Nonetheless, the high-frequency information in MEG signals is being actively investigated for neural encoding. Notably, it was found that in human subjects who are planning a reaching movement, the 70–90 Hz gamma-band activity originating from the medial aspect of the posterior parietal cortex (PPC) was synchronized and direction-sensitive [66]. These results in human subjects are compatible with the functional organization of monkey PPC derived from intracranial recordings. From the viewpoint of BCI research, these findings may suggest new approaches for developing control signals utilizing such high-frequency components in MEG, or in EEG as well [67].

A merit of using MEG is that magnetic fields are less distorted by the skull layer than are electric fields. However, studies so far have shown that the performance and training times for EEG- and MEG-based BCIs are comparable [68]. In addition, the instrumentation necessary for MEG is more sophisticated and more expensive than that for EEG. These factors have tended to discourage BCI research using MEG recording so far.

4.3.2.3 fMRI

Functional magnetic resonance imaging or functional MRI (fMRI) [69–71] measures changes in the blood flow (i.e., the hemodynamic response) related to neural activity in the brain. It samples very large numbers of spatial locations spanning the whole brain and provides an ongoing stream of information from the many measurement points at the same time. Compared to prior methods for acquiring brain signals, fMRI therefore provides measurements that are highly distributed and highly parallel, on the order of millimeter resolution. For example, a modern MRI scanner can currently sample from $\sim 2^{16}$ spatial locations per second, each location (i.e., each voxel) with a dimension on the order of 3x3x3 mm. In fMRI, the same volume is sampled repeatedly at short, regular intervals (e.g., once per second) using an imaging contrast, such as the blood-oxygen-level-dependent (BOLD) contrast [72], that is sensitive to the hemodynamic response. The intensities of BOLD contrast are related to the changes in the deoxyhemoglobin concentration in the brain tissue. When neurons are activated, increases in blood flow are associated with increases in local glucose metabolism and increases in local oxygen consumption. The changes in local deoxyhemoglobin concentration are reflected in the brightness of the MRI image voxels at each time point. It has also been reported that a strong colocalization of fMRI activation and electrophysiological sources exist during hand movement and motor imagery [43, 73]. fMRI imaging is thought to be quite safe. It does not use an exogenous contrast agent. Typically, it does not involve any invasive procedure, injections, drugs, radioactive substances, or X-rays. It requires an instrument that provides a strong external magnetic field and radio-frequency energy pulses.

fMRI images can be processed in real time as they are collected, namely, as real-time fMRI (rtfMRI) [74] so that the resulting information is immediately available and can thus be used for feedback purpose. For example, the mental states inferred from the rtfMRI can be used to guide a person's cognitive process or a clinician's interventions in the case of psychiatric disorders. The advantage of using fMRI for neurofeedback is the high spatial resolution and deep penetration. The direct sampling of three-dimensional volume information in small voxels enables the detection of activity in all areas of the brain, including deep structures such as the amygdala. In contrast, EEG/MEG measurements near the surface of the head are made far from these locations and the spatial resolution for EEG/MEG source imaging of deep brain activity is relatively limited. However, recent studies have suggested the possibility of detecting deep brain activity from EEG and MEG as validated from intracranial recordings (see Chapter 13).

On the other hand, an essential limit of rtfMRI or fMRI lies in its underlying mechanism: it measures changes in blood flow rather than neuronal activity. The technique is therefore inherently indirect and noisy. Most importantly, there is an intrinsic delay of several seconds in the response of fMRI, no matter how fast the images can be obtained. This means that the feedback given to a subject is delayed by several seconds. This could affect the usefulness of rtfMRI in many BCI applications.

4.3.2.4 NIRS

Functional near-infrared spectroscopy (fNIRS) is another noninvasive technique. It utilizes light in the near-infrared range (700 to 1000 nm) to determine the oxygenation, blood flow, and metabolic status of localized cortical regions. It is similar to BOLD-fMRI in terms of the imaging contrast; that is, it measures the hemodynamic response. It can produce relatively well-localized signals with a spatial resolution on the order of centimeters, and it provides information related to neural activity. However, since the images rely on the shallow-penetrating photons, NIRS operates effectively only for brain structures that are on or near the brain surface. NIRS is also inherently limited in its imaging contrast (i.e., hemodynamic responses), which results in a temporal resolution on the order of seconds and a delay of several seconds for feedback. Thus, in terms of information transfer rate, fNIRS-based BCIs are likely to be less effective than BCIs based on electromagnetic signals. Compared to fMRI, it stands as a compromise between imaging capability and practical usability (i.e., fNIRS is inexpensive and portable). Its flexibility of use, portability, and affordability make NIRS a viable alternative for clinical studies and possibly for practical use.

4.3.3 Neural Signals Used by BCIs

4.3.3.1 Sensorimotor Rhythms

Electromagnetic recording from the brain at rest exhibits endogenous oscillatory activity that is widespread across the entire brain. As shown in Fig. 4.5, this activity can be split into several bands. This spontaneous activity consists mainly of oscillations in the alpha-frequency band (8–13 Hz), which is called the *mu* rhythm when focused over the sensorimotor cortex and the visual alpha rhythm when focused over the visual cortex. This idling oscillation is thought to be caused by complex thalamocortical networks 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 neurons increases. The under-

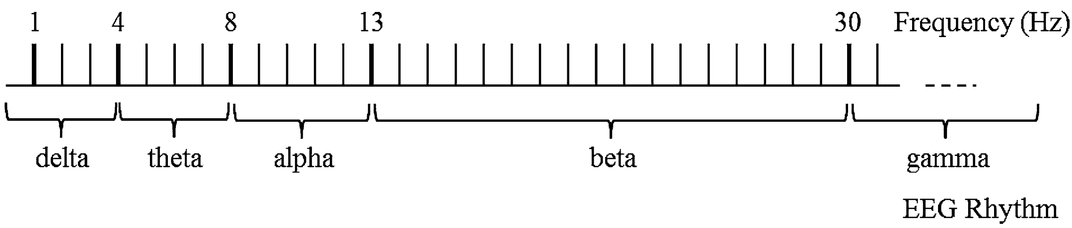

Fig. 4.5 Various signal bands present in the EEG signal. The delta band ranges from 0.5 to 3 Hz and the theta band ranges from 4 to 7 Hz. Most BCI systems use components in the alpha band (8–13 Hz) and the beta band (14–30 Hz). The gamma band, which is just beginning to be applied in BCI, is >30 Hz

lying membrane properties of neurons, the dynamics of synaptic processes, the strength and complexity of connections in the neuronal network, and influences from multiple neurotransmitter systems also play a role in determining the oscillations.

Other oscillations detected over the sensorimotor cortex occur in the beta frequency band (14–30 Hz) and in the gamma band (>30 Hz). Together with the *mu* rhythm, these oscillations recorded over sensorimotor cortex are called sensorimotor rhythms (SMRs). They originate in sensorimotor cortex and change with motor and somatosensory function. These oscillations occur continually during "idling" or rest. During nonidling periods, however, these oscillations change in amplitude and/or frequency, and these changes are evident in the EEG or MEG. Task-related modulation in sensorimotor rhythms is usually manifested as an amplitude decrease in the low-frequency components (alpha/beta band) (also known as event-related desynchronization (ERD) [75]). In contrast, an amplitude increase in a frequency band is known as event-related synchronization (ERS) [75]. For example, it has been found that the planning and execution of movement lead to predictable decreases in the alpha and beta frequency bands [75]. Also, as illustrated in Fig. 4.6, many studies have demonstrated that motor imagery can cause ERD (and often ERS) in primary sensorimotor areas [75, 77–80]. Such characteristic changes in EEG rhythms can be used to classify brain states relating to the planning/imagining of different types of limb movement. This is the basis of neural control in EEG-based BCIs using motor imagery paradigms. Studies have demonstrated that people can learn to increase and decrease sensorimotor rhythm amplitude over one hemisphere using motor imagery strategies and thereby control physical or virtual devices [13, 14, 18, 29–31, 63, 81, 82].

4.3.3.2 Slow Cortical Potentials

A completely different type of signal measured by EEG is the slow cortical potential (SCP) (see Fig. 4.7) that is caused by shifts in the depolarization levels of pyramidal neurons in cortex. Negative SCP generally reflects cortical activation, while positive SCP generally reflects reduced activation. SCP occurs from 0.5 to 10 seconds after the onset of an internal event and is thus considered a slow cortical potential [83]. People can learn to control SCPs and use them to operate a simple BCI [84].

4.3.3.3 The P300 Event-Related Potential

The *P300* is an endogenous event-related potential (ERP) component in the EEG and occurs in the context of the "oddball paradigm" [85]. In this paradigm, users are subject to events that can be categorized into two distinct categories. Events in one of the two categories occur only rarely. The user is presented with a task that can be accomplished only by categorizing each event into one of the two categories. When an event from the rare category is presented, it elicits a P300 response in the EEG. As shown in Fig. 4.8, this is a large positive wave that occurs approximately 300 msec after event onset. The amplitude of the P300 component that is inversely proportional to

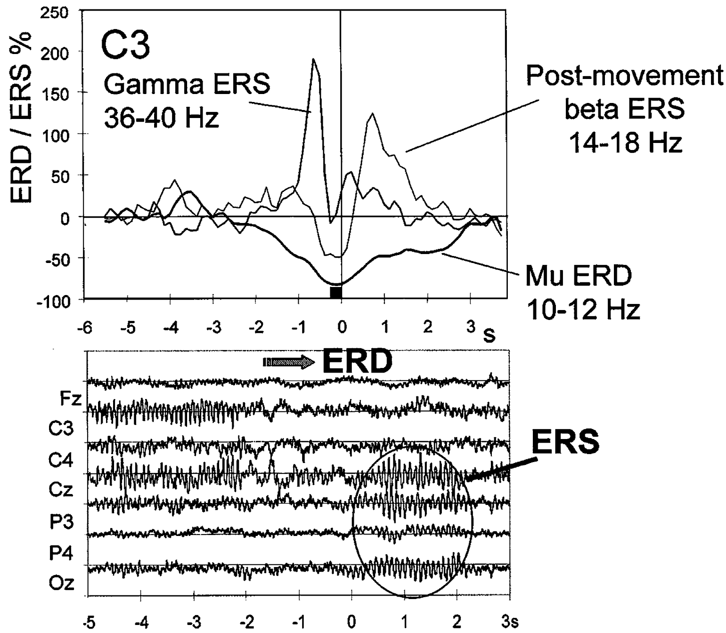

Fig. 4.6 Event-related desynchronization (ERD) and event-related synchronization (ERS) phenomena before and after movement onset. ERD/ERS is a time-locked event-related potential (ERP) associated with sensory stimulation or mental imagery tasks. ERD is the result of a decrease in the synchronization of neurons, which causes a decrease of power in specific frequency bands; and it 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 it can be identified by an increase in signal amplitude. (From Pfurtscheller and Neuper [76], with permission, © 2001 IEEE)

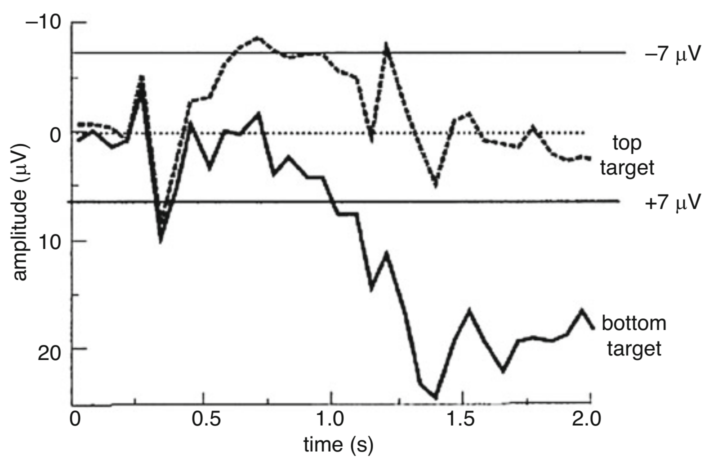

Fig. 4.7 Slow cortical potential (SCP) signals to convey different intents. SCPs are caused by shifts in the dendritic depolarization levels of certain cortical neurons. They occur from 0.5 to 10 seconds after the onset of an internal event and are thus considered a slow cortical potential. (From Kübler et al. [83], with permission)

the frequency of 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.

4.3.3.4 Event-Related Potentials

Exogenous event-related potentials (ERPs) are responses that occur in the EEG at a fixed time after a particular visual, auditory, or somatosensory stimulus. The most common way to derive ERP from EEG recording is aligning the signals

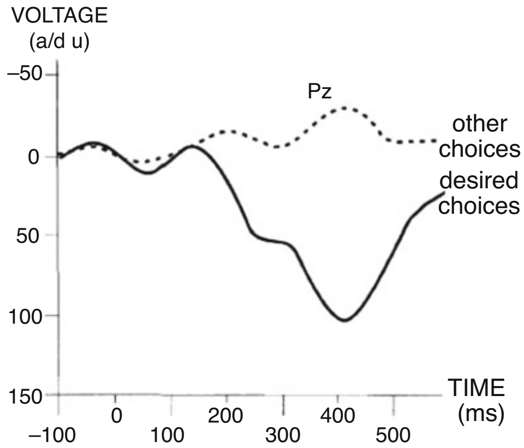

Fig. 4.8 P300 ERP component. When the user sees objects randomly flashed on a screen, the P300 response occurs when the user sees the flash of the object the user is looking for (or wishes to select), while the flashes of the other objects do not elicit this response. The amplitude of the P300 component is inversely proportional to the rate at which the desired object is presented and occurs approximately 300 msec after the object is displayed. It is a natural response and requires no user training. (From Kubler et al. [83], with permission)

according to the stimulus onset and then averaging them. The number of stimuli averaged typically range from a few (e.g., in BCI applications) to hundreds or thousands in other neuroscience research. ERPs are sometimes characterized as "exogenous" or "endogenous." In general, exogenous ERPs are shorter latency and are determined almost entirely by the evoking stimulus, while endogenous ERPs are longer latency and are determined to a considerable extent by concurrent brain activity (e.g., the nature of the task in which the BCI user is engaged).

