Brain–Computer Interfaces: A Gentle Introduction

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Stardate 3012.4: The U.S.S. Enterprise has been diverted from its original course to meet its former captain Christopher Pike on Starbase 11. When Captain Jim Kirk and his crew arrive, they find out that Captain Pike has been severely crippled by a radiation accident. As a consequence of this accident Captain Pike is completely paralyzed and confined to a wheelchair controlled by his brain waves. He can only communicate through a light integrated into his wheelchair to signal the answers "yes" or "no". Commodore Mendez, the commander of Starbase 11, describes the condition of Captain Pike as follows: "He is totally unable to move, Jim. His wheelchair is constructed to respond to his brain waves. He can turn it, move it forwards, backwards slightly. Through a flashing light he can say 'yes' or 'no'. But that's it, Jim. That is as much as the poor ever can do. His mind is as active as yours and mine, but it's trapped in a useless vegetating body. He's kept alive mechanically. A battery driven heart. . . ."

This episode from the well-known TV series Star Trek was first shown in 1966. It describes a man who suffers from locked-in syndrome. In this condition, the person is cognitively intact but the body is paralyzed. In this case, paralyzed means that any voluntary control of muscles is lost. People cannot move their arms, legs, or faces, and depend on an artificial respirator. The active and fully functional mind is trapped in the body – as accurately described in the excerpt of the Star Trek episode above. The only effective way to communicate with the environment is with a device that can read brain signals and convert them into control and communication signals.

Such a device is called a brain–computer interface (BCI). Back in the 60s, controlling devices with brain waves was considered pure science fiction, as wild and fantastic as warp drive and transporters. Although recording brain signals from the human scalp gained some attention in 1929, when the German scientist Hans Berger recorded the electrical brain activity from the human scalp, the required technologies for measuring and processing brain signals as well as our understanding of brain function were still too limited. Nowadays, the situation has changed. Neuroscience

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research over the last decades has led to a much better understanding of the brain. Signal processing algorithms and computing power have advanced so rapidly that complex real-time processing of brain signals does not require expensive or bulky equipment anymore.

The first BCI was described by Dr. Grey Walter in 1964. Ironically, this was shortly before the first Star Trek episode aired. Dr. Walter connected electrodes directly to the motor areas of a patient's brain. (The patient was undergoing surgery for other reasons.) The patient was asked to press a button to advance a slide projector while Dr. Walter recorded the relevant brain activity. Then, Dr. Walter connected the system to the slide projector so that the slide projector advanced whenever the patient's brain activity indicated that he wanted to press the button. Interestingly, Dr. Walter found that he had to introduce a delay from the detection of the brain activity until the slide projector advanced because the slide projector would otherwise advance before the patient pressed the button! Control before the actual movement happens, that is, control without movement – the first BCI!

Unfortunately, Dr. Walter did not publish this major breakthrough. He only presented a talk about it to a group called the Ostler Society in London [1]. There was little progress in BCI research for most of the time since then. BCI research advanced slowly for many more years. By the turn of the century, there were only one or two dozen labs doing serious BCI research. However, BCI research developed quickly after that, particularly during the last few years. Every year, there are more BCI-related papers, conference talks, products, and media articles. There are at least 100 BCI research groups active today, and this number is growing.

More importantly, BCI research has succeeded in its initial goal: proving that BCIs can work with patients who need a BCI to communicate. Indeed, BCI researchers have used many different kinds of BCIs with several different patients. Furthermore, BCIs are moving beyond communication tools for people who cannot otherwise communicate. BCIs are gaining attention for healthy users and new goals such as rehabilitation or hands-free gaming. BCIs are not science fiction anymore. On the other hand, BCIs are far from mainstream tools. Most people today still do not know that BCIs are even possible. There are still many practical challenges before a typical person can use a BCI without expert help. There is a long way to go from providing communication for some specific patients, with considerable expert help, to providing a range of functions for any user without help.

The goal of this chapter is to provide a gentle and clear introduction of BCIs. It is meant for newcomers of this exciting field of research, and it is also meant as a preparation for the remaining chapters of this book. Readers will find answers to the following questions: What are BCIs? How do they work? What are their limitations? What are typical applications, and who can benefit from this new technology?

1 What is a BCI?

Any natural form of communication or control requires peripheral nerves and muscles. The process begins with the user's intent. This intent triggers a complex process in which certain brain areas are activated, and hence signals are sent via the peripheral nervous system (specifically, the motor pathways) to the corresponding muscles, which in turn perform the movement necessary for the communication or control task. The activity resulting from this process is often called motor output or efferent output. Efferent means conveying impulses from the central to the peripheral nervous system and further to an effector (muscle). Afferent, in contrast, describes communication in the other direction, from the sensory receptors to the central nervous system. For motion control, the motor (efferent) pathway is essential. The sensory (afferent) pathway is particularly important for learning motor skills and dexterous tasks, such as typing or playing a musical instrument.

A BCI offers an alternative to natural communication and control. A BCI is an artificial system that bypasses the body's normal efferent pathways, which are the neuromuscular output channels [2]. Figure 1 illustrates this functionality.

Instead of depending on peripheral nerves and muscles, a BCI directly measures brain activity associated with the user's intent and translates the recorded brain activity into corresponding control signals for BCI applications. This translation involves signal processing and pattern recognition, which is typically done by a computer. Since the measured activity originates directly from the brain and not from the peripheral systems or muscles, the system is called a Brain–Computer Interface.

A BCI must have four components. It must record activity directly from the brain (invasively or non-invasively). It must provide feedback to the user, and must do so in realtime. Finally, the system must rely on intentional control. That is, the user must choose to perform a mental task whenever s/he wants to accomplish a goal with the BCI. Devices that only passively detect changes in brain activity that occur without any intent, such as EEG activity associated with workload, arousal, or sleep, are not BCIs.

Although most researchers accept the term "BCI" and its definition, other terms has been used to describe this special form of human–machine interface. Here are some definitions of BCIs found in BCI literature:

> Wolpaw et al.: "A direct brain-computer interface is a device that provides the brain with a new, non-muscular communication and control channel". [2].

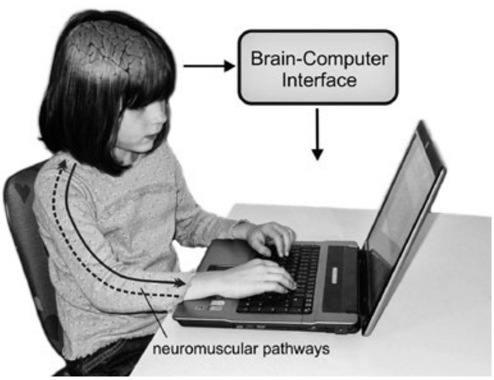

Fig. 1 A BCI bypasses the normal neuromuscular output channels

Donoghue et al.: "A major goal of a BMI (brain-machine interface) is to provide a command signal from the cortex. This command serves as a new functional output to control disabled body parts or physical devices, such as computers or robotic limbs" [3]

Levine et al.: "A direct brain interface (DBI) accepts voluntary commands directly from the human brain without requiring physical movement and can be used to operate a computer or other technologies." [4]

Schwartz et al.: "Microelectrodes embedded chronically in the cerebral cortex hold promise for using neural activity to control devices with enough speed and agility to replace natural, animate movements in paralyzed individuals. Known as cortical neural prostheses (CNPs), devices based on this technology are a subset of neural prosthetics, a larger category that includes stimulating, as well as recording, electrodes." [5]

Brain–computer interfaces, brain–machine interfaces (BMIs), direct brain interfaces (DBIs), neuroprostheses – what is the difference? In fact, there is no difference between the first three terms. BCI, BMI, and DBI all describe the same system, and they are used as synonyms.

"Neuroprosthesis," however, is a more general term. Neuroprostheses (also called neural prostheses) are devices that cannot only receive output from the nervous system, but can also provide input. Moreover, they can interact with the peripheral and the central nervous systems. Figure 2 presents examples of neuroprostheses, such as cochlear implants (auditory neural prostheses) and retinal implants (visual neural prostheses). BCIs are a special category of neuroprostheses.