ERPs are related to the ERD/ERS described above. ERPs reflect in large part activity in the ongoing EEG that is phase-locked by the stimuli. Typically, after averaging, the ERP contains information about very low-frequency components (i.e., <1 Hz). Other components are canceled out in the process of averaging across repetitions, and the information above 1 Hz is poorly represented. An alternative way to characterize task-related EEG signals is to examine the rhythmic activity before averaging, in terms of power (ERD/ERS) or phase. This method does not require averaging and thus can be applied to single trials. Therefore, it is useful for BCI control (although it is still subject to the limitations of its signal-to-noise ratio).

The ERP most commonly used in BCIs is the visual evoked potential (VEP), which occurs in response to a visual stimulus. One frequently used VEP is the steady-state visual evoked potential (SSVEP). SSVEPs and other VEPs depend on the user's gaze direction and thus require muscular control. To produce such signals, the user looks at one of the several objects on a screen that flicker at different frequencies in the alpha or beta bands. Frequency analysis of the SSVEP shows a peak at the frequency of the object at which the user is looking. Thus, a BCI can use the frequency of this peak to determine which object the user wants to select [86, 87].

4.3.3.5 Spikes and Local Field Potentials

Both spikes and local field potentials are acquired from microelectrodes implanted through invasive techniques. Spikes reflect the action potentials of individual neurons. Since the CNS appears to encode information in the firing rates of neurons, recording spiking activity may be highly useful. Local field potentials (LFPs) represent mainly synchronized events (largely in the frequency range of <300 Hz) in neural populations. The major sources of LFPs are synaptic potentials (which are also the major sources for EEG/MEG/ECoG). Other integrative somadendritic processes, including voltage-dependent membrane oscillations and after-potentials following somadendritic spikes, can contribute to LFPs. LFPs and their different band-limited components (e.g., theta (4–7 Hz), alpha, beta, gamma) are tightly related to cortical processing. Gamma-band LFP activity is especially tightly coupled to spiking activity. Because LFPs reflect signals from many neurons, their spatial resolution (and possibly their functional specificity) is lower than that of spiking activity. See next chapter for BCIs using intracortical recordings.

4.4 Signal Processing

The goal of BCI signal processing is to extract features from the acquired signals and translate them into logical control commands for BCI applications. A feature in a signal can be viewed as a reflection of a specific aspect of the physiology and anatomy of the nervous system. Based on this definition, the goal of feature extraction for BCI applications is to obtain features that accurately and reliably reflect the intent of the BCI user.

4.4.1 Feature Extraction

The goal of all processing and extraction techniques is to characterize an item (i.e., the desired user selection) by discernible measures whose values are similar for those in the same category but different for items in another category. Such characterization is accomplished by choosing relevant features from the numerous choices available. This selection process is necessary since 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.

In addition, even though a BCI user is able to generate detectable signals that convey her or his intent, signal acquisition methods also capture noise generated by other unrelated activity in or outside of the brain. Thus, it is important that feature extraction maximize the signal-to-noise ratio.

4.4.1.1 Artifact/Noise Removal and Signal Enhancement

Artifact or noise removal plays an important role in EEG-based BCIs. Since signals are often captured across several electrodes over a series of points in time, existing methods concentrate on either spatial-domain processing or temporal-domain processing or both. To minimize noise in the signal, it is important to understand its sources. First, noise can be captured from neural sources when brain signals not related to the target signal are recorded. Noise can also be generated by non-neural sources such as muscular movements, particularly of the facial muscles. This type of noise in EEG is especially important as signals generated by muscular movements may have much higher amplitudes and can easily be mistaken for actual EEG activity. The problem is further complicated when the frequencies and scalp locations of the non-neural noise and the chosen EEG features are similar.

Typically non-CNS artifacts are the result of unwanted potentials from eye movements, EMG, and other non-neural sources. They are often more prominent in the EEG than brain signals. Simple instructions to the user to not use facial muscles can help and trials that contain such artifacts can be disregarded, but these approaches are not always adequate to remove such noise. Mathematical operations such as linear transformations and component analyses are also used for artifact removal.

After artifact removal, spatial filtering techniques are useful for enhancing features with a specific spatial distribution. In BCI systems that use *mu* or alpha rhythms, the selection of spatial filters can greatly affect the signal-to-noise ratio [88]. 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* [89, 90] 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. It is the second derivative of the spatial voltage distribution and thus is effectively a spatial high-pass filter that emphasizes the contributions from the neural areas closest to the recording electrode (node of interest) [91]. Spline functions can be used to more accurately estimate the surface Laplacian from EEG recordings [92], but in most BCI applications finite difference estimates are used from EEG recordings in a few electrodes due to computational efficiency.

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, while 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 rapid responses required.

4.4.1.2 Feature Extraction Methods

The methods for extracting features depend largely on the type of neural signals used in the BCI and the characteristics associated with the underlying neural process. For neural signals representing mass responses of a large number of neurons (EEG/MEG/ECoG), defining features by spatial location is as important as defining them by temporal/spectral characteristics. In order to optimize the spatial information, the channels used for BCI control are usually a selected subset of a few channels. These can be selected with methods such as principal components analysis (PCA), common spatial pattern analysis (CSP) [93], and independent component analysis (ICA) [94], or based on a priori knowledge of the functional organization of the relevant cortical area(s). Electrophysiological source imaging (ESI) methods have also been proposed as a spatial deconvolution approach to extracting spatial information about the features used in a BCI [13, 59–63].

In order to define the temporal/spectral parameters of the chosen features, the neural signals are usually subjected to time-frequency analysis. Frequency-based features have been widely used in signal processing because of their ease of application, computational efficiency, and straightforward interpretation. Because these features do not provide time-domain information, they are not sensitive to the nonstationary nature of EEG signals. Thus, mixed time–frequency representations (TFRs) that map a one-dimensional signal into a two-dimensional function of time and frequency can be used to analyze the time-varying spectral content of the signals. A typical example is the extraction of the ERD feature in sensorimotor rhythms, which can be obtained using a traditional moving-average method (as shown in Fig. 4.9), an envelope-extraction method (Fig. 4.10), or a TFR method based on wavelets (Fig. 4.11). Parametric approaches are also commonly used to estimate the time/frequency features, such as autoregressive (AR) modeling for stationary signals and adaptive autoregressive modeling for nonstationary signals, which are widely implemented in online BCI systems due to their computational efficiency. However, it is worth noting that such parametric modeling approaches usually require predetermined parameters, such as the model order [95], which can influence BCI performance.

Neural network, especially deep neural network (or deep learning), is attracting more and more attention for feature extraction and feature translation. An early effort was to use neural networks for classifying motor imagery tasks [96]. Several studies using deep learning approaches showed moderate success on offline analysis of existed public BCI data sets [97, 98]; however, the effectiveness has to be further validated by more extensive online experiments. On the contrary to the moderate success in conventional BCI applications, the neural network approach seems to be more successful in the speech BCI. Angrick et al. designed a densely connected 3D convolutional neural networks to reconstruct the spoken words from ECoG signals in the auditory cortex and obtained relatively high-quality speech [41]. Akbari et al. used a deep neural network to estimate the parameters of a speech vocoder directly and achieve relatively high performance on a digit recognition task [36]. Instead of directly decoding the parameters of a speech synthesizer from the ECoG signals, Anumanchipalli and colleagues used a two-stage approach to solve the problem. They first decoded the articulatory kinematic features from the continuous ECoG signals by training a recurrent neural network. Then they translated the kinematic features into the acoustic sound via a general model, which map the recorded speech into the movements of the vocal-tract articulators via a recurrent neural network by their previously accumulated data [11]. They showed successful reconstruction efficacy in closed vocabulary tests, and human listeners could identify and transcribe the reconstructed speech. Further investigation is needed to delin-

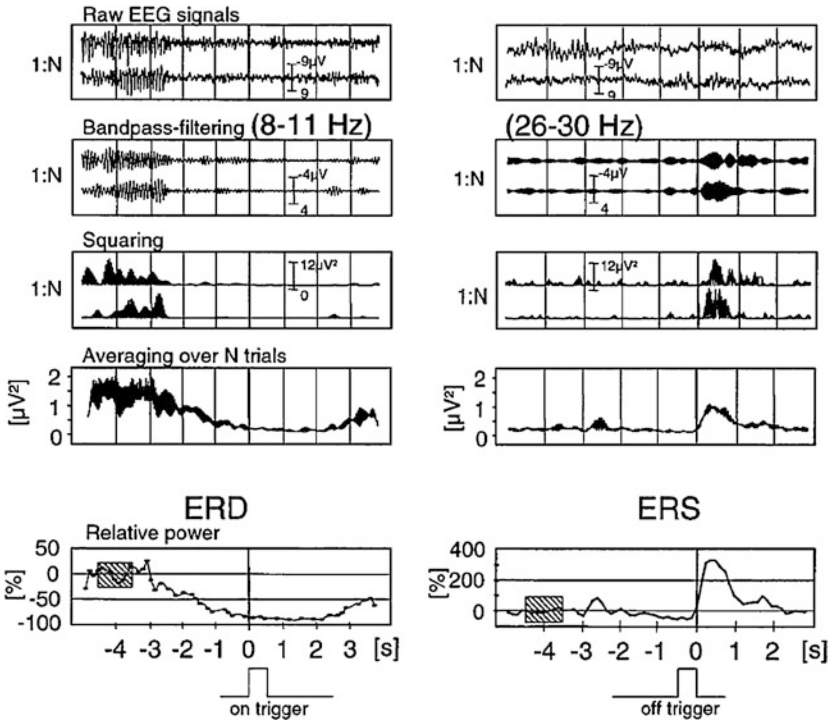

Fig. 4.9 Techniques used to extract ERD and ERS from raw EEG signals. First, the raw EEG signal from each trial is band-pass filtered. Second, the amplitude samples are squared to obtain the power samples. Third, the power samples are averaged across all trials. Finally, variability is reduced and the graph is smoothed by averaging over time samples. (From Pfurtscheller and Lopes da Silva [75], with permission from Elsevier)

eate the sources of these successes, that is, due to the deep learning algorithms or due to the use of invasive ECoG signals (vs. EEG).

4.4.1.3 Feature Selection and Dimensionality Reduction

Feature selection algorithms are used in BCI designs to find the most informative features for determining the user's intent. This approach is especially useful for BCI designs with high-dimensional input data, as it reduces the dimension of the feature space. Since a feature selection block reduces the complexity of the translation problem, higher translation accuracies (i.e., higher accuracies of determining the user's intent) can be achieved.

As discussed by Blum and Langley [99], feature selection techniques can be divided into three major categories. In the first category, called embedded algorithms, the feature selection is a part of the translation (also called classification) method. The feature selection procedure adds or removes features to counteract prediction errors as new training data are introduced. Embedded algorithms, however, are of little use when there is a high level of interaction among relevant features.

In the second category, filter algorithms, specific features are selected prior to, and independent of, the translation process. These algorithms work by removing irrelevant features (those providing redundant data or contaminated by noise) prior to training the translation technique. One approach to filtering involves calculating each feature's correlation with the user's intent and then selecting a fixed number of features with the highest scores. Another filtering approach derives higher-order features based on features from the raw data, sorts these higher-order features based on the amount of variance they explain, and then selects a fixed number of the highest-scoring features.

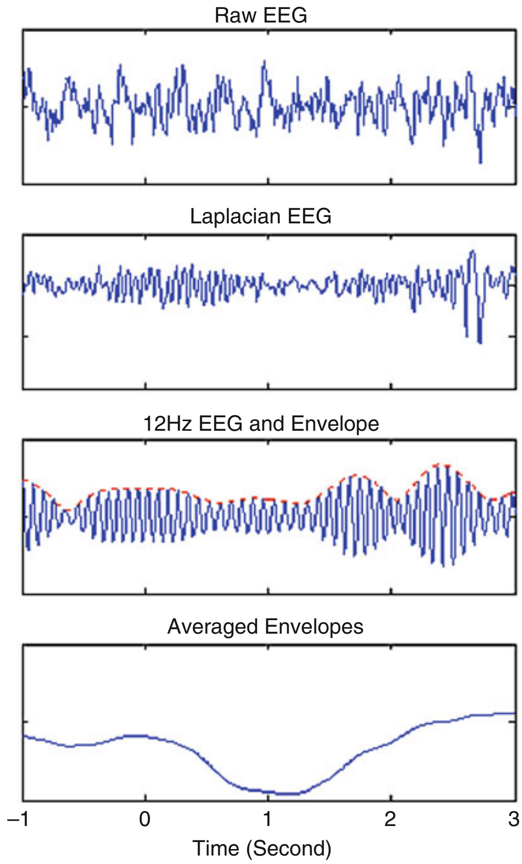

Fig. 4.10 Steps of feature extraction for sensorimotor rhythms. It is difficult to detect a coherent component in the raw EEG signal depicted in the top frame because there is a lot of noise in the signal. The second frame shows the signal after being processed through a surface Laplacian filter that focuses on EEG components in a specific spatial frequency range. As shown in the third frame, the signal is then band-pass filtered to isolate the frequencies of interest. The features become evident in the fourth frame as they are extracted by using a grand averaging method over a fixed bin or window size

The final category consists of wrapper algorithms. Wrapper algorithms select features by using the translation algorithms to rate the viability or quality of a feature set. Rather than selecting a feature set based on the results of the translation, these algorithms use 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.