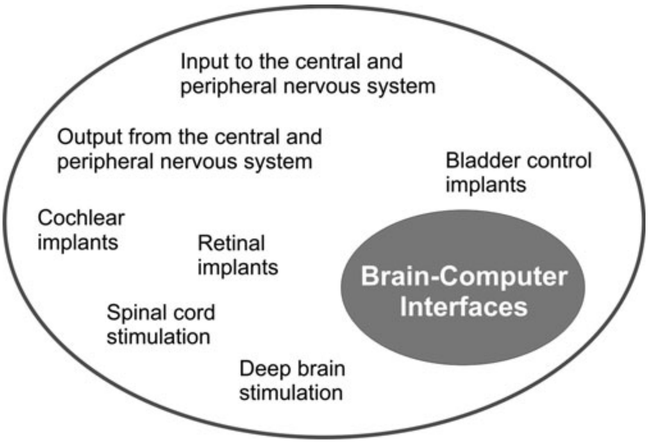

Fig. 2 Neuroprostheses can stimulate and/or measure activity from the central or peripheral nervous system. BCIs are a special subcategory that provides an artificial output channel from the central nervous system

They are, as already described in the definitions above, direct artificial output channels from the brain. Unlike other human–computer interfaces, which require muscle activity, BCIs provide "non-muscular" communication. One of the most important reasons that this is significant is that current BCI systems aim to provide assistive devices for people with severe disabilities that can render people unable to perform physical movements. Radiation accidents like the one in the Star Trek episode described above are unlikely today, but some diseases can actually lead to the locked-in syndrome.

Amyotrophic lateral sclerosis (ALS) is an example of such a disease. The exact cause of ALS is unknown, and there is no cure. ALS starts with muscle weakness and atrophy. Usually, all voluntary movement, such as walking, speaking, swallowing, and breathing, deteriorates over several years, and eventually is lost completely. The disease, however, does not affect cognitive functions or sensations. People can still see, hear, and understand what is happening around them, but cannot control their muscles. This is because ALS only affects special neurons, the large alpha motor neurons, which are an integral part of the motor pathways. Death is usually caused by failure of the respiratory muscles.

Life-sustaining measures such as artificial respiration and artificial nutrition can considerably prolong the life expectancy. However, this leads to life in the locked-in state. Once the motor pathway is lost, any natural way of communication with the environment is lost as well. BCIs offer the only option for communication in such cases. More details about ALS and BCIs can be found in the chapters "Brain–Computer Interface in Neurorehabilitation" and "Brain–Computer Interfaces for Communication and Control in Locked-in Patients" of this book.

So, a BCI is an artificial output channel, a direct interface from the brain to a computer or machine, which can accept voluntary commands directly from the brain without requiring physical movements. A technology that can listen to brain activity that can recognize and interpret the intent of the user? Doesn't this sound like a mind reading machine? This misconception is quite common among BCI newcomers, and is presumably also stirred up by science fiction and poorly researched articles in popular media. In the following section, we explain the basic principles of BCI operation. It should become apparent that BCIs are not able to read the mind.

2 How Do BCIs Work?

BCIs measure brain activity, process it, and produce control signals that reflect the user's intent. To understand BCI operation better, one has to understand how brain activity can be measured and which brain signals can be utilized. In this chapter, we focus on the most important recording methods and brain signals. Chapter "Brain Signals for Brain–Computer Interfaces" of this book gives a much more detailed representation of these two topics.

2.1 Measuring Brain Activity (Without Surgery)

Brain activity produces electrical and magnetic activity. Therefore, sensors can detect different types of changes in electrical or magnetic activity, at different times over different areas of the brain, to study brain activity.

Most BCIs rely on electrical measures of brain activity, and rely on sensors placed over the head to measure this activity. Electroencephalography (EEG) refers to recording electrical activity from the scalp with electrodes. It is a very well established method, which has been used in clinical and research settings for decades. Figure 3 shows an EEG based BCI. EEG equipment is inexpensive, lightweight, and comparatively easy to apply. Temporal resolution, meaning the ability to detect changes within a certain time interval, is very good. However, the EEG is not without disadvantages: The spatial (topographic) resolution and the frequency range are limited. The EEG is susceptible to so-called artifacts, which are contaminations in the EEG caused by other electrical activities. Examples are bioelectrical activities caused by eye movements or eye blinks (electrooculographic activity, EOG) and from muscles (electromyographic activity, EMG) close to the recording sites. External electromagnetic sources such as the power line can also contaminate the EEG.

Furthermore, although the EEG is not very technically demanding, the setup procedure can be cumbersome. To achieve adequate signal quality, the skin areas that are contacted by the electrodes have to be carefully prepared with special abrasive

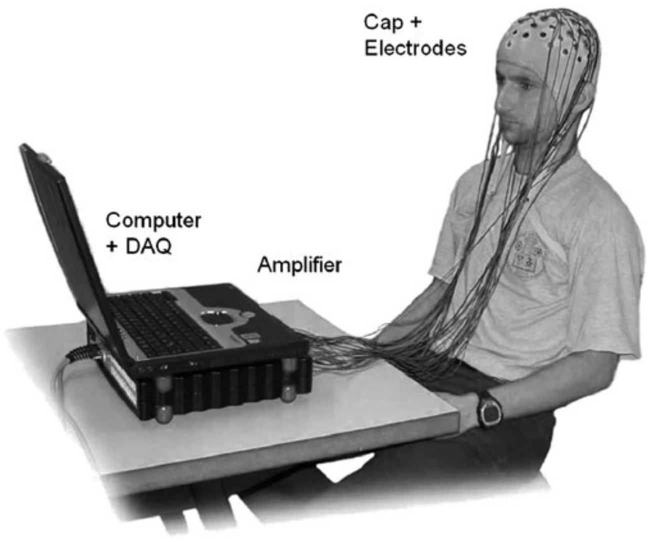

Fig. 3 A typical EEG based BCI consists of an electrode cap with electrodes, cables that transmit the signals from the electrodes to the biosignal amplifier, a device that converts the brain signals from analog to digital format, and a computer that processes the data as well as controls and often even runs the BCI application

electrode gel. Because gel is required, these electrodes are also called wet electrodes. The number of electrodes required by current BCI systems range from only a few to more than 100 electrodes. Most groups try to minimize the number of electrodes to reduce setup time and hassle. Since electrode gel can dry out and wearing the EEG cap with electrodes is not convenient or fashionable, the setting up procedure usually has to be repeated before each session of BCI use. From a practical viewpoint, this is one of largest drawbacks of EEG-based BCIs. A possible solution is a technology called dry electrodes. Dry electrodes do not require skin preparation nor electrode gel. This technology is currently being researched, but a practical solution that can provide signal quality comparable to wet electrodes is not in sight at the moment.

A BCI analyzes ongoing brain activity for brain patterns that originate from specific brain areas. To get consistent recordings from specific regions of the head, scientists rely on a standard system for accurately placing electrodes, which is called the International 10–20 System [6]. It is widely used in clinical EEG recording and EEG research as well as BCI research. The name 10–20 indicates that the most commonly used electrodes are positioned 10, 20, 20, 20, 20, and 10% of the total nasion-inion distance. The other electrodes are placed at similar fractional distances. The inter-electrode distances are equal along any transverse (from left to right) and antero-posterior (from front to back) line and the placement is symmetrical. The labels of the electrode positions are usually also the labels of the recorded channels. That is, if an electrode is placed at site C3, the recorded signal from this electrode is typically also denoted as C3. The first letters of the labels give a hint of the brain region over which the electrode is located: Fp – pre-frontal, F – frontal, C – central, P – parietal, O – occipital, T – temporal. Figure 4 depicts the electrode placement according to the 10–20 system.