For certain situations, existing signals are not sufficient for high accuracy feature extraction. Some methods introduce more signals to capture additional information about the state of the brain (e.g., by using 56 electrodes where only 2 were previously used). For example, the 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 [100].

4.4.2 Feature Translation

Translation techniques are algorithms developed with the goal of converting the input features (independent variable) into device control commands (dependent variables) that achieve the user's intent [10]. Translation techniques used widely in other areas of signal processing are adapted to BCI technology. Ideally, the translation algorithm will convert the chosen features into output commands that achieve the user's intent accurately and reliably. Furthermore, an effective translation algorithm will adapt so as to adjust for spontaneous changes in the features and will also encourage and facilitate the user's acquisition of better control over the features.

There are numerous types of feature translation algorithms. Some use simple characteristics such as amplitude or frequency, and some use single features. Some advanced algorithms utilize a combination of spatial and temporal features produced by one or more physiological processes. Algorithms currently in use include, but are not limited to, linear classifiers, Fisher discriminants, Mahalanobis distance-based classifiers, neural networks (NN), support vector machines (SVM), hidden Markov models, and Bayesian classifiers. A thorough literature review for classification algorithms of EEG-based BCI has recently been carried out [101]. Lotte et al. summarized the newly developed feature translation or classification methods including the adaptive classifier, matrix and tensor classifier, transfer learning and deep learning besides the previously

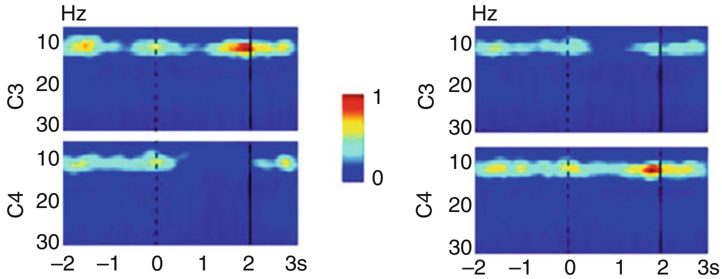

Fig. 4.11 Time-frequency representations (TFRs) of sensorimotor rhythms during motor imagery. TFRs were re-aligned at time = 0 s (dashed line) and the target times were normalized to be 2 s (solid line). (From Yuan et al. [63], with permission from IEEE, © 2008 IEEE)

commonly used linear classifier, nonlinear Bayesian classifier, classifier combinations, etc. [101]. The adaptive classifier seems to provide superior performance to static ones in general. This is intuitive since the EEG signals are nonstationary signals and adaptive approaches are better at tracking the changes in the dynamic process than the static approaches. However, since BCI systems are a two-learners system, that is, the human and the machine, the adaptation frequency might be critical. Either too fast adaptation or too infrequent adaptation might be detrimental to the BCI system [26–28]. A good amount of comparisons between adaptive and static classifiers in the literature is offline analysis or comparison within a single session. Thus, the superiority of using adaptive classifiers in many studies probably does not account for the learning process of subjects [102]. More careful investigation has to be conducted to clarify the conditions further when adaptive classifiers improve both the subject's learning and the system's performance. Transfer learning and deep learning methods also show improvements in certain cases, but their benefits remain uncertain yet. Transfer learning might be good when building a general model from a large population of participants. It might decrease or eliminate the tedious or costly training period. Deep learning showed remarkable success in the speech BCI recently; however, whether it provides superior performance in more general applications needs further investigation. Particularly, the Riemannian geometry–based method seems to work very well in a variety of BCI paradigms including motor imagery, ERPs, and SSVEP-based BCI. The covariance matrix of EEG signals during the BCI task contains abundant task-related information. The Riemannian geometry–based methods map the covariance matrix of EEG trials into the geometrical space and the computation is in a Riemannian manifold, which is a non-Euclidean space [103]. The covariance matrix of EEG signals could be treated as the notion of the traditional basic data points. Thus, the ideas of the center of mass and nearest neighbors could be applied intuitively in the geometrical space. The previous research result of the Riemannian approach showed good robustness to noise [104]. Further investigations and especially under real-time experimental settings are warranted to validate the efficacy.

Whatever translation algorithm is used, the outcomes of translation can be control commands in two ways: continuous or discrete. The following section details the difference between these two ways of translation.

4.4.2.1 Continuous Feature Translation

In continuous feature translation, consecutive output commands are generated continually based on the features. Examples of this translation are the kinematic parameters (arm position, velocity, etc.) that control a prosthetic arm. The features are usually derived from short-time windowed signals and are then continuously fed into the translation algorithm so that dynamic outcomes are obtained for BCI control. A fixed translation algorithm can be used for continuous feature translation. Algorithms that adapt can often yield better performance. Due to the demands of processing the features in consecutive short-time windows, the choice of feature extraction methods and translation methods should favor those with less computational load, which may not be those algorithms that perform best in offline testing. However, the advantage of using continuous translation is that it allows the users to adjust their strategies in the course of control. This is beneficial for learning by the user as well as by the BCI.

4.4.2.2 Discrete Feature Translation

In contrast, discrete feature translation produces periodic commands at fixed intervals. An example of this type of translation is a BCI that uses a P300 signal. A P300-based BCI will typically issue a command every several seconds. Thus, it is particularly suited for applications such as word processing, which requires discrete letter selections, and less suited for applications such as multidimensional robotic arm control, which is best implemented by a continuous series of output commands.

4.5 Major BCI Applications

4.5.1 Replacing Lost Communication

An important application for BCI technology is providing a new method for communication so that a person who has lost normal means of communication can interact with his or her external environment. Current BCIs are suitable for environmental control (e.g., temperature, lights, television), for answering yes/no questions, and for simple word processing or e-mailing.

While such communication can be provided through brain control, there are alternative options not involving neural signals. Those who retain the control of only a single muscle can often use this for communication. For example, the electric activity associated with finger muscles, eyebrows, or the diaphragm can be used to build an alternative control channel that may be faster and more accurate than current BCIs driven by neural signals. Thus, BCIs are particularly needed for users who lack all muscle control or whose remaining control is easily fatigued or otherwise unreliable. These people include those who are nearly totally paralyzed but retain cognitive function (e.g., people with advanced ALS) and those who have movement disorders that abolish useful muscle control (e.g., people with severe cerebral palsy). Although people with these disorders may have lost the ability to control any muscle movement, their cognitive function may still be intact and they may therefore have the potential to control a BCI and use it to communicate. For these locked-in people, conventional communication methods based on muscle activity may have little to offer them so that even the simplest BCI-based communication, like the ability to say yes or no, can be extremely valuable.

Thus far, most current BCI research has been carried out in healthy subjects. A few studies have been conducted to test the feasibility of BCI communication in severely disabled people in laboratory settings or even in their homes. The transfer of current BCI communication systems into use by severely disabled people for useful purposes faces several challenges. First, the disease states that abolish voluntary muscle control may also impair user control of the signal features used by a BCI. For example, ALS may lead to loss of cortical neurons, which might conceivably affect generation or control of the sensorimotor rhythms or evoked potentials used for BCI-based communication. Thus, it may be important to develop diverse BCI systems that are based on various types of neural signals so that more options can be provided for different types of brain impairments. Furthermore, damage to prefrontal cortex (e.g., in multiple sclerosis, Parkinson's disease, or ALS) can impair attention and thereby adversely affect BCI use. For these users, a long-duration training protocol may be problematic. Thus, for these users, BCI systems that require minimal training, such as SSVEP-based systems, may be most suitable.

4.5.2 Replacing Lost Motor Function and Promoting Neuroplasticity to Improve Defective Function

Perhaps the highest degrees of control achieved so far in BCI development is with neuroprostheses developed for restoring motor function. The state-of-the-art in movement control is multidimensional and point-to-point (and continuous) control of a robotic arm. In humans, sensorimotor rhythm modulation based on noninvasive EEG recordings has demonstrated three-dimensional control of a computer cursor [81, 105] or continuous real-time flight control of a virtual helicopter [29, 31] or physical quadcopter [30], or real-time operation of a powered wheelchair [12], or continuous control of a robotic arm [13, 14]. A direct decoding of three-dimensional movement trajectory from human EEGs has also been reported [54]. Such replacement of motor function could be valuable for patients who suffer from various degrees of paralysis. It is estimated that there are currently over two million people in the United States alone suffering from paralysis. Additionally, every year there are approximately 12,000 new cases of spinal cord injury in the United States. The list of causes of paralysis is extensive and includes stroke, cerebral palsy, ALS, multiple sclerosis, muscular dystrophies, trauma, and other neurodegenerative conditions. Many individuals suffer from permanent loss of motor function. A neuroprosthesis, therefore, offers an opportunity to get back a useful substitute for normal motor control. While conventional options based on limited muscle activity may also provide such function, BCI-operated neuroprostheses could provide an embodied prosthetic control that is directly related to the user's intention. For example, when users want to move their arms, they could instead move a robotic arm by communicating with the BCI their intention to move their own arms. They would not have to use different muscle activity, such as eye-blinking, to move a robotic arm.

Another exciting possible application of BCI technology is promoting neuroplasticity to restore lost function. Studies have shown that training for and using BCIs can lead to changes in neural activity that facilitate the use of prosthetic devices, especially when combined with functional electric stimulation (FES) [106, 107]. Such learning-related changes are especially important for people with brain injuries, such as those who have suffered from stroke [20, 108]. In a study using MEG recordings, patients with chronic hand hemiplegia after stroke successfully learned to use motor imagery to control their sensorimotor rhythms, and they were able to use a BCI to control an orthotic device that opened and closed their paralyzed hands [109]. As shown in Fig. 4.12, subjects' performances steadily improved as they learned to use the device. Comparison between the early and late training stages revealed enhanced sensorimotor rhythms in the ipsilesional hemisphere, which was the hemisphere used to control the device. Several randomized controlled studies have indicated that assisting movement with FES coupled to BCI use can substantially improve upper-limb function in individuals who have been mildly to moderately [110] or severely [20, 108, 111] impaired by stroke. Studies with both invasive and noninvasive BCIs also indicate that learning-related changes can occur over days to months [26, 102]. Interestingly, once users have learned to operate a neuroprosthesis with a BCI, they retain this skill months later without intervening use [18], suggesting a long-term learning-related change in neural circuits. Thus, BCIs might be used to help actually restore motor function by promoting beneficial neuroplasticity in neuromuscular pathways.

4.5.3 Supplementing Normal Function

BCI technology may also be used to supplement normal neuromuscular function. This is particularly true when considering BCI applications for use in the daily life of healthy individuals for the purpose of enhancing quality of life or functionality. One potential application is to aid navigation by means of BCI use. Controlling a computer cursor represents one such application aimed not

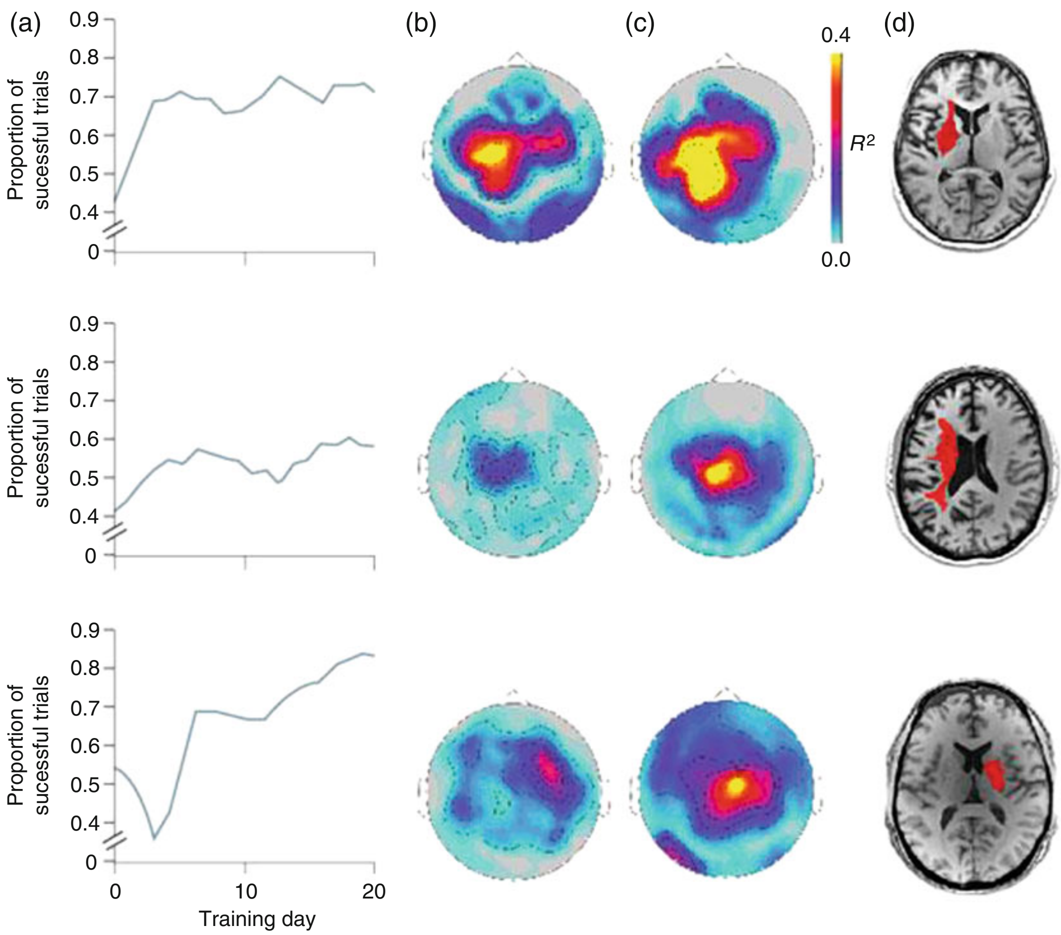

Fig. 4.12 Patients with chronic hand hemiplegia after stroke were trained to move a cursor on a screen via modulation of ipsilesional sensorimotor *mu* rhythm recorded by MEG. Successful trials with the BCI resulted in the opening or closing of the patient's paralyzed hand via a mechanized orthosis. This figure shows the results from three patients. (**a**) The performance of these patients across sessions indicates that the proportion of successful trials increased over time. The statistical maps for the correlations between sensorimotor *mu* rhythm amplitudes from signals recorded from sensors above the ipsilesional primary motor cortex, and successful performance at **b** (early) or **c** (late) training time points demonstrate modulation of sensorimotor rhythms with BCI training. Red and yellow colors identify areas where there was a high degree of correlation. (**d**) Single axial MRI scans obtained for each patient. Each patient's lesion is highlighted in red. (From Dimyan and Cohen [198], with permission, © 2011 Nature)

only at helping disabled people to gain control of external devices, but also serving as a means for healthy individuals to control external devices without using normal neuromuscular channels. Studies have shown promise in accomplishing navigation in a virtual world, including moving a computer cursor [18, 81], walking in a virtual world [112], continuous real-time controlling of flight of a helicopter in a three-dimensional virtual campus [29, 31] or physical campus [30], and recently, real-time controlling of a robotic arm [13, 14].