While most BCIs rely on sensors placed outside of the head to detect electrical activity, other types of sensors have been used as well [7]. Magnetoencephalography (MEG) records the magnetic fields associated with brain activity. Functional magnetic resonance imaging (fMRI) measures small changes in the blood oxygenation level-dependent (BOLD) signals associated with cortical activation. Like fMRI also near infrared spectroscopy (NIRS) is a hemodynamic based technique for assessment of functional activity in human cortex. Different oxygen levels of the blood result in different optical properties which can be measured by NIRS. All these methods have been used for brain–computer communication, but they all have drawbacks which make them impractical for most BCI applications: MEG and fMRI are very large devices and prohibitively expensive. NIRS and fMRI have poor temporal resolution, and NIRS is still in an early stage of development [7–9].

2.2 *Measuring Brain Activity (With Surgery)*

The techniques discussed in the last section are all non-invasive recording techniques. That is, there is no need to perform surgery or even break the skin. In contrast, invasive recording methods require surgery to implant the necessary

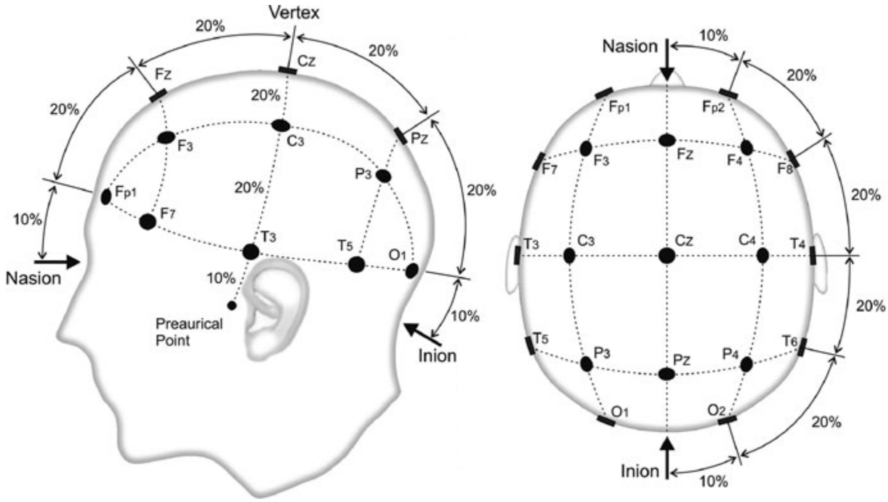

Fig. 4 The international 10–20 system: the left image shows the left side of the head, and the right side presents the view from above the head. The nasion is the intersection of the frontal and nasal bones at the bridge of the nose. The inion is a small bulge on the back of the skull just above the neck

sensors. This surgery includes opening the skull through a surgical procedure called a craniotomy and cutting the membranes that cover the brain. When the electrodes are placed on the surface of the cortex, the signal recorded from these electrodes is called the electrocorticogram (ECoG). ECoG does not damage any neurons because no electrodes penetrate the brain. The signal recorded from electrodes that penetrate brain tissue is called intracortical recording.

Invasive recording techniques combine excellent signal quality, very good spatial resolution, and a higher frequency range. Artifacts are less problematic with invasive recordings. Further, the cumbersome application and re-application of electrodes as described above is unnecessary for invasive approaches. Intracortical electrodes can record the neural activity of a single brain cell or small assemblies of brain cells. The ECoG records the integrated activity of a much larger number of neurons that are in the proximity of the ECoG electrodes. However, any invasive technique has better spatial resolution than the EEG.

Clearly, invasive methods have some advantages over non-invasive methods. However, these advantages come with the serious drawback of requiring surgery. Ethical, financial, and other considerations make neurosurgery impractical except for some users who need a BCI to communicate. Even then, some of these users may find that a noninvasive BCI meets their needs. It is also unclear whether both ECoG and intracortical recordings can provide safe and stable recording over years. Long-term stability may be especially problematic in the case of intracortical recordings. Electrodes implanted into the cortical tissue can cause tissue reactions that lead to deteriorating signal quality or even complete electrode failure. Research on invasive

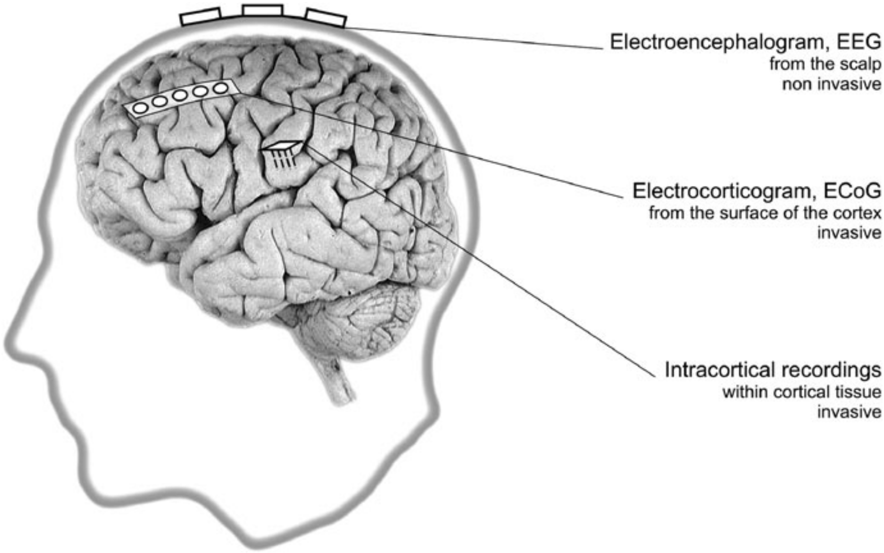

Fig. 5 Three different ways to detect the brain's electrical activity: EEG, ECoG, and intracortical recordings

BCIs is difficult because of the cost and risk of neurosurgery. For ethical reasons, some invasive research efforts rely on patients who undergo neurosurgery for other reasons, such as treatment of epilepsy. Studies with these patients can be very informative, but it is impossible to study the effects of training and long term use because these patients typically have an ECoG system for only a few days before it is removed.

Chapters "Intracortical BCIs: A Brief History of Neural Timing" through "A simple, spectral-change based, electrocorticographic Brain–Computer Interface" in this book describe these difficulties and give a more comprehensive overview of this special branch of BCI research. Figure 5 summarizes the different methods for recording bioelectrical brain activity.

2.3 Mental Strategies and Brain Patterns

Measuring brain activity effectively is a critical first step for brain–computer communication. However, measuring activity is not enough, because a BCI cannot read the mind or decipher thoughts in general. A BCI can only detect and classify specific patterns of activity in the ongoing brain signals that are associated with specific tasks or events. What the BCI user has to do to produce these patterns is determined by the mental strategy (sometimes called experimental strategy or approach) the BCI system employs. The mental strategy is the foundation of any brain–computer communication. The mental strategy determines what the user has to do to volitionally produce brain patterns that the BCI can interpret. The mental strategy also sets certain constraints on the hardware and software of a BCI, such as the signal processing techniques to be employed later. The amount of training required to successfully use a BCI also depends on the mental strategy. The most common mental strategies are selective (focused) attention and motor imagery [2, 10–12]. In the following, we briefly explain these different BCIs. More detailed information about different BCI approaches and associated brain signals can be found in chapter "Brain Signals for Brain–Computer Interfaces".

2.3.1 Selective Attention

BCIs based on selective attention require external stimuli provided by the BCI system. The stimuli can be auditory [13] or somatosensory [14]. Most BCIs, however, are based on visual stimuli. That is, the stimuli could be different tones, different tactile stimulations, or flashing lights with different frequencies. In a typical BCI setting, each stimulus is associated with a command that controls the BCI application. In order to select a command, the users have to focus their attention to the corresponding stimulus. Let's consider an example of a navigation/selection application, in which we want to move a cursor to items on a computer screen and then we want to select them. A BCI based on selective attention could rely on five stimuli. Four stimuli are associated with the commands for cursor movement: left, right, up, and down. The fifth stimulus is for the select command. This system would allow two dimensional navigation and selection on a computer screen. Users operate this BCI by focusing their attention on the stimulus that is associated with the intended command. Assume the user wants to select an item on the computer screen which is one position above and left of the current cursor position. The user would first need to focus on the stimulus that is associated with the up command, then on the one for the left command, then select the item by focusing on the stimulus associated with the select command. The items could represent a wide variety of desired messages or commands, such as letters, words, instructions to move a wheelchair or robot arm, or signals to control a smart home.