A challenge in using BCI technology to supplement normal function is the limited information transfer rate compared with that of normal muscular control. A healthy subject will prefer manual typing over BCI use to accomplish that task. BCI might provide an additional degree of freedom, such as a third arm control [19]. In some certain cases, BCI might support some tasks that need more than two hands and the accuracy is not a critical issue; thus, it might be beneficial to the healthy population. Nevertheless, BCI technology controls may meet the need for cases in which high information transfer rate is not an essential factor and nonmuscular control is desirable.

4.5.4 Augmenting/Virtualizing Reality with BCI

The development of virtual reality (VR) and augmented reality (AR) gives researchers better tools in the end-user interaction [34, 113, 114]. The combination of BCI with VR/AR might result in better users' embodiment and engagement. Especially in certain conditions such as stroke rehabilitation, VR/AR may play a unique and vital role [115]. Patients who lose their ability to move might struggle to perform motor imagination like healthy participants [116]. In VR, an avatar is easily created and the avatar might induce a perception illusion of the body ownership in certain conditions [117]. This included perception of immersion might be facilitated to the neural rehabilitation since this change of perception alters the underlying cognitive process. Bermudaz and colleagues used a first-person perspective VR in their BCI system, and they combined a personalized training in the virtual environment as well [118]. Their data showed users' enjoyment and engagement for the BCI-VR system in a group of healthy subjects, although Coogan et al. [34] did not observe improved performance in a group of healthy subjects with VR setting as compared to a traditional setting. In their studies, Johnson et al. [115] showed a substantial improvement of behavior in motor recovery when using BCI and VR in stroke subjects. Although the combination of BCI and VR seems promising in some applications such as stroke rehabilitation, due to the few numbers of subjects in previous literature, further studies with a larger scale of the subject population need to be performed.

4.5.5 Providing Neurofeedback

Neurofeedback could be dated back with experiments showing that humans could self-control electroencephalographic signals in real time [119]. An essential part of a typical BCI system is providing neurofeedback, which is then translated into a control command interacting with a peripheral device such as a computer cursor [18], a quadcopter [30], or a robotic arm [14]. As a progenitor of BCI technology, providing neurofeedback could be used for self-modulating the psychophysiological signals in the brain for self-regulation instead of commanding peripheral devices [120, 121]. In the research field of adaptive neurofeedback, the brain activation is treated as the independent variable and the behavior and thought are treated as dependent variables. It could open an exciting field of innovative treatment for patients with psychopathological conditions such as attention deficit disorder [17, 122], etc. The BCI technology might enhance the cognitive function of the aging population [123] or provide novel approaches to improve the sustained attention status, for example, providing a more sensitive feedback signal such that users can learn to sense upcoming attentional lapses earlier and prevent them from manifesting in behavior [17].

The long-term effect of neurofeedback and the transfer benefits in clinical treatment are still unknown. Furthermore, the causal brain–behavior relationship, which might help to understand the underlying neural mechanism of neurofeedback, is needed. Thus, further investigations of these questions using a more rigorous experimental design, for example, excluding the placebo effect, should be performed [121].

4.6 Examples of EEG-Based BCI Systems

With the growing kinds and combinations of signals, feature extraction methods, and translation techniques, the number and variety of different BCI systems are increasing rapidly [124]. Basic research typically starts using offline analyses, where signal acquisition is followed by feature extraction and translation as a separate step. This type of BCI simulation allows researchers to refine and test extraction and translation algorithms before testing them in actual online use. On the other hand, ultimately, any new BCI technique needs to be tested online to assess its performance.

A useful categorization of BCI systems is *external* versus *internal*. External BCI systems, also known as *exogenous* BCI systems, classify based on a fixed temporal context in regard to an external stimulus not under the user's control. These systems use brain signals evoked by external stimuli, such as VEPs. 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 with regard to an internal event. These systems use brain signals evoked by tasks such as motor imagery and usually require significant user training.

In another widely accepted BCI categorization as proposed by Zander et al. [125], the BCIs are categorized as active, reactive, and passive. An active BCI is a BCI that derives its outputs from brain activity that is directly consciously controlled by the user, independently from external events; a reactive BCI is a BCI that derives its outputs from brain activity arising in reaction to external stimulation, the user indirectly modulates that; a passive BCI is a BCI that derives its outputs from arbitrary brain activity without the purpose of voluntary control, for enriching a human–computer interaction with implicit information [125].

4.6.1 General-Purpose Software *Platforms* for BCI Research

With the advances in BCI research and development that have taken place during the past decades, the number of laboratories conducting BCI research has grown substantially. However, when building new BCI systems, problems often arise in trying to integrate hardware and software from different sources. As more BCI paradigms are proposed, it is very useful to have a general software platform for comprehensive evaluation of different BCI methodologies.

Such a general platform should readily support different BCI methodologies and facilitate the interchange of data and experimental protocols [126].

BCI2000 Perhaps the most widely used general-purpose software platform for BCI research is BCI2000 (http://www.bci2000.org/). BCI2000 was developed and is being maintained by the BCI laboratory at the Wadsworth Center, New York State Department of Health, Albany, New York, USA, in collaboration with the University of Tübingen in Germany [127]. Figure 4.13 shows the overall structure of BCI2000. It consists of four modules (Source, Signal Processing, User Application, and Operator Interface) that communicate with each other. BCI2000 supports the incorporation of different data acquisition hardware, signal-processing routines, and experimental paradigms. BCI researchers can use it to start their research quickly and effectively. The se of BCI2000 is free for academic and research institutions. A detailed description of the BCI2000 software platform and its practical applications can be found in Schalk et al. [127].

OpenViBE It is another popular open-source BCI platform that has grown fast in recent years [128]. OpenViBE is a C++ based software platform designed for real-time processing of biosignal data. The key features of the platform are (i) modularity and reusability. The platform consists of a set of software modules devoted to data acquisition, signal processing, and visualization, as well as to the interaction with virtual reality (VR). (ii) The platform is designed for different types of users, including BCI researchers, clinicians, VR developers, etc. (iii) The platform operates independently from different software targets and hardware devices. (iv) The platform can be integrated with high-end VR applications. Meanwhile, its graphical

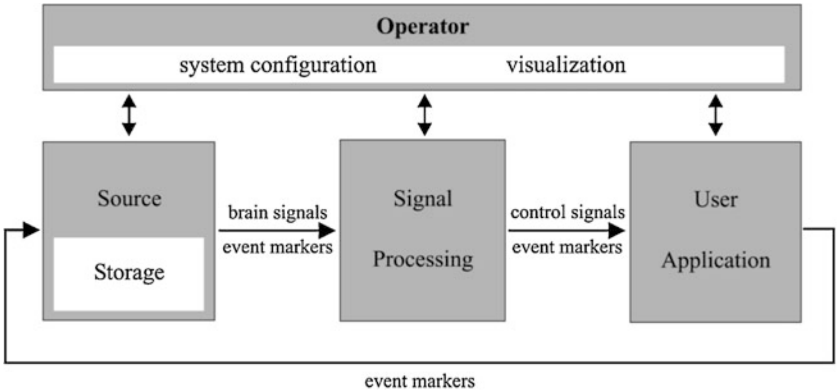

Fig. 4.13 BCI2000 design. BCI2000 consists of four modules: Operator, Source, Signal Processing, and Application. The Operator module acts as a central relay for system configuration and online presentation of results to the investigator. It also defines onset and offset of operation. During operation, information (i.e., signals, parameters, or event markers) is communicated from the Source module to the Signal Processing to the User Application module and back to the Source module. (From Schalk et al. [127], with permission)

language for designing signal-processing chains is attractive [129].

4.6.2 BCIs Based on Sensorimotor Rhythms

Wolpaw and coworkers developed a BCI system that allows users to control to move a computer cursor in one, two, or three dimensions. The EEG is recorded as the users actively controlled *mu* and/or *beta* rhythm power (amplitude squared) at one or several specific electrode locations over sensorimotor cortex. The EEG power spectra are calculated by an autoregressive method to generate the feature vector [18, 81]. This method provides multidimensional control that is comparable in speed and accuracy to that achieved to date in humans with microelectrodes implanted in cortex [130].

Pfurtscheller and coworkers developed a BCI system that used *mu* rhythm EEG recordings measured over sensorimotor cortex. The raw EEG signals were filtered to yield the *mu* 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 classifier with reference vectors generated by a learning vector quantization (LVQ) method. LVQ is a vector quantization method in which 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 by assigning it to the class label of the reference vector to which it is closest [131].

He and colleagues investigated the possibility of using BCI control based on sensorimotor rhythms for continuous navigation of an object in a virtual three-dimensional world [29, 31], or physical world [13, 14, 30]. Control signals were derived from motor imagery tasks, and intelligent control strategies were used to improve the performance of navigation. By using a constant forward flying velocity, three-dimensional navigation was reduced to two-dimensional navigation, which allowed human subjects to fly a virtual helicopter to any point in the three-dimensional space [31]. Further studies have enabled human subjects to perform fast, accurate, and continuous control of a virtual helicopter in three-dimensional space [29]. In this BCI system, the virtual helicopter's forward-backward translation and elevation controls were actuated through the modulation of sensorimotor rhythms that were converted to forces applied to the virtual helicopter at every simulation time step, and the helicopter's angle of left or right rotation was linearly mapped, with higher resolution, from sensorimotor rhythms associated with other motor imaginations. These different resolutions of control allow for interplay between general intent actuation and fine control as is seen in the gross and fine movements of the arm and hand. Subjects controlled the helicopter with the goal of flying through rings (targets) randomly positioned and oriented in a three-dimensional space. After establishing the technique, He and colleagues further demonstrated that human subjects could fly a physical quadcopter to any point in a 3-D real world using control of EEG signals recorded from scalp [30]. Figure 4.14 illustrates the study design where a sitting subject performs multidimensional control of the flight of a quadcopter to fully explore an unconstrained 3-D space to any target point in the 3-D space.

In another study, Meng et al. demonstrated that healthy human subjects could operate a robotic arm to reach and grasp objects in a complex 3-D environment using only their thoughts through motor imagination [14]. Using the combination of two sequential low dimensional controls, efficient control of a robotic arm for performing tasks requiring multiple degrees of freedom was achieved. Additionally, the participants maintained their ability to modulate their brain rhythms to control the robotic arm over multiple months. It showed the potential of human operation of prosthetic limbs using noninvasive EEG-based BCI technology. Later on, Edelman et al. [13] presented a noninvasive framework using EEG to achieve the continuous control of a robotic arm for random target tracking. Their continuous pursuit task and associated training paradigm promoted the participant's engagement; this enhanced engagement demonstrated nearly 60% of behavioral improvement for traditional center-out tasks and more than 500% improvement in the proposed continuous pursuit task. Additionally, the noninvasive electrophysiological source imaging approach further improved the BCI control compared to the traditional technique in sensor space. Such advances in the noninvasive

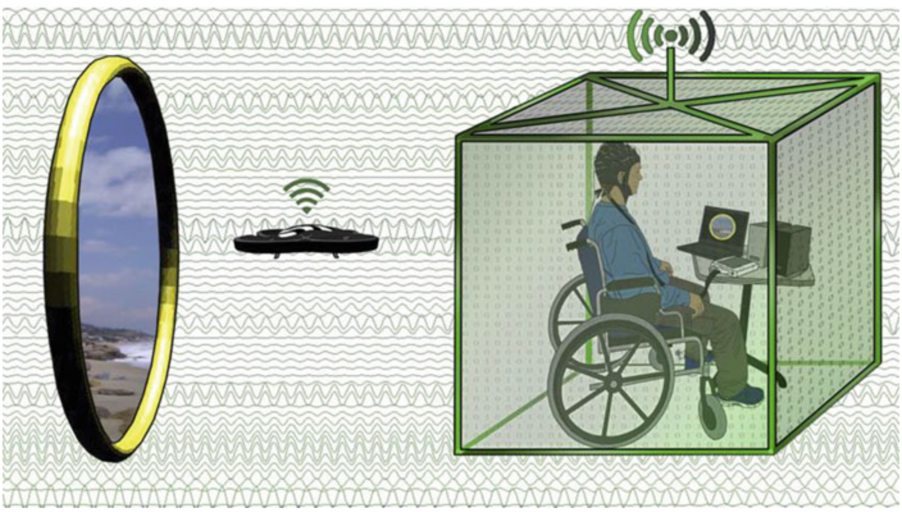

Fig. 4.14 A diagrammatic representation of an EEG-based BCI system for control of a quadcopter. The bioelectric signal generated from motor imaginations of the hands is represented in the background of the figure. The signal is acquired through the amplifiers in the subjects' workstation where it is then digitized and passed to the computer system. The raw signal is processed in real time in the computer. The movement of the quadcopter is driven by the control signal, which is sent regularly through WiFi. At the same time, a camera that is mounted in the quadcopter sends the video images to the computer as well. The subject adjusts control and adapts to the control parameter of the system based on the visual feedback from the video. Restoration of autonomy and the ability to freely explore the world are the driving factors for the development of the system. (From LaFleur et al. [30], licensed under CC BY 3.0)

Fig. 4.15 EEG BCI control of a robotic arm in humans. By integrating both the user and machine learning aspects of BCI technology, continuous control of a robotic arm has been demonstrated using EEG source imaged signals. Comparing BCI performance of robotic arm and virtual cursor control demonstrated the ease of translating neural control of a virtual object to a realistic assistive device useful for clinical applications. (From Edelman et al. [13] with Permission)

robotic arm control promise major impacts on the eventual development and implementation of neuroprosthetic limbs. Figure 4.15 illustrates the BCI control of the robotic arm for continuous tracking of a computer cursor from EEG source imaged signals in human subjects.