A 5-choice BCI like this could be based on visual stimuli. In fact, visual attention can be implemented with two different BCI approaches, which rely on somewhat different stimuli, mental strategies, and signal processing. These approaches are named after the brain patterns they produce, which are called P300 potentials and steady-state visual evoked potentials (SSVEP). The BCIs employing these brain patterns are called P300 BCI and SSVEP BCI, respectively.

A P300 based BCI relies on stimuli that flash in succession. These stimuli are usually letters, but can be symbols that represent other goals, such as controlling a cursor, robot arm, or mobile robot [15, 16]. Selective attention to a specific flashing symbol/letter elicits a brain pattern called P300, which develops in centro-parietal brain areas (close to location Pz, as shown in Fig. 3) about 300 ms after the presentation of the stimulus. The BCI can detect this P300. The BCI can then determine the symbol/letter that the user intends to select.

Like a P300 BCI, an SSVEP based BCI requires a number of visual stimuli. Each stimulus is associated with a specific command, which is associated with an output the BCI can produce. In contrast to the P300 approach, however, these stimuli do not flash successively, but flicker continuously with different frequencies in the range of about 6–30 Hz. Paying attention to one of the flickering stimuli elicits an SSVEP in the visual cortex (see Fig. 5) that has the same frequency as the target flicker. That is, if the targeted stimulus flickers at 16 Hz, the resulting SSVEP will also flicker at 16 Hz. Therefore, an SSVEP BCI can determine which stimulus occupies the user's attention by looking for SSVEP activity in the visual cortex at a specific frequency. The BCI knows the flickering frequencies of all light sources, and when an SSVEP is detected, it can determine the corresponding light source and its associated command.

BCI approaches using selective attention are quite reliable across different users and usage sessions, and can allow fairly rapid communication. Moreover, these approaches do not require significant training. Users can produce P300s and SSVEPs without any training at all. Almost all subjects can learn the simple task of focusing on a target letter or symbol within a few minutes. Many types of P300 and SSVEP BCIs have been developed. For example, the task described above, in which users move a cursor to a target and then select it, has been validated with both P300 and SSVEP BCIs [15, 17]. One drawback of both P300 and SSVEP BCIs is that they may require the user to shift gaze. This is relevant because completely locked-in patients are not able to shift gaze anymore. Although P300 and SSVEP BCIs without gaze shifting are possible as well [10, 18], BCIs that rely on visual attention seem to work best when users can shift gaze. Another concern is that some people may dislike the external stimuli that are necessary to elicit P300 or SSVEP activity.

2.3.2 Motor Imagery

Moving a limb or even contracting a single muscle changes brain activity in the cortex. In fact, already the preparation of movement or the imagination of movement also change the so-called sensorymotor rhythms. Sensorimotor rhythms (SMR) refer to oscillations in brain activity recorded from somatosensory and motor areas (see Fig. 6). Brain oscillations are typically categorized according to specific frequency bands which are named after Greek letters (delta: < 4 Hz, theta: 4–7 Hz, alpha: 8–12 Hz, beta: 12–30 Hz, gamma: > 30 Hz). Alpha activity recorded from sensorimotor areas is also called mu activity. The decrease of oscillatory activity in a specific frequency band is called event-related desynchronization (ERD). Correspondingly, the increase of oscillatory activity in a specific frequency band is called event-related synchronization (ERS). ERD/ERS patterns can be volitionally produced by motor imagery, which is the imagination of movement without actually performing the movement. The frequency bands that are most important for motor imagery are mu and beta in EEG signals. Invasive BCIs often also use gamma activity, which is hard to detect with electrodes mounted outside the head.

Topographically, ERD/ERS patterns follow a homuncular organization. Activity invoked by right hand movement imagery is most prominent over electrode location C3 (see Fig. 4). Left hand movement imagery produces activity most prominent

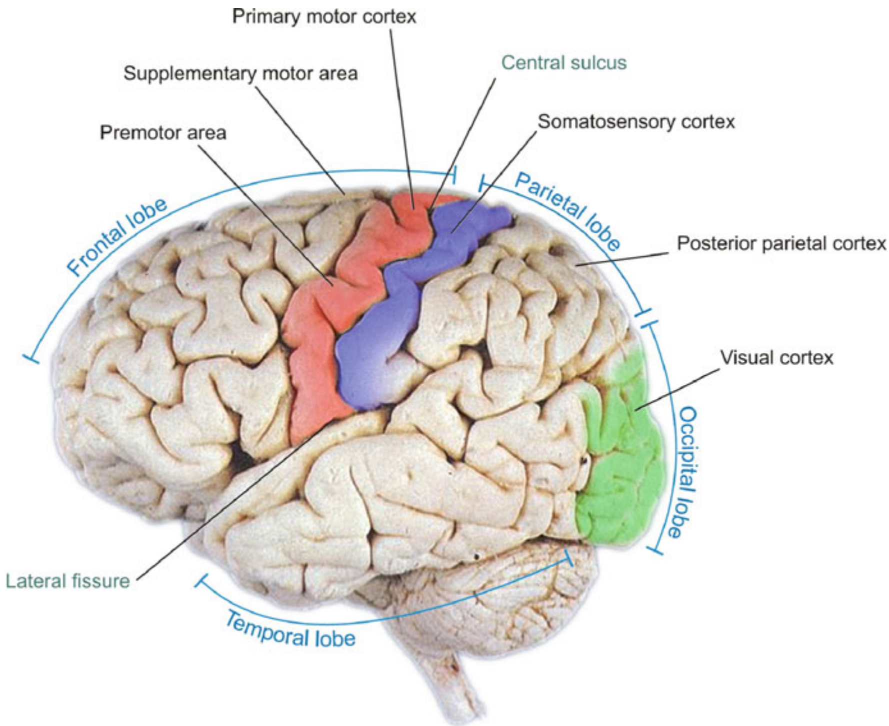

Fig. 6 The cerebrum is subdivided into four lobes: frontal, parietal, occipital, and temporal lobe. The central sulcus divides the frontal lobe from the parietal lobe. It also separates the precentral gyrus (*indicated in red*) and the postcentral gyrus (*indicated in blue*). The temporal lobe is separated from the frontal lobe by the lateral fissure. The occipital lobe lies at the very back of the cerebrum. The following cortical areas are particularly important for BCIs are: motor areas, somatosensory cortex, posterior parietal cortex, and visual cortex

over C4. That is, activity invoked by hand movement imagery is located on the contralateral (opposide) side. Foot movement imagery invokes activity over Cz. A distinction between left and right foot movement is not possible in EEG because the corresponding cortical areas are too close. Similarly, ERD/ERS patterns of individual fingers cannot be discriminated in EEG. To produce patterns that can be detected, the cortical areas involved have to be large enough so that the resulting activity is sufficiently prominent compared to the remaining EEG (background EEG). Hand areas, foot areas, and the tongue area are comparatively large and topographically different. Therefore, BCIs have been controlled by imagining moving the left hand, right hand, feet, and tongue [19].

ERD/ERS patterns produced by motor imagery are similar in their topography and spectral behavior to the patterns elicited by actual movements. And since these patterns originate from motor and somatosensory areas, which are directly connected to the normal neuromuscular output pathways, motor imagery is a particularly suitable mental strategy for BCIs. The way how motor imagery must be performed to best use a BCI can be different. For example, some BCIs can tell if the users are thinking of moving your left hand, right hand, or feet. This can lead to a BCI that allows 3 signals, which might be mapped on to commands to move left, right, and select. Another type of motor imagery BCI relies on more abstract, subject-specific types of movements. Over the course of several training sessions with a BCI, people can learn and develop their own motor imagery strategy. In a cursor movement task, for instance, people learn which types of imagined movements are best for BCI control, and reliably move a cursor up or down. Some subjects can learn to move a cursor in two [20] or even three [21] dimensions with further training.

In contrast to BCIs based on selective attention, BCIs based on motor imagery do not depend on external stimuli. However, motor imagery is a skill that has to be learned. BCIs based on motor imagery usually do not work very well during the first session. Instead, unlike BCIs on selective attention, some training is necessary. While performance and training time vary across subjects, most subjects can attain good control in a 2-choice task with 1–4 h of training (see chapters "The Graz Brain–Computer Interface", "BCIs in the Laboratory and at Home: The Wadsworth Research Program", and "Detecting Mental States by Machine Learning Techniques: The Berlin Brain–Computer Interface" in this book). However, longer training is often necessary to achieve sufficient control. Therefore, training is an important component of many BCIs. Users learn through a process called operant conditioning, which is a fundamental term in psychology. In operant conditioning, people learn to associate a certain action with a response or effect. For example, people learn that touching a hot stove is painful, and never do it again. In a BCI, a user who wants to move the cursor up may learn that mentally visualizing a certain motor task such as a clenching one's fist is less effective than thinking about the kinaesthetic experience of such a movement [22]. BCI learning is a special case of operant conditioning because the user is not performing an action in the classical sense, since s/he does not move. Nonetheless, if imagined actions produce effects, then conditioning can still occur. During BCI use, operant conditioning involves training with feedback that is usually presented on a computer screen. Positive feedback indicates that the brain signals are modulated in a desired way. Negative or no feedback is given when the user was not able to perform the desired task. BCI learning is a type of feedback called neurofeedback. The feedback indicates whether the user performed the mental task well or failed to achieve the desired goal through the BCI. Users can utilize this feedback to optimize their mental tasks and improve BCI performance. The feedback can be tactile or auditory, but most often it is visual. Chapter "Neurofeedback Training for BCI Control" in this book presents more details about neuro-feedback and its importance in BCI research.

2.4 Signal Processing

A BCI measures brain signals and processes them in real time to detect certain patterns that reflect the user's intent. This signal processing can have three stages: preprocessing, feature extraction, and detection and classification.

Preprocessing aims at simplifying subsequent processing operations without losing relevant information. An important goal of preprocessing is to improve signal quality by improving the so-called signal-to-noise ratio (SNR). A bad or small SNR means that the brain patterns are buried in the rest of the signal (e.g. background EEG), which makes relevant patterns hard to detect. A good or large SNR, on the other hand, simplifies the BCI's detection and classification task. Transformations combined with filtering techniques are often employed during preprocessing in a BCI. Scientists use these techniques to transform the signals so unwanted signal components can be eliminated or at least reduced. These techniques can improve the SNR.

The brain patterns used in BCIs are characterized by certain features or properties. For instance, amplitudes and frequencies are essential features of sensorimotor rhythms and SSVEPs. The firing rate of individual neurons is an important feature of invasive BCIs using intracortical recordings. The feature extraction algorithms of a BCI calculate (extract) these features. Feature extraction can be seen as another step in preparing the signals to facilitate the subsequent and last signal processing stage, detection and classification.

Detection and classification of brain patterns is the core signal processing task in BCIs. The user elicits certain brain patterns by performing mental tasks according to mental strategies, and the BCI detects and classifies these patterns and translates them into appropriate commands for BCI applications.

This detection and classification process can be simplified when the user communicates with the BCI only in well defined time frames. Such a time frame is indicated by the BCI by visual or acoustic cues. For example, a beep informs the user that s/he could send a command during the upcoming time frame, which might last 2–6 s. During this time, the user is supposed to perform a specific mental task. The BCI tries to classify the brain signals recorded in this time frame. This type of BCI does not consider the possibility that the user does not wish to communicate anything during one of these time frames, or that s/he wants to communicate outside of a specified time frame.

This mode of operation is called synchronous or cue-paced. Correspondingly, a BCI employing this mode of operation is called a synchronous BCI or a cue-paced BCI. Although these BCIs are relatively easy to develop and use, they are impractical in many real-world settings. A cue-pased BCI is somewhat like a keyboard that can only be used at certain times.

In an asynchronous or self-paced BCI, users can interact with a BCI at their leisure, without worrying about well defined time frames [23]. Users may send a signal, or choose not to use a BCI, whenever they want. Therefore, asynchronous BCIs or self-paced BCIs have to analyse the brain signals continuously. This mode of operation is technically more demanding, but it offers a more natural and convenient form of interaction with a BCI. More details about signal processing and the most frequently used algorithms in BCIs can be found in chapters "Digital Signal Processing and Machine Learning" and "Adaptive Methods in BCI Reaearch – An Introductory Tutorial" of this volume.

3 BCI Performance

The performance of a BCI can be measured in various ways [24]. A simple measure is classification performance (also termed classification accuracy or classification rate). It is the ratio of the number of correctly classified trials (successful attempts to perform the required mental tasks) and the total number of trials. The error rate is also easy to calculate, since it is just the ratio of incorrectly classified trials and the total number of trials.

Although classification or error rates are easy to calculate, application dependent measures are often more meaningful. For instance, in a mental typewriting application the user is supposed to write a particular sentence by performing a sequence of mental tasks. Again, classification performance could be calculated, but the number of letters per minute the users can convey is a more appropriate measure. Letters per minute is an application dependent measure that assesses (indirectly) not only the classification performance but also the time that was necessary to perform the required tasks.

A more general performance measure is the so-called information transfer rate (ITR) [25]. It depends on the number of different brain patterns (classes) used, the time the BCI needs to classify these brain patterns, and the classification accuracy. ITR is measured in bits per minute. Since ITR depends on the number of brain patterns that can be reliably and quickly detected and classified by a BCI, the information transfer rate depends on the mental strategy employed.

Typically, BCIs with selective attention strategies have higher ITRs than those using, for instance, motor imagery. A major reason is that BCIs based on selective attention usually provide a larger number of classes (e.g. number of light sources). Motor imagery, for instance, is typically restricted to four or less motor imagery tasks. More imagery tasks are possible but often only to the expense of decreased classification accuracy, which in turn would decrease in the information transfer rate as well.

There are a few papers that report BCIs with a high ITR, ranging from 30 bits/min [26, 27] to slightly above 60 bits/min [28] and, most recently, over 90 bits per minute [29]. Such performance, however, is not typical for most users in real world settings. In fact, these record values are often obtained under laboratory conditions by individual healthy subjects who are the top performing subjects in a lab. In addition, high ITRs are usually reported when people only use a BCI for short periods. Of course, it is interesting to push the limits and learn the best possible performance of current BCI technology, but it is no less important to estimate realistic performance in more practical settings. Unfortunately, there is currently no study available that investigates the average information transfer rate for various BCI systems over a larger user population and over a longer time period so that a general estimate of average BCI performance can be derived. The closest such study is the excellent work by Kübler and Birbaumer [30].

Furthermore, a minority of subjects exhibit little or no control [11, 26, 31,]. The reason is not clear, but even long sustained training cannot improve performance for those subjects. In any case, a BCI provides an alternative communication channel, but this channel is slow. It certainly does not provide high-speed interaction. It cannot compete with natural communication (such as speaking or writing) or traditional man-machine interfaces in terms of ITR. However, it has important applications for the most severely disabled. There are also new emerging applications for less severely disabled or even healthy people, as detailed in the next section.

4 Applications

BCIs can provide discrete or proportional output. A simple discrete output could be "yes" or "no", or it could be a particular value out of N possible values. Proportional output could be a continuous value within the range of a certain minimum and maximum. Depending on the mental strategy and on the brain patterns used, some BCIs are more suitable for providing discrete output values, while others are more suitable for allowing proportional control [32]. A P300 BCI, for instance, is particularly appropriate for selection applications. SMR based BCIs have been used for discrete control, but are best suited to proportional control applications such as 2-dimensional cursor control.