4.6.3 BCIs Based on P300

The P300-BCI has now become one of the widely used and successful BCI paradigms. The P300 is a positive deflection in the ERP, with a latency of 200 to 700 ms after stimulus onset (see Fig. 4.8). The response is elicited when subjects attend to a sequence of stimulus events, including an infrequently presented target (i.e., the “oddball”) event. The P300 response is typically recorded over central-parietal areas.

Most P300-BCIs use the visual P300 ERP with the row/column paradigm (RCP) [6, 38]. In the RCP, a matrix (e.g., 6 × 6 cells) containing the alphabet, numbers, and other items is presented to the user for selection. The rows and columns of the matrix flash in a random order (see Fig. 4.16). The subject attends to the desired item letter and counts how many times the row and column containing it flashes. Since P300 potentials are prominent only in the responses elicited by the target stimulus, the computer is able, after a sufficient number of repetitions, to identify the row and column that evoke a P300 response. The item at the intersection of this row and column is recognized as the target item, that is, the item desired by the user.

P300-based BCIs have been tested in severely disabled people [132]. Current research focuses on improving system performance such as speed, accuracy, consistency, and user comfort [133–136]. Hong et al. [137] proposed a new type of BCI speller (i.e., the N200-speller) that uses a motion-onset visual ERP component. This system has the advantage of lower luminance and contrast thresholds and thus reduces the discomfort of bright stimuli.

4.6.4 BCIs Based on Visual Evoked Potentials

Among noninvasive EEG-based BCIs, systems based on visual evoked potentials (VEPs) have been studied extensively. VEPs recorded over occipital areas are triggered by the sensory stimulation of a subject’s visual field. VEPs reflect visual information-processing mechanisms in the brain. The stimulation of the central visual field evokes larger VEPs than does peripheral stimulation. A

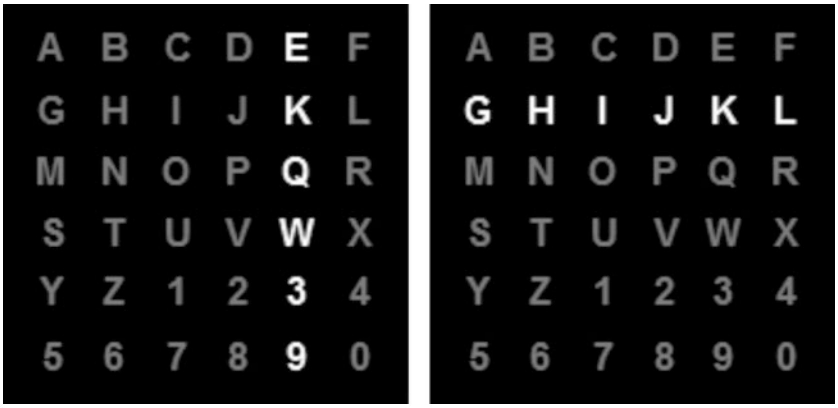

Fig. 4.16 Classical visual P300-based BCI: the row/column paradigm. The rows and columns of the matrix flash in random order. The infrequent event (i.e., the row or column containing the item the BCI user wishes to select) has a 1/6 probability of appearing

VEP-based BCI is a tool that can identify a target on which a user is visually fixated via the analysis of concurrently recorded EEG. In a VEP-based BCI, each target is coded by a unique stimulus sequence, which in turn evokes a unique VEP pattern. To ensure reliable identification, VEPs derived from different stimulus sequences should be orthogonal, or near orthogonal, to each other in some transform domain (e.g., the frequency domain).

Stimulus sequence design is an important consideration for an SSVEP-based BCI. Depending on the specific stimulus sequence (i.e., the modulation approach) used, current SSVEP-based BCIs fall into four categories: frequency-modulated VEP (f-VEP) BCIs [138, 139]; time-modulated VEP (t-VEP) BCIs [140, 141]; code-modulated VEP (c-VEP) BCIs [142]; and phase-modulated VEP BCIs (p-VEP) [87, 143].

As shown in Fig. 4.17a [144], each target in a frequency-modulated (f-VEP) BCI flickers at a different frequency. This generates a periodic visual evoked response with the same fundamental frequency as that of the flickering stimulus, as well as its harmonics. Because the flicker frequency of f-VEP BCIs is usually higher than 6 Hz, the evoked responses from consecutive flashes of the target overlap with each other. This generates a periodic sequence of VEPs—a steady-state visual evoked potential (SSVEP)—which is frequency locked to the flickering target. As such, f-VEP BCIs are often referred to as SSVEP BCIs. Target identification can be achieved through power spectral analysis. In past decades, the robustness of f-VEP BCI systems has been convincingly demonstrated in many laboratory and clinical tests. The advantages of an f-VEP BCI include simple system configuration, little or no user training, and high information transfer rate (ITR) (30–60 bits/min).

As shown in Fig. 4.17b [144], in time-modulated VEP (t-VEP) BCIs, the flash sequences of different targets are mutually independent. This may be achieved by requiring that flash sequences for different targets are strictly nonoverlapping, or by randomizing the duration of ON and OFF states in each target's flash sequence. The briefly flashed stimuli elicit visual evoked potentials, which have short latencies and durations.

In a t-VEP BCI, a synchronous signal must be given to the EEG amplifier for marking the flash onset of each target. t-VEPs are time-locked and phase-locked to visual stimulus onset. Thus, since the flash sequences for all targets are mutually independent, averaging over several short epochs synchronized according to the flash onset time of each possible target will produce VEPs for each possible target. Since foveal (i.e., fixation point) VEPs are larger than peripheral VEPs, the target producing the largest average peak-to-valley VEP

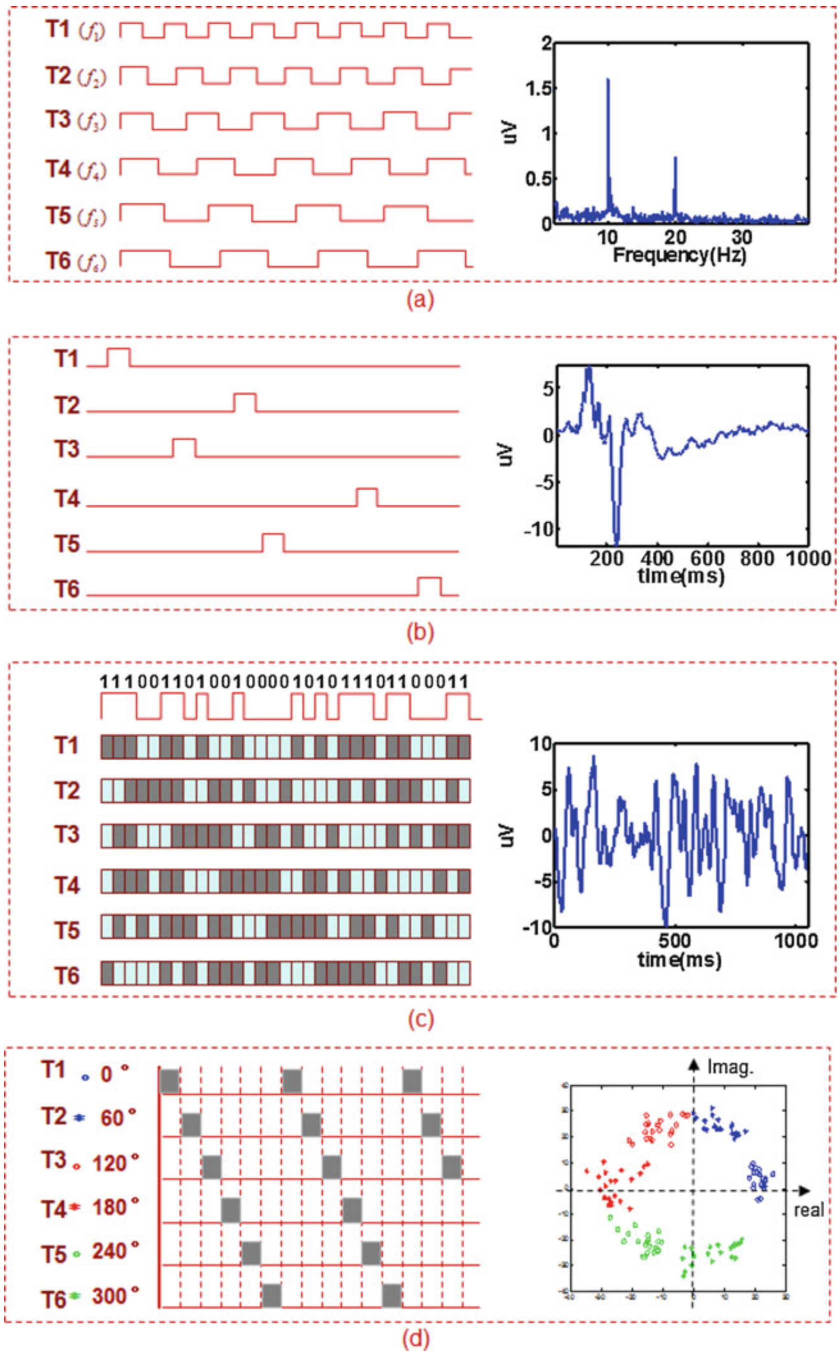

Fig. 4.17 Examples of stimulations of VEP BCIs. (**a**) Left: The stimulus sequences of an f-VEP-based BCI. Targets flash at different frequencies. Right: The power spectrum of the VEP derived from a target flickering at 10 Hz. (**b**) Left: The stimulus sequences of a t-VEP-based BCI. Target flashes are mutually independent. Right: The evoked response to a single stimulus. (**c**) Left: The stimulus sequences of a c-VEP-based BCI. Right: A sample of time course of the evoked response. (**d**) Left: The stimulus sequences of a p-VEP-based BCI. The phase difference between adjacent targets is 60 degree. Right: The phase distribution of response signals from stimuli with different phases. (Revised from Bin et al. [144] and Wang et al. [40] with permission)

amplitude can be identified as the fixation target. An accurate target identification in a t-VEP BCI requires averaging over many epochs. Furthermore, to prevent the overlap of two consecutive VEPs, t-VEP BCIs usually have low stimulus rates (4 Hz). Thus t-VEP BCIs have a relatively low information transfer rate (30 bits/min).

In a code-modulated (c-VEP) BCI, pseudorandom stimulus sequences are used. The most commonly used pseudorandom sequence in c-VEP BCIs is the m-sequence. M-sequences have an autocorrelation functions that are a very close approximation to a unit impulse function and are nearly orthogonal to its time lag sequence. Thus, in c-VEP BCIs, an m-sequence and its time lag sequence can be used for different stimulus targets. Sample stimulation sequences and their time course of evoked potentials are shown in Fig. 4.17c [144]. At the beginning of each stimulation cycle, a synchronous signal, which provides a trigger for target identification, is given to the EEG amplifier. The template matching method is generally used for target identification.

A c-VEP-based BCI system was developed by Sutter in 1984. Bin et al. [142] described a PC-based c-VEP BCI and tested it in five subjects. The average information transfer rate (ITR) reached 108 ± 12 bits/min, with a maximum of 123 bits/min for one of the subjects studied.

As shown in Fig. 4.17d [40], in a phase-modulated VEP (p-VEP) BCI, several targets flicker at the same frequency but with different phases so that more targets can be presented in less time. Jia et al. [143] proposed a coding method using a combination of frequency and phase information. With this method, they developed a BCI system with 15 targets and only three stimulus frequencies. Through the optimization of lead position, reference phase, data segment length, and harmonic components, the average ITR exceeded 60 bits/min in a simulated online test with ten subjects.

Wang et al. [40] and Bin et al. [144] summarized the pros and cons of VEP BCIs. The advantages of VEP BCIs are their simplicity, lower training time, and high information transfer rate. The disadvantages of the system are the need for good gaze control (which people with severe neuromuscular disabilities may lack) and visual fatigue from prolonged fixation.

The most significant progress in an SSVEP-based BCI is the improvement of information transfer rate (ITR) of the systems. Chen et al. developed a new joint frequency-phase modulation method in their SSVEP-based BCI speller (see Fig. 4.18) to enhance the discriminability between SSVEPs with a very narrow frequency range. The system obtained an impressive high ITR of 5.32bits/s or 319.2bits/min [145]. Nakanishi et al. recently presented a novel data-driven spatial filtering approach for SSVEP detection. The ITR in this system was as high as 325 bits/min [146].

4.6.5 BCIs Based on Auditory Evoked Potentials

BCIs that use visual stimuli have been shown to be effective as we discussed earlier. However, some severely disabled people may have difficulty using a BCI that requires good vision, due to compromised vision or loss of eye movement control. Nevertheless, even in severely paralyzed patients, such as those suffering from ALS, hearing is usually preserved. Thus, a BCI based on auditory evoked potentials (AEP-BCI) becomes an alternative paradigm.