In fact, the range of possible BCI applications is very broad – from very simple to complex. BCIs have been validated with many applications, including spelling devices, simple computer games, environmental control, navigation in virtual reality, and generic cursor control applications [26, 33, 34].

Most of these applications run on conventional computers that host the BCI system and the application as well. Typically, the application is specifically tailored for a particular type of BCI, and often the application is an integral part of the BCI system. BCIs that can connect and effectively control a range of already existing assistive devices, software, and appliances are rare. An increasing number of systems allow control of more sophisticated devices, including orthoses, prostheses, robotic arms, and mobile robots [35–40]. Figure 7 shows some examples of BCI applications, most of which are described in detail in this book (corresponding references are given in the figure caption).

The concluding chapter discusses the importance of an easy to use "universal" interface that can allow users to easily control any application with any BCI. There is little argument that such an interface would be a boon to BCI research. BCIs can control any application that other interfaces can control, provided these applications can function effectively with the low information throughput of BCIs. On the other hand, BCIs are normally not well suited to controlling more demanding and complex applications, because they lack the necessary information transfer rate. Complex tasks like rapid online chatting, grasping a bottle with a robotic arm, or playing some computer games require more information per second than a BCI can provide. However, this problem can sometimes be avoided by offering short cuts.

For instance, consider an ALS patient using a speller application for communication with her caregiver. The patient is thirsty and wants to convey that she wants to drink some water now. She might perform this task by selecting each individual

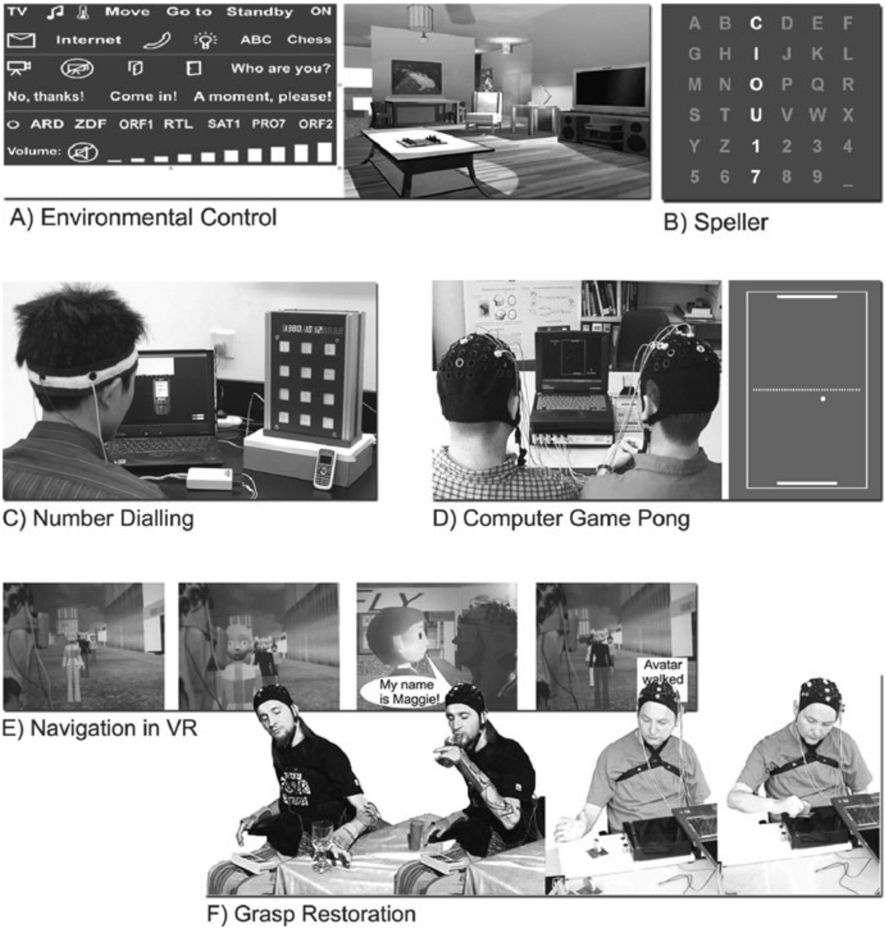

Fig. 7 Examples of BCI applications. (**a**) Environmental control with a P300 BCI (see chapter "The First Commercial Brain–Computer Interface Environment"), (**b**) P300 Speller (see chapter "BCIs in the Laboratory and at Home: The Wadsworth Research Program"), (**c**) Phone number dialling with an SSVEP BCI (see chapter "Practical Designs of Brain–Computer Interfaces Based on the Modulation of EEG Rhythms"), (**d**) Computer game Pong for two players, E) Navigation in a virtual reality environment (see chapter "The Graz Brain–Computer Interface"), (**f**) Restoration of grasp function of paraplegic patients by BCI controlled functional electrical stimulation (see chapter "Non invasive BCIs for neuroprostheses control of the paralysed hand")

letter and writing the message "water, please" or just "water". Since this is a wish the patient may have quite often, it would be useful to have a special symbol or command for this message. In this way, the patient can convey this particular message much faster, ideally with just one mental task. Many more short cuts might allow other tasks, but these short cuts lack the flexibility of writing individual messages. Therefore, an ideal BCI would allow a combination of simple commands to convey information flexibly and short cuts that allow specific, common, complex commands.

In other words, the BCI should allow a combination of process-oriented (or low-level) control and goal-oriented (or high level) control [41, 42]. Low-level control means the user has to manage all the intricate interactions involved in achieving a task or goal, such as spelling the individual letters for a message. In contrast, goal-oriented or high-level control means the users simply communicate their goal to the application. Such applications need to be sufficiently intelligent to autonomously perform all necessary sub-tasks to achieve the goal. In any interface, users should not be required to control unnecessary low-level details of system operation.

This is especially important with BCIs. Allowing low-level control of a wheelchair or robot arm, for example, would not only be slow and frustrating but potentially dangerous. Figure 8 presents two such examples of very complex applications.

The semi-autonomous wheelchair Rolland III can deal with different input modalities, such as low-level joystick control or high-level discrete control. Autonomous and semi-autonomous navigation is supported. The rehabilitation robot FRIEND II (Functional Robot Arm with User Friendly Interface for disabled People) is a semi-autonomous system designed to assist disabled people in activities of daily living. It is system based on a conventional wheelchair equipped with a stereo camera system, a robot arm with 7 degrees-of-freedom, a gripper with force/torque sensor, a smart tray with tactile surface and weight sensors, and a computing unit consisting of three independent industrial PCs. FRIEND II can perform certain operations

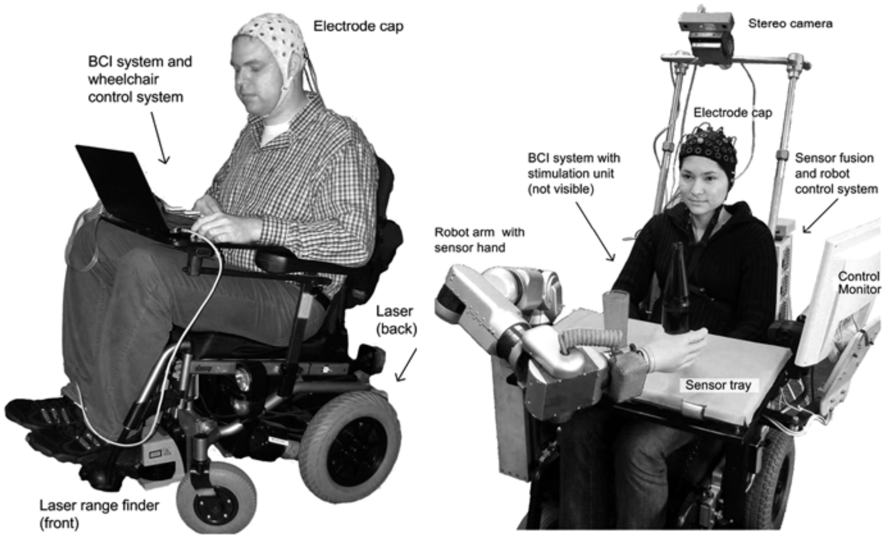

Fig. 8 Semi-autonomous assistive devices developed at the University of Bremen that include high level control: Intelligent wheelchair Rolland III, and rehabilitation robot FRIEND II (modified from [35])

completely autonomously. An example of such an operation is a "pour in beverage" scenario. In this scenario, the system detects the bottle and the glass (both located at arbitrary positions on the tray), grabs the bottle, moves the bottle to the glass while automatically avoiding any obstacles on the tray, fills the glass with liquid from the bottle while avoiding pouring too much, and finally puts the bottle back in its original position – again avoiding any possible collisions.