AEPs are the brain's response to external auditory stimuli. Two types of AEP-based BCIs have been explored. One uses auditory stimuli as feedback in order to help subjects learn to regulate their sensorimotor rhythms [147] or to regulate the slow cortical potential [148]. The second type of system uses an auditory "oddball" paradigm [149, 150]. Most current AEP-based BCIs use an "oddball" paradigm [149, 150]. As in the case of the visual P300 described earlier in this chapter, the auditory stimuli in auditory oddball BCIs are divided into two types: frequently presented non-targets and rarely presented targets. For example, spoken digits could comprise a stimulus sequence. The digits would be presented in random order and used to represent the possible selections. In the sequence, all the digits would be standard non-target stimuli except for

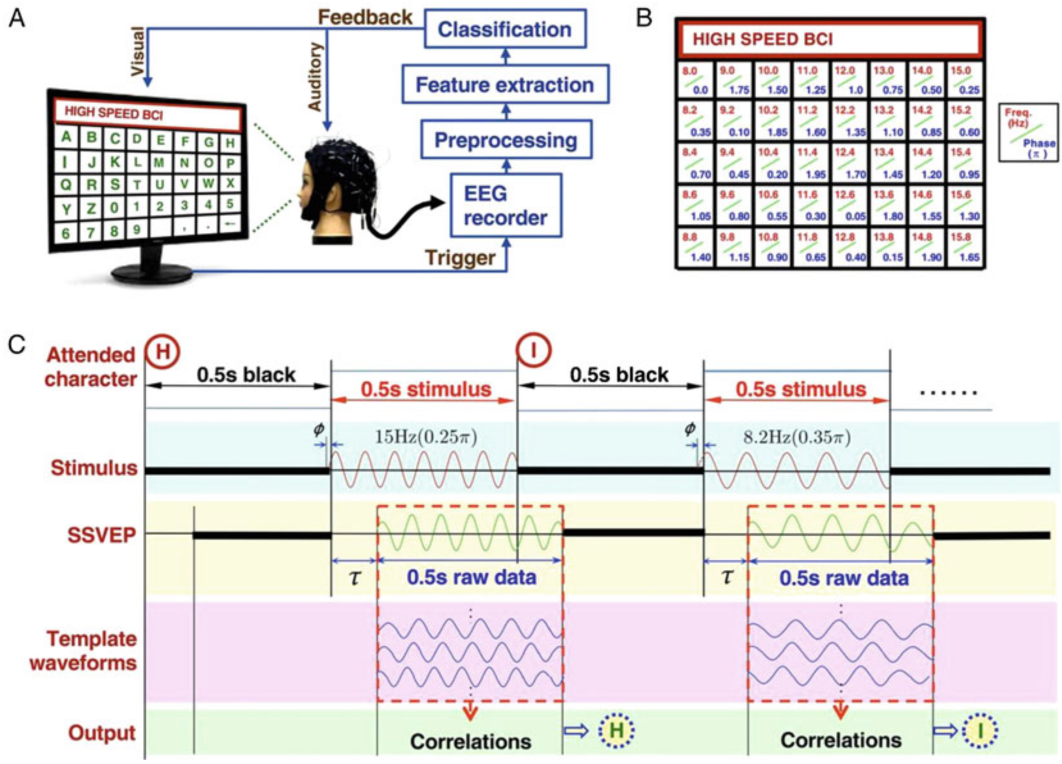

Fig. 4.18 Closed-loop system design of an SSVEP-based BCI speller with high information transfer rate. (**a**) System diagram of the BCI speller, which consists of four main procedures: visual stimulation, EEG recording, real-time data processing, and feedback presentation. The 5 × 8 stimulation matrix includes the 26 letters of the English alphabet, 10 numbers, and 4 symbols (i.e., space, comma, period, and backspace). Real-time data analysis recognizes the attended target character through preprocessing, feature extraction, and classification. (**b**) Frequency and phase values used for encoding each character in the stimulation matrix. The frequencies range from 8.0 to 15.8 Hz with an interval of 0.2 Hz. The phase interval between two neighboring frequencies is 0.35π. (**c**) Examples of spelling characters "H" (15.0 Hz, 0.25π) and "I" (8.2 Hz, 0.35π) with the BCI speller. An intertrial interval of 0.5 s is used for directing gaze to a target before the stimulation matrix starts to flash for 0.5 s. The 0.5-s-long EEG epoch with a delay of τ (~140 ms) to the stimulation is extracted for target identification. The target character can be determined by the decoding algorithm based on the correlations between the single-trial SSVEP and individual SSVEP templates. (From Chen et al. [145] with permission)

one target stimulus, that is, the subject's desired choice. The subject is instructed to pay attention to the target digit and perform a mental task when the target digit is spoken (e.g., count each time it is heard). The auditory ERPs in response to the target stimulus are similar to those in visual P300-based BCIs. An auditory spelling system was proposed by Furdea et al. [149] and tested with four ALS patients [151]. To compare a user's performance with the auditory and visual modalities, a 5x5 visual support matrix was displayed to the participants. Rows were coded with numbers 1–5, and columns with numbers 6–10. The flashes in a typical visual P300 speller were replaced by spoken digits. As in a visual P300 speller, the subjects using the auditory system were instructed to first select the row number and then the column number containing the target letter. The auditory system was first tested with healthy subjects. Nine of 13 subjects achieved accuracies above 70% [149]. In the study by Kubler et al. [151], four ALS patients used the system and performed above chance level.

Compared to the visual spelling system, users' performance with the auditory speller was lower and the peak latencies of the auditory ERPs were longer. However, for severely disabled people with compromised vision or loss of eye movement control, AEP-based BCIs might provide a preferred way to communicate with the external world and thus are worthy of further study. Recently, the research has shown that the proper training can improve the performance of the auditory ERP-based BCI, specifically the information transfer rate [152].

4.6.6 Hybrid BCI

The concept of hybrid BCIs was proposed to further improve the performance of BCIs beyond that of BCIs with a single approach [153]. The hybrid BCIs fulfill the following criteria: the activity should be directly acquired from the brain; at least one of the multiple brain signal acquisition modalities should be employed in acquiring such activity; the signals must be processed in real-time/online to establish communication between the brain and the computer; feedback describing the outcomes of the brain activity for communication and control must be provided.

Although BCI shows great promising applications in the healthy population, stroke patients, ALS patients, etc., it still faces the challenge of performance variation, relatively low information transfer rate compared to the normal body function, to name a few. It is reasonable to combine the users' preserved body movements as one of the control sources with the traditional BCI output to fully benefit the daily use or daily rehabilitation of the end users.

Hybrid BCIs can be configured in two ways: (i) a combination of two different brain signal acquisition modalities (e.g., EEG and fNIRS) [154, 155]; (ii) a combination of a brain signal acquisition modality with one or more nonbrain signal acquisition modalities (e.g., EEG and EMG, EOG, ECG) [156, 157]. Hong et al. presented a comprehensive review of the recent development in hybrid BCIs [158].

In addition to combining different signal acquisition modalities, some hybrid BCIs are designed by decoding multiple tasks using a single modality. For example, SSVEP is combined with motor imagery or P300-based tasks using EEG-based signal detection [159].

The main objectives of hybrid BCI development are (i) to increase the number of brain commands for control applications; (ii) to enhance the BCI classification accuracy; and (iii) to shorten the brain command detection time. In fact, nonbrain signals in hybrid BCIs such as EMG and EOG are useful either to increase the number of commands or to remove motion artifacts in EEG recordings to improve the classification accuracy of the BCI system.

Hybrid BCI allows the potential patient candidates to fully utilize their reserved body movement such as EOG to enhance the imperfect BCI performance by decoding their brain waves [160]. Soekadar et al. demonstrated a group of six naïve individuals performed independent and self-initiated reaching and grasping activity outside of the laboratory [161].

Hybrid BCIs are suited to both disable persons and healthy people. For healthy individuals, hybrid BCIs can be useful in the environment with multiple tasks utilizing several devices [162] or entertainment [163]. Also, hybrid BCIs may give better information about the mental workload and fatigue, cognitive functions, and vigilance of a person to avoid some accidents.

4.6.7 Attention-Based BCI

Attention-based BCIs could be implemented by a covert attention or overt attention paradigm. In a covert attention paradigm, the subject is instructed to look at a centrally located fixation point. The subject's task is to follow another point without overt eye movement. In contrast, in an overt attention, the subject's task is to use overt eye movements while they attend to a moving object.

In a conventional SSVEP BCI system, the subject overtly directs attention to one of the stimuli by changing his or her gaze direction. The attended stimulus elicits enhanced SSVEP responses at the corresponding frequency over occipital brain areas. This kind of system is considered a "dependent" BCI since muscle activity such as that producing gaze shifting may be necessary. Therefore, it might not be usable by people who have lost control of gaze direction.

A large number of psychophysical and neurophysiological studies have shown that people can covertly shift attention to different spatial locations without redirecting gaze. In addition, shifting attention to one out of several superimposed objects can improve behavioral performance (reaction time and accuracy) and increase neuronal responses compared to paradigms in which the object is unattended. This covert attention could be decoded and applied to build a BCI system [164]. Kelly et al. [165, 166] reported a BCI based on spatial visual selective attention. Two bilateral flickers with superimposed letter sequences were presented to the subjects. The subjects covertly attended to one of the two bilateral flickers for target selection. Greater than 70% average accuracy was achieved with this system. Zhang et al. [167] explored a nonspatial visual selective attention-based BCI. Two sets of dots with different colors and flicker frequencies, rotating in opposite directions, were used to induce the perception of two superimposed, transparent surfaces. Because the surfaces flickered at different frequencies, they elicited distinguishable SSVEPs. By selectively attending to one of the two surfaces, the SSVEP amplitude at the corresponding frequency was enhanced so that the subjects could select between two different BCI outputs. This system was tested in healthy subjects in a 3-day online training program. An average online classification accuracy of 72.6 ± 16.1% was achieved on the last training day. Tonin and colleagues used a covert attention paradigm for a two-class classification problem [168, 169]. The BCI system operated based on covert visuospatial attention without relying on any evoked responses. The mean online accuracy across eight healthy subjects was 70.6 ± 1.5% and 88.8 ± 5.8% for the best subject. Previously, the covert attention was successfully used to build a one-dimensional online BCI system.

A recent study demonstrated that decoding of overt spatial attention might be more efficient and show comparable one-dimensional and two-dimensional BCI performance compared to the conventional motor imagery–based BCI [105]. Furthermore, it was shown that overt spatial attention and motor imagery could function independently and simultaneously. Thus, a 3-D BCI control is realized through the solely endogenous modulation of attentions by simultaneously performing both the overt spatial attentional and sensorimotor rhythm modulations. Figure 4.19 illustrates high-dimensional cursor control BCI via the combination of overt spatial attention and motor imagery modulation. The use of hybrid control signals allowed achieving as high as 12 targets, leading to a group average information transfer rate of 29.7 ± 1.6 bits/min in nine human subjects [105].

Visual selective attention-based BCIs have thus far provided only binary control. However, their performance with gaze independence encourages further study, including the development of a multiple-selection system. These systems may be a good option for paralyzed people who cannot control well gaze direction. It might enable them to achieve control of a BCI by employing covert attention shifts instead of changes of gaze direction [170].

4.6.8 BCIs for Brain-to-Brain Communications and Interactions

BCI has been explored beyond the setting of a single brain to computer/device. Babiloni and colleagues have shown multiple brain communications by simultaneous recordings of EEG as revealed in functional connectivity that existed among the multiple brains in a social setting [171, 172]. Their work demonstrated brain-to-brain communications and suggested the possibility of multiple brain interactions. An interesting approach integrating EEG BCI with transcranial magnetic stimulation (TMS) to realize brain-to-brain interface where EEG BCI was used to decode the intent and TMS was used to transmit the information into a brain was reported [173, 174]. Recently, Rao and colleagues showed brain-to-brain interactions in

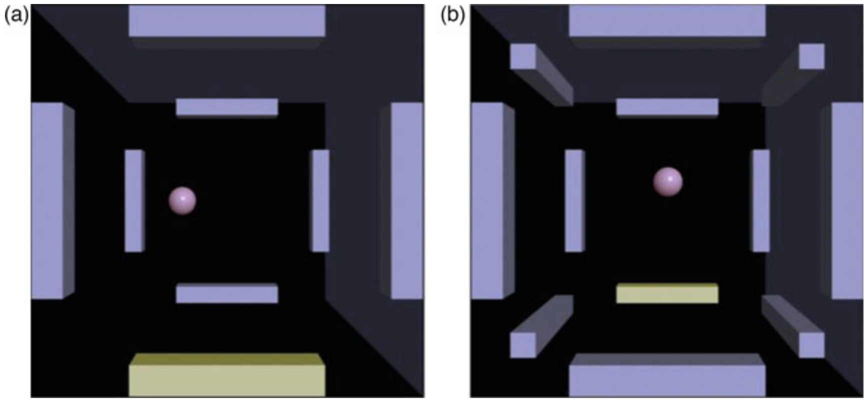

Fig. 4.19 Realization of 3-D BCI for cursor control via the combination of overt spatial attention and motor imagery modulation. (**a**) A scene of the 8 target 3-D cursor control task. The highlighted bar indicated the target to hit. (**b**) A scene of the 12 target 3-D cursor control task where the highlighted bar indicated the target to hit. (From Meng et al. [105] with Permission, © 2018 IEEE)

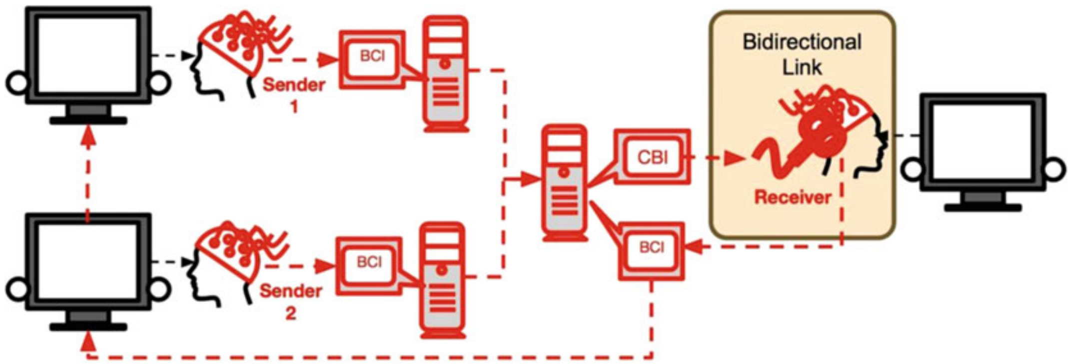

Fig. 4.20 Direct brain-to-brain communication and interaction using BCI. Two participants ("Sender 1" and "Sender 2") each use an SSVEP BCI to convey information about a collaborative task directly to the brain of the third participant ("Receiver"). Information from each Sender is transmitted over the internet to the Receiver's brain via a computer–brain interface (CBI) based on TMS. After consciously processing the two inputs from the Senders, the Receiver uses a BCI based on EEG to execute an action in the task. (From Jiang et al. [175], licensed under CC BY 4.0)

a social setting involving SSVEP BCI and TMS for online transmitting and receiving information and interacting [175]. In a computer-based game setting, two senders each used an SSVEP BCI to convey information to a third individual—receiver—as coded by transcranial magnetic stimulation (see Fig. 4.20). Such brain-to-brain communications and interactions may represent further applications, especially in the general population.