These assistive devices offload much of the work from the user onto the system. The wheelchair provides safety and high-level control by continuous path planning and obstacle avoidance. The rehabilitation robot offers a collection of tasks which are performed autonomously and can be initiated by single commands. Without this device intelligence, the user would need to directly control many aspects of device operation. Consequently, controlling a wheelchair, a robot arm, or any complex device with a BCI would be almost impossible, or at least very difficult, time consuming, frustrating, and in many cases even dangerous. Such complex BCI applications are not broadly available, but are still topics of research and are being evaluated in research laboratories. The success of these applications, or actually of any BCI application, will depend on their reliability and on their acceptance by users.

Another factor is whether these applications provide a clear advantage over conventional assistive technologies. In the case of completely locked-in patients, alternative control and communication methodologies do not exist. BCI control and communication is usually the only possible practical option. However, the situation is different with less severely disabled or healthy users, since they may be able to communicate through natural means like speech and gesture, and alternative control and communication technologies based on movement are available to them such as keyboards or eye tracking systems. Until recently, it was assumed that users would only use a BCI if other means of communication were unavailable. More recent work showed a user who preferred a BCI over an eye tracking system [43]. Although BCIs are gaining acceptance with broader user groups, there are many scenarios where BCIs remain too slow and unreliable for effective control. For example, most prostheses cannot be effectively controlled with a BCI.

Typically, prostheses for the upper extremities are controlled by electromyographic (myoelectric) signals recorded from residual muscles of the amputation stump. In the case of transradial amputation (forearm amputation), the muscle activity recorded by electrodes over the residual flexor and extensor muscles is used to open, close, and rotate a hand prosthesis. Controlling such a device with a BCI is not practical. For higher amputations, however, the number of degrees-of-freedom of a prostheses (i.e. the number of joints to be controlled) increases, but the number of available residual muscles is reduced. In the extreme case of an amputation of the entire arm (shoulder disarticulation), conventional myoelectric control of the prosthetic arm and hand becomes very difficult. Controlling such a device by a BCI may seem to be an option. In fact, several approaches have been investigated to control prostheses with invasive and non-invasive BCIs [39, 40, 44]. Ideally, the control of prostheses should provide highly reliable, intuitive, simultaneous, and proportional control of many degrees-of-freedom. In order to provide sufficient flexibility, low-level control is required. Proportional control in this case means the user can modulate speed and force of the actuators in the prosthesis. “Simultaneous” means that several degrees-of-freedom (joints) can be controlled at the same time. That is, for instance, the prosthetic hand can be closed while the wrist of the hand is rotated at the same time. “Intuitive” means that learning to control the prosthesis should be easy. None of the BCI approaches that have been currently suggested for controlling prostheses meets these criteria. Non-invasive approaches suffer from limited bandwidth, and will not be able to provide complex, high-bandwidth control in the near future. Invasive approaches show considerable more promise for such control in the near future. However, then these approaches will need to demonstrate that they have clear advantages over other methodologies such as myoelectric control combined with targeted muscle reinnervation (TMR).

TMR is a surgical technique that transfers residual arm nerves to alternative muscle sites. After reinnervation, these target muscles produce myoelectric signals (electromyographic signals) on the surface of the skin that can be measured and used to control prosthetic devices [45]. For example, in persons who have had their arm removed at the shoulder (called “shoulder disarticulation amputees”), residual peripheral nerves of arm and hand are transferred to separate regions of the pectoralis muscles.

Figure 9 shows a prototype of a prosthesis with 7 degrees-of-freedom (7 joints) controlled by such a system. Today, there is no BCI that can allow independent control of 7 different degrees of freedom, which is necessary to duplicate all the movements that a natural arm could make. On the other hand, sufficiently independent control signals can be derived from the myoelectric signals recorded from the

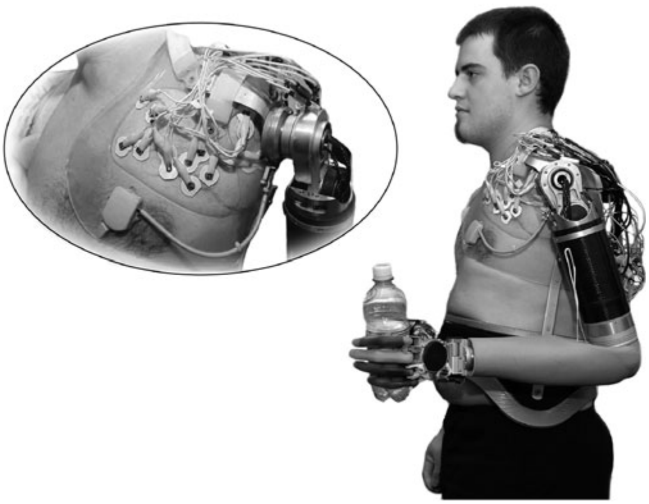

Fig. 9 Prototype of a prosthesis (Otto Bock HealthCare Products, Austria) with 7 degrees-of-freedom fitted to a shoulder disarticulation amputee with targeted muscle reinnervation (TMR). Control signals are recorded from electrodes mounted on the left pectoralis muscle

pectoralis. Moreover, control is largely intuitive, since users invoke muscle activity in the pectoralis in a similar way as they did to invoke movement of their healthy hand and arm. For instance, the users' intent to open the hand of their "phantom limb" results in particular myoelectric activity patterns that can be recorded from the pectoralis, and can be translated into control commands that open the prosthetic hand correspondingly. Because of this intuitive control feature, TMR based prosthetic devices can also be seen as thought-controlled neuroprostheses. Clearly, TMR holds the promise to improve the operation of complex prosthetic systems. BCI approaches (non-invasive and invasive) will need to demonstrate clinical and commercial advantages over TMR approaches in order to be viable.

The example with prostheses underscores a problem and an opportunity for BCI research. The problem is that BCIs cannot provide effective control because they cannot provide sufficient reliability and bandwidth (information per second). Similarly, the bandwidth and reliability of modern BCIs is far too low for many other goals that are fairly easy with conventional interfaces. Rapid communication, most computer games, detailed wheelchair navigation, and cell phone dialing are only a few examples of goals that require a regular interface.

Does this mean that BCIs will remain limited to severely disabled users? We think not, for several reasons. First, as noted above, there are many ways to increase the "effective bandwidth" of a BCI through intelligent interfaces and high level selection. Second, BCIs are advancing very rapidly. We don't think a BCI that is as fast as a keyboard is imminent, but substantial improvements in bandwidth are feasible. Third, some people may use BCIs even though they are slow because they are attracted to the novel and futuristic aspect of BCIs. Many research labs have demonstrated that computer games such as Pong, Tetris, or Pacman can be controlled by BCIs [46] and that rather complex computer applications like Google Earth can be navigated by BCI [47]. Users could control these systems more effectively with a keyboard, but may consider a BCI more fun or engaging. Motivated by the advances in BCI research over the last years, companies have started to consider BCIs as possibility to augment human–computer interaction. This interest is underlined by a number of patents and new products, which are further discussed in the concluding chapter of this book.