4.7 BCI Performance Assessment and Training

A BCI user controls brain signal features that the BCI can recognize and translate into control commands. The performance of BCIs can be affected by the differences among users, by the varying signal-processing abilities of the BCI systems, or by the signal acquisition protocols used in the BCI systems. In order to better understand the impact of these factors, researchers usually assess BCI performance with respect to one factor at a time.

For example, for communication systems, the traditional unit of measure is the amount of information transferred in a unit of time. Therefore, the performance measure can be indicated by bits per trial and bits per minute. This provides a tangible measure for making intra-system and inter-system performance comparisons. For other systems aimed at replacing motor function, it is not only the attainment of the goal (i.e., reaching a target location) that matters, but also how well the continuous trajectories are reconstructed. Therefore, the performance measure can be indicated by statistical measures for goodness of fit, such as the coefficient of determination (r^2).

4.7.1 User Performance Assessment

The square of the Pearson product-moment correlation coefficient (PPMCC) is denoted as r^2 and has been widely used in the assessment of BCI user performance.

The PPMCC between two variables X and Y is defined as the covariance of the two variables divided by the product of their standard deviations:

$$\rho_{X,Y} = \frac{\operatorname{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E\left[(X - \mu_X)(Y - \mu_Y)\right]}{\sigma_X \sigma_Y} \tag{4.1}$$

where μ_x, μ_y, σ_x, and σ_y are the mean and standard deviation of X and Y, respectively.

Substituting estimates of the covariances and variances based on samples gives the sample correlation coefficient, commonly denoted by r:

$$r = \frac{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)^2} \sqrt{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2}} \tag{4.2}$$

where r ranges between $+1$ and -1. Its square (r^2) then has a value between 0 and 1. A value of r^2 close to 1 indicates a strong linear relationship between X and Y, whereas values close to 0 indicate that there is very little linear correlation.

In BCI systems, user performance can be defined as the level of correlation between the user's intent and the brain signal feature(s) that the BCI translates into its output commands.

4.7.2 System Performance Assessment

Many different BCI systems have been studied. They differ in inputs, outputs, translation algorithms, and other characteristics. To compare and evaluate the performance of different BCI systems, an objective measure is required. BCIs provide the capability of communication between brain signals and external devices. Therefore, the information transfer rate (ITR) has been used as one of the primary metrics to evaluate BCI system performance.

Most current BCI systems translate the user's brain signal features into output commands by a regression method or by a classification method. The former has the advantage of requiring only one translation function for each dimension of the matrix of possible output commands, while the latter requires additional functions as additional output commands are added.

Currently, the most popular method for ITR calculation was defined by Wolpaw et al. in 1998 [176] and discussed further in McFarland et al. [177]. The definition is a simplified computational model based on the Shannon channel theory under several assumptions. The measure of ITR is the bit rate B (bits/symbol) as shown in Eq. (4.3).

$$B = \log_2 N + P \log_2 P + (1 - P)\log_2\left[(1 - P)/(N - 1)\right] \tag{4.3}$$

where N is the number of possible selections, P is the accuracy (probability that the desired selection will be selected), and B is the bits per trial. If the execution time per symbol selection is

T, then the bits per minute B_t can be calculated as follows.

$$B_t = B^* (60/T) \tag{4.4}$$

It is worth noting that the use of Eq. (4.3) and Eq. (4.4) is conditional, because the following assumptions were used in the derivation of Eq. (4.3).

1. BCI systems are memoryless and stable transmission channels.
2. All the output commands (i.e., selections) have the same probability of selection ($p(w_i) = 1/N$)
3. The translation accuracy is the same for all the selections ($p(y_i/x_i) = p(y_j/x_j)$).
4. The translation error is equally distributed among all the remaining selections $\underset{j \neq i}{p}(y_j/x_i) = \frac{1-p(y_i/x_i)}{N-1}$.
5. The translation accuracy is above the chance level.

The resulting ITR by Eqs. (4.3) and (4.4) depends on both speed and accuracy. Figure 4.21 illustrates the relationship between accuracy and bit rate for different numbers of selections.

In reality, r^2 and ITR are just two factors that can be used for BCI performance assessment. Other factors important for BCI evaluation include invasiveness, training time, ease and comfort of use, cost, and others. The significance of

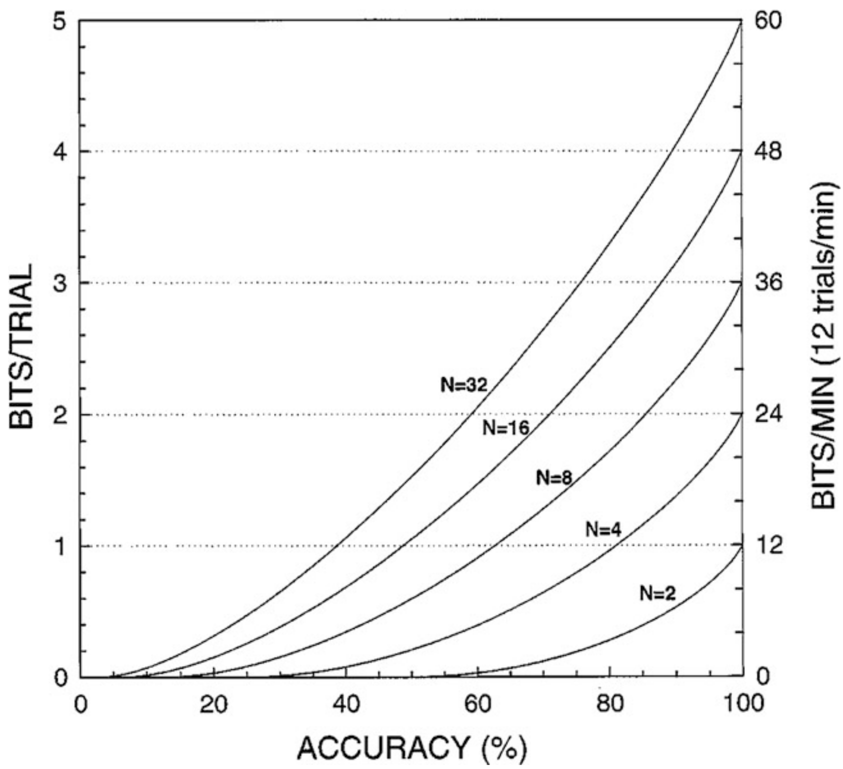

Fig. 4.21 Information transfer rate in bits/trial (i.e., bits/selection) and in bits/min (for 12 trials/min) when the number of possible choices (i.e., N) is 2, 4, 8, 16, or 32. As derived from Pierce [195] (and originally from [196]), if a trial has N possible choices, if each choice has the same probability of being the one that the user desires, if the probability (P) that the desired choice will actually be selected is always the same, and if each of the other (i.e. undesired) choices has the same probability of selection (i.e., $(1 - P)/(N - 1)$), then bit rate, or bits/trial (B), is $B = \log_2 N + P \log_2 P + (1 - P)\log_2[(1 - P)/(N - 1)]$. For each N, bit rate is shown only for accuracy $\geq 100 = N$ (i.e., $\geq$chance). (From Wolpaw et al. [10], with permission)

these various factors may vary across different BCI applications.

4.8 Future Perspectives

4.8.1 Expectations

BCI research and development evokes a great deal of excitement in scientists, engineers, clinicians, and the public in general. This excitement is largely in response to the considerable promise of BCIs. With continued development, they may replace or restore useful function to people severely disabled by neuromuscular disorders. In addition, BCIs might augment natural motor outputs for pilots, surgeons, other professionals, or ordinary citizens for daily activities. They might also give new opportunities and challenges to artists, athletes, and video-gaming enthusiasts. Furthermore, BCIs might also conceivably improve rehabilitation methods for people with strokes, head trauma, and other devastating disorders. At the same time, it is clear that this exciting future can become reality only if BCI researchers and developers address and resolve problems in crucial areas including signal acquisition, BCI validation and dissemination, and reliability.

4.8.2 Signal Acquisition and Processing

BCI systems depend on the sensors and the related hardware that record the crucial brain signals. Improvements in this hardware are needed. EEG-based (noninvasive) BCIs should: have electrodes that do not need skin abrasion or conductive gel (i.e., so-called dry electrodes); be small and portable; use comfortable, convenient, and attractive mountings; be easy to set up; work for many hours without needing maintenance; work reliably in any environment; use telemetry rather than connecting wires; and interface easily with many different applications. Reliable performance in all relevant environments may be especially hard to ensure and should therefore be a major research goal. The biggest challenge for an EEG-based BCI maybe the further development of signal processing and machine learning techniques that can reliably and accurately decode and delineate the intention signals from relatively noisy EEG signals. This would require innovations in machine learning, signal processing, and classification algorithms, as well as advancement in systems neuroscience research.

BCIs that employ implanted electrodes (i.e., invasive BCIs) face a number of complex issues, some of which are not yet fully understood. These systems require hardware that: is safe and completely implantable; stays intact, functional, and reliable for many years; records stable signals for many years; transmits the recorded signals using telemetry; is able to be recharged in situ (or has batteries that last for many years); has external components that are durable, comfortable, convenient, and unobtrusive; and interfaces readily with a range of high-performance applications. While considerable progress has been made in the past several years, it is not yet clear which possible solutions will be most successful, or how successful they can be. Fundamental innovations in sensor technology may be needed for invasive BCIs to achieve their full promise.

4.8.3 Clinical and Practical Validation

Various noninvasive and invasive BCIs are being developed. As this work proceeds and BCIs start to actually be used clinically, two key questions must be addressed: how capable and reliable a particular BCI can get; and which BCIs are the best choices for a particular clinical or practical purpose. To address the first question, each candidate BCI should be optimized and the limits on users' capacities with it should be determined. Engaging the second question will require some consensus among researchers concerning which applications to use for comparing BCIs and concerning how their performance should be measured. One obvious example is the question of whether BCIs that use intracortical signals can perform better than BCIs that use ECoG signals, or even EEG signals, and if their performance justifies the necessary electrode implantation by surgery. For many people, invasive BCIs will need to perform much better to be considered preferable to noninvasive BCIs. Although the degree of freedom for a neuroprosthetic control increased from seven to ten [178, 179] and the information transfer rate has increased dramatically for invasive BCIs [180, 181] in the past few years, significant improvement was also achieved for noninvasive BCIs as well [13, 105, 145]. It is as yet unclear whether they can do so. Contrary to widespread expectations, the available data seem not to provide a clear answer to this critical question.

Furthermore, the widespread clinical usage of BCIs by people with disabilities requires definite validation of their real-life value in efficacy, practicality, and effect on the quality of life. Such validation depends on multidisciplinary groups able and willing to perform chronic studies of real-life use in complex and frequently difficult environments. These studies, which are just beginning, are a critical step if BCIs are to achieve their promise. The results of these studies could also shape the development of BCIs for the general population. The clear validation of BCIs for functional rehabilitation after strokes or in other disorders will be similarly demanding and will necessarily entail direct comparisons with the outcomes of conventional methods alone.

4.8.4 BCI Training

The effectiveness of a BCI depends on the capacity of the user to produce brain signals that reflect intent and that the BCI can decode accurately and reliably into output commands that achieve that intent [10, 32, 182]. Control of brain activity is harder to achieve than control of motor activity partly because the user can neither identify nor discern the activity. The user can only comprehend EEG activity through the feedback received from the BCI system. Different BCI systems use different strategies to help users learn to control the crucial brain signals.

Many BCIs ask the user to perform specific cognitive tasks that generate recognizable EEG components (i.e., components that the BCI can decode into intent). *Motor imagery* tasks have been the most widely used cognitive task. For each selection, the user imagines or plans one of the several motor movements (i.e., left- or right-hand movement) based on visual or aural cues. Research has shown that this generates brain signals (e.g., from sensorimotor cortex) that can be detected by EEG or fMRI [43, 63]. After several training sessions, the user is usually able to produce a specific pattern of signal features (e.g., amplitudes in specific frequency bands at specific locations) by performing a specific cognitive task.