We are especially optimistic about BCIs for new user groups for two reasons. First, BCIs are becoming more reliable and easier to apply. New users will need a BCI that is robust, practical, and flexible. All applications should function outside the lab, using only a minimal number of EEG channels (ideally only one channel), a simple and easy to setup BCI system, and a stable EEG pattern suitable for online detection. The Graz BCI lab developed an example of such a system. It uses a specific motor imagery-based BCI designed to detect the short-lasting ERS pattern in the beta band after imagination of brisk foot movement in a single EEG channel [48]. Second, we are optimistic about a new technology called a "hybrid" system, which is composed of 2 BCIs or at least one BCI and another system [48–50]. One example of such a hybrid BCI relies on simple, one-channel ERD BCI to activate the flickering lights of a 4-step SSVEP-based hand orthosis only when the SSVEP system was needed for control [48].

Most present-day BCI applications focus on communication or control. New user groups might adopt BCIs that instead focus on neurorehabilitation. This refers to the goal of using a BCI to treat disorders such as stroke, ADHD, autism, or emotional disorders [51–53].

A BCI for neurorehabilitation is a new concept that uses neurofeedback and operant conditioning in a different way than a conventional BCI. For communication and control applications, neurofeedback is necessary to learn to use a BCI. The ultimate goal for these applications is to achieve the best possible control or communication performance. Neurofeedback is only a means to that end. In neurofeedback and neuro-rehabilitation applications, the situation is different. In these cases, the training itself is the actual application. BCIs are the most advanced neurofeedback systems available. It might be the case that modern BCI technology used in neurofeedback applications to treat neurological or neuropsychological disorders such as epilepsy, autism or ADHD is more effective than conventional neurofeedback. Neuro-rehabilitation of stroke is another possible BCI neurorehabilitation application. Here, the goal is to apply neuro-physiological regultion to foster cortical reorganization and compensatory cerebral activation of brain regions not affected by stroke [54]. Chapter Brain–Computer Interface in Neurorehabilitation of this book discusses this new direction in more detail.

5 Summary

A BCI is new direct artificial output channel. A conventional BCI monitors brain activity and detects certain brain patterns that are interpreted and translated to commands for communication or control tasks. BCIs may rely on different technologies to measure brain activity. A BCI can be invasive or non-invasive, and can be based on electrophysiological signals (EEG, ECoG, intracortical recordings) or other signals such as NIRS or fMRI. BCIs also vary in other ways, including the mental strategy used for control, interface parameters such as the mode of operation (synchronous or asynchronous), feedback type, signal processing method, and application. Figure 10 gives a comprehensive overview of BCI components and how they relate to each other.

BCI research over the last 20 years has focused on developing communication and control technologies for people suffering from severe neuromuscular disorders that can lead to complete paralysis or the locked-in state. The objective is to provide these users with basic assistive devices. Although the bandwidth of present-days BCIs is very limited, BCIs are of utmost importance for people suffering from complete locked-in syndrome, because BCIs are their only effective means of communication and control.

Advances in BCI technology will make BCIs more appealing to new user groups. BCI systems may provide communication and control to users with less severe disabilities, and even healthy users in some situations. BCIs may also provide new means of treating stroke, autism, and other disorders. These new BCI applications and groups will require new intelligent BCI components to address different

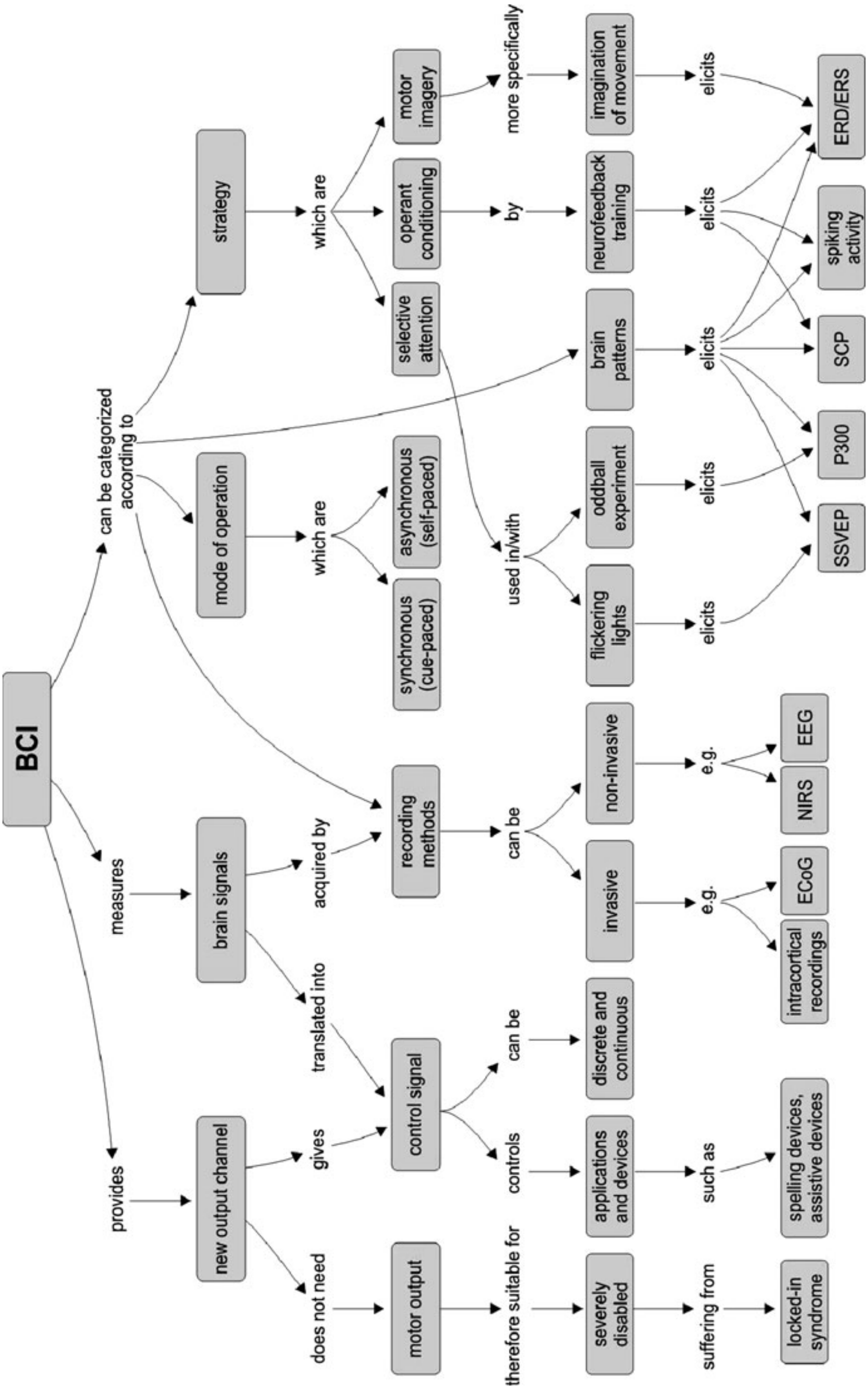

Fig. 10 Brain–computer interface concept-map

challenges, such as making sure that users receive the appropriate visual, proprioceptive, and other feedback to best recover motor function.

As BCIs become more popular with different user groups, increasing commercial possibilities will likely encourage new applied research efforts that will make BCIs even more practical. Consumer demand for reduced cost, increased performance, and greater flexibility and robustness may contribute substantially to making BCIs into more mainstream tools.

Our goal in this chapter was to provide a readable, friendly overview to BCIs. We also wanted to include resources with more information, such as other chapters in this book and other papers. Most of this book provides more details about different aspects of BCIs that we discussed here, and the concluding chapter goes "back to the future" by revisiting future directions. While most BCIs portrayed in science fiction are way beyond modern technology, there are many significant advances being made today, and reasonable progress is likely in the near future. We hope this chapter, and this book, convey not only some important information about BCIs, but also the sense of enthusiasm that we authors and most BCI researchers share about our promising and rapidly developing research field.

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