Other cognitive tasks can be used, such as arithmetic (addition of a series of numbers), visual counting (sequential visualization of numbers), geometric figure rotation (visualization of rotation of a 3-D object around an axis), letter composition (nonvocal letter composition), and baseline (relaxation). Studies have shown that these tasks produce components detectable in the EEG [56, 183, 184].

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.

The major focus of BCI development thus far has been to provide communication for severely disabled people. It is possible that some potential users have disorders that are also cognitively debilitating in ways that preclude their control of signals from areas of the brain that may be important for BCI control. The left hemisphere of the brain, for example, is the center of activity for tasks involving language, numbers, and logic, while 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 performed. When using a set of cognitive tasks during training, the 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. P300 responses, for example, require less training time than that needed by a user learning to control sensorimotor rhythms. As mentioned earlier, choosing contrasting cognitive tasks accelerates training. It is also important to maintain consistent training regiments to ensure that subjects retain their ability to control their EEG components.

The tasks used in training carry forward into general BCI usage. The method of training, therefore, is associated with the method of signal acquisition. Neuronal activity generated by specific cognitive tasks is focused in specific areas of the brain. This allows signal acquisition to occur over a few electrodes that encompass these areas.

Studies have suggested the use of mindful meditation helps subjects to perform better in motor imagery paradigm BCI and learn faster [185]. Such mindful meditation may be considered as preprocessing training as they prepare subjects better for the motor imagery tasks, thus leading to enhanced performance in the subsequent BCI experiments.

4.8.5 Recognition of BCI Efficiency and Inefficiency

Until now, the total number of human patients recruited in the invasive BCI studies, especially counting studies with implanted neural chips, is still a small double-digit number. It is hard to say whether every subject might be able to achieve high performance yet. Most of the human BCI studies are still using noninvasive recording technology due to its applicability to both the healthy population and the general patient population (except for those with clinical needs of implanting electrodes). However, there is a certain proportion of subjects who do not respond to certain BCI modalities. The proportion of nonresponders for the P300-based BCI [186] and SSVEP-based BCI [187] is generally small, that is, less than 10%. However, there is ample evidence to show that there is a non-negligible number of subjects (estimated around 20%–30%) who could not generate reliable brain rhythms to be classified in sensorimotor rhythm BCIs [188, 189]. They were named as "BCI illiterate" previously. In recent years, a lot of work has been done to find novel approaches improving the BCI performance in order to reduce the number of BCI illiterates [185, 190] or to investigate the factors that might predict the performance of BCI users [188, 191, 192]. The recognition of BCI efficiency and inefficiency is an important issue. Because there might not be a universal BCI paradigm that would be suitable for everybody, it is meaningful to find out what kind of population is suitable for a certain type of BCI technology. Thus, the BCI nonresponders could be screened out for a particular paradigm before more intensive experiments are conducted. It would save both subjects' and researchers' time and cost for an inappropriate BCI technology [102]. On the other hand, exploring the underlying factors or mechanism that might affect the BCI performance would be vital to advance the development of BCI technology itself. Blankertz et al. suggested that the idling sensorimotor rhythm during resting state might be an important predictor of BCI system based on endogenous motor imagination [188]. Grosse-Wentrup and Scholkopf suggested that performance variation within subjects might be closely related to the attentional networks in the gamma band (>40 Hz) [191]. Further, understanding these factors will help improve the recognition of the BCI inefficiency. Additionally, some other studies seek to reduce the numbers of BCI illiterate by designing various new paradigms. For example, Cassady et al. recruited participants with/without mindful meditation experience and found that the meditation practitioners achieve similar good performance in shorter training sessions, which suggested that practicing meditation might facilitate BCI skill acquisition [185]. Yao et al. applied vibrotactile stimulations on subjects' both wrists and asked the participants to either sense the vibration or performing conventional motor imagination. They found a significant improvement in BCI performance when using the combination of sensation and motor imagery compared to either using motor imagery or sensation alone [190]. More recently, Meng and He investigated the effect of training on BCI performance based on motor imagery paradigm. Their results suggested that training could improve subjects' performance quickly in three sessions of practice and the improvement is particularly significant in the group of low BCI performers, that is, participants who might be recognized as BCI illiterate using the conventional standard of 70% accuracy [102]. Therefore, the BCI inefficiency might be dependent on a specific BCI paradigm and the subject population. Future studies should carefully select their population of subjects and specify their BCI experimental design when determining the BCI inefficient subjects.

4.8.6 Reciprocal Learning Between the Machine and the Brain

BCIs provide the CNS with the chance to master novel skills in which brain signals substitute for the spinal motoneurons that produce natural muscle-based skills. Muscle-based skills rely for their initial mastery and long-term preservation on continual activity-dependent plasticity in many CNS areas, from the cortex to the spinal cord. This plasticity, which can require practice over many months or even years, allows infants to learn to walk and talk, children to master reading, writing, and arithmetic, and adults to acquire many different athletic and intellectual skills.

The acquisition and maintenance of BCI-based skills, such as robust multidimensional movement control, depend on comparable plasticity [13, 14, 18, 29, 44, 81, 193]. BCI operation requires the successful interaction of two adaptive controllers, the CNS and the BCI—continuous learning in machine learning algorithms used in BCIs and in the CNS through neuroplasticity. The BCI needs to adapt so that its output commands correspond to the intent of the user. Concurrently, the BCI needs to encourage and facilitate CNS plasticity that improves the reliability and precision with which the brain signals encode the intent of the user. In summary, the BCI and CNS need to work together to master and maintain a partnership that is reliable in all circumstances. The work required to realize this essential partnership has just started. It engages basic neuroscientific questions and may produce valuable new insights into CNS function. Thus, BCI research has importance for neuroscience in general, independent of the practical uses that are the primary focus of most BCI research and development.

The fundamental importance of CNS adaptation implies that the key problems in BCI research are neurobiological. The principles that determine how the CNS masters, improves, and preserves its natural muscle-based skills are likely to be the best guide for designing BCI systems. CNS control of actions is typically distributed among multiple areas. While cortical areas may define the goal and the broad outlines of an action, the details (especially high-speed sensorimotor interactions) are often managed subcortically. Furthermore, control is distributed in the CNS in accord with the demands of the task. Piano playing can require cortical control of every finger individually, while merely grasping an object may not do so.

The performance of BCIs is also likely to benefit from comparable distribution of control. In this case, the distribution would be between the BCI's output commands (i.e., the user's intent) and the application that receives the commands and then converts them into action. The most effective distribution will probably vary with the BCI and with the application.

The natural muscle-based CNS outputs are products of the combined contributions of numerous areas from the cortex to the spinal cord. This reality suggests that BCI performance might be improved and stabilized by employing signals from more than one brain area and by employing brain signal features that represent relationships among different areas (e.g., coherences). By permitting the CNS to operate more in the way it does

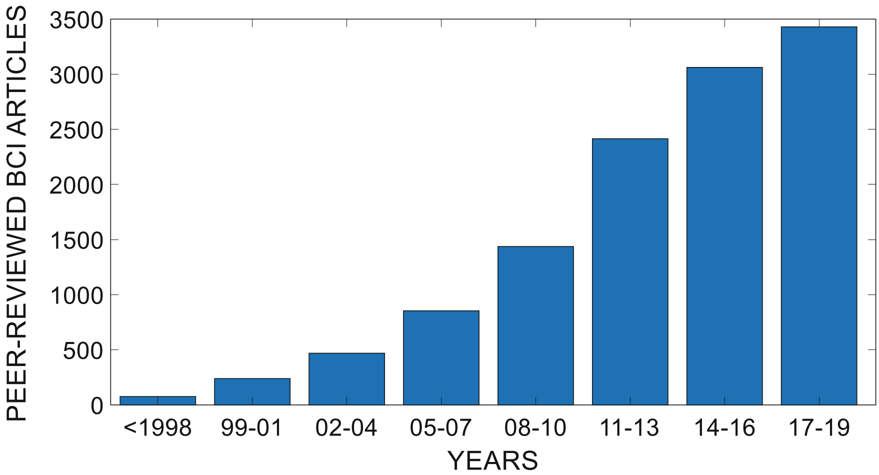

Fig. 4.22 Peer-reviewed BCI articles in the scientific literature. Over the past 30 years, BCI research, which was previously limited to a very few research groups, has become an extremely active and rapidly growing scientific field. The majority of research articles have been published in the last 6 years. (The statistics is from Web of Science Core Collection by using keywords brain computer interface or brain machine interface, Language English, Document Types: article. From 1980 to January 21, 2020)

in producing muscle-based actions, this approach could substantially increase BCI reliability.

Lastly, the feedback that present-day BCIs give their users is primarily visual and thus relatively slow and often imprecise. Natural muscle-based skills rely on multiple types of sensory input (e.g., proprioceptive, cutaneous, visual, auditory). BCIs that control applications that produce complex high-speed movements (e.g., limb movements) would benefit from sensory feedback that is faster, more precise, and more comprehensive than vision alone. Work seeking to provide such feedback using stimulators in cortex or elsewhere has begun [194]. The best techniques will almost certainly vary with the BCI, the application, and the user's disability (e.g., peripheral inputs may not be useful in many people with spinal cord injuries).

4.9 Conclusion

Numerous researchers throughout the world are realizing BCI systems that some years ago might have been considered science fiction. Figure 4.22 illustrates the publication years of peer-reviewed BCI articles that have appeared to date according to the Web of Science database by inputting the keywords "brain–computer interface" or "brain–machine interface" and shows that a majority of all the articles ever published have appeared just in the past several years. These BCIs use a variety of different brain signals, recording techniques, and signal-processing methods. They can operate a wide variety of different applications, including communication programs, cursors on computer screens, drones, wheelchairs, and robotic arms. A small number of people with severe disabilities are already employing BCIs for simple communication and control functions in their everyday lives. With improved signal acquisition hardware and sensors, machine learning software, definitive clinical and practical validation, and, better integration of neuroscience with machine learning, BCIs could become a major new technology for people with disabilities, and for the general population as well.

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Homework

1. Answer the following questions about the general aspects of BCI.
   (1.1) Define brain–computer interface (BCI) in your own words.
   (1.2) Describe at least 3 examples of BCI according to different signal resources and explain their pros and cons.
   (1.3) Describe what the unique challenges of BCI research are.
   (1.4) If you want to decode people's imagery movement, which brain areas do you want to choose in order to build an EEG-based BCI?
2. Answer the following questions about the BCI signal acquisition.
   (2.1) What is the spatial resolution of noninvasive techniques such as EEG, MEG, and fMRI?
   (2.2) What is the spatial resolution of invasive techniques such as ECoG, multiunit recording?
   (2.3) What is the temporal resolution of noninvasive techniques such as EEG, MEG, and fMRI?
   (2.4) For EEG-based BCI, does increasing the electrode number help to improve the decoding accuracy of motor imagination? Why?
   (2.5) Does the combination of different noninvasive modalities help to improve the decoding accuracy such as the simultaneous acquisition of EEG and fMRI? Please explain why?
3. Answer the following questions about the BCI feature extraction.
   (3.1) What kind of features could be extracted to decode the event-related potentials (ERP)?
   (3.2) Is it possible to decode the ERP in single trials? Please explain.
   (3.3) What kind of features could be used to decode the motor imagery–induced sensorimotor rhythms?
4. Answer the following questions about the SSVEP BCI.
   (4.1) What is the limitation to use a computer monitor as the display of the flicker in a steady-state visual evoked potential (SSVEP)–based BCI?
   (4.2) Download one of the examples (shared data, e.g., S1.mat, http://thubci.org/en/index.php?s=/home/index/nr/id/100/page/1.html) from the shared data in the 'Wang et al (2016). A benchmark dataset for SSVEP-based brain–computer interfaces. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(10), 1746-1752.' Plot the power spectrum of electrode Oz from any one of the 40 targets in a single block and the average from all of the six blocks.
5. Answer the following questions about the motor imagery–based BCI.
   (5.1) Download one of the examples (shared data, e.g., S1_LR_20150130.mat) from the shared data in [14] and Readme file to learn the structure of the shared data.
   (5.2) Extract the multichannel signals of each trial; calculate the average feedback duration for the example session.
   (5.3) Calculate the average band power (8–13 Hz) of channel C3 and C4 over all of the left trials, respectively.
   (5.4) Calculate the average band power (8–13 Hz) of channel C3 and C4 over all of the right trials, respectively.
   (5.5) Compare the above average band power for left trials and right trials. Describe the difference.
6. What kinds of classification algorithms are commonly used in the EEG–based BCI?
7. Answer the following questions about robotic arm control using BCI.
   (7.1) Please explain what are the pros and cons to control a prosthetic or robotic arm by using different types of noninvasive BCI, such as SSVEP based and sensorimotor rhythm based.
   (7.2) What is the challenge for control of a high degree of freedom (DoF) robotic arm by noninvasive BCIs? Please de-

scribe your solution of controlling a high DoF robotic arm.

8. Answer the following questions about BCI applications.
   (8.1) What BCI could be used as a tool? Please describe at least three examples.
   (8.2) Please describe how BCIs could be used to induce tactile sensation neurofeedback.
9. Answer the following questions about the hybrid BCI.
   (9.1) Please describe an example of the hybrid BCI.
   (9.2) Please describe your solution of driving a wheelchair mounting with an assistive robotic arm to help drinking and eating via a hybrid BCI.
10. Answer the following questions about information transfer rate of BCI.
   (10.1) What is the state-of-the-art information transfer rate (ITR) of different types of noninvasive–based BCIs?
   (10.2) Please describe a possible solution of increasing the ITR of a noninvasive sensorimotor rhythm–based BCI and explain why it might work.
11. Answer the following questions about BCI development.
   (11.1) Please list three most important questions to be addressed in order to significantly improve the field of BCI.
   (11.2) Please discuss the potential of BCI application in the clinical field.

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