Chapter 2
Basics of Brain Computer Interface

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Abstract Brain-Computer Interface (BCI) is a fast-growing emergent technology in which researchers aim to build a direct channel between the human brain and the computer. It is a collaboration in which a brain accepts and controls a mechanical device as a natural part of its representation of the body. The BCI can lead to many applications especially for disabled persons. Most of these applications are related to disable persons in which they can help them in living as normal people. Wheelchair control is one of the famous applications in this field. In addition, the BCI research aims to emulate the human brain. This would be beneficial in many fields including the Artificial Intelligence and Computational Intelligence. Throughout this chapter, an introduction to the main concepts behind the BCI is given, the concepts of the brain anatomy is explained, and the BCI different signals are stated. In addition, the used hardware and software for the BCI are elaborated.

Keywords Brain computer interface · Systems of BCI · BCI monitoring hard ware and software · BCI trends

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2.1 Introduction

Brain Computer Interface (BCI) is a direct connection between computer(s) and human brain. It is the most recent development of Human Computer Interface (HCI). Unlike the traditional input devices (keyboard, mouse, pen… etc.), the BCI reads the waves produced from the brain at different locations in the human head, translates these signals into actions, and commands that can control the computer (s). The BCI can lead to many applications especially for disabled persons such as [1]: (1) new ways for gamers to play games using their heads, (2) social interactions; enabling social applications to capture feelings and emotions, (3) helping— partially or fully-disabled people to interact with different computational devices, and (4) helping understanding more about brain activities and human neural networks. These applications depend on the basic understanding of how the brain works. BCI applications utilize the brain and its nervous system functions where the human's central nervous system consists of the spinal cord and the brain. One of its tasks is to process and integrate incoming sensory stimuli received via peripheral nerves and to give impulses back to actuators, e.g. to muscles or glands which cause automatic or voluntary action. Furthermore the central nervous system, particularly the brain, is responsible for higher integrative abilities such as thinking, learning, production, and understanding of speech, memory, emotion etc. Finally vegetative functions such as respiration and the cardio-vascular system are controlled by the central nervous system.

The brain computer interface was not studied only for human but also for animals. A Monkey in 2008 [2] was able to move a screen cursor as well as controlling a robot arm. The benefit of such study is to know how animals can think and discover their brains as well. In addition, BCI is used with different human patients capturing their brain signals. The BCI science goes beyond a communication tool for people are not able to communicate. It is gaining more attention from healthy people for other purposes such as rehabilitation or hands-free gaming. However, BCI tools still limited and need expert to deal with them which is one of the BCI research challenges.

However, there are many challenges that faces the BCI when used in real world tasks as follows:

(1) *Low BCI signal strength*: it has been noticed that extracting signals from the brain is not an easy task since the signal strength in most of the cases are low. In most of the cases, signal amplification is required. Many of the used toolkits include such amplifiers where some others do not include good amplifiers.

(2) *Data transfer rate (bandwidth)*: the best data transfer rate from a subject was 3 characters. Certainly, this is very low data transfer that makes the BCI applications suffer from fast response as well as accurate control.

(3) *High error rate*: it is obvious that due to the low data transfer rate and the low signal strength, the error percentage became high. In addition, the brain signal is very high variability. Therefore, the expected error rate is high.

(4) *Inaccurate signal classification*: brain have some centers that signals can be captured from them using electrodes. Classifying the captured signals suffer from high interference and inaccurate classification. There are many signal classification techniques are utilized including the computational intelligence techniques that are recently proposed by authors in [3].

The goal of this chapter is to provide the reader with basic concepts of the BCI as a science and from it came from. The anatomy of the brain is elaborated for better understanding to the brain signals. The chapter goes on by providing the different signals that were able to be captured recently. These signals are classified and their characteristics are explained. Finally, the chapter explains the current hardware and software components of the BCI including the commercial devices and their properties.

2.2 Brain Anatomy

Amazingly, nothing in the world can be compared with the human brain. The three-pound organ controls all body functions including receiving and interpreting information from the outside world, and expressing the essence of the mind and soul. Intelligence, creativity, emotion, and memories are a few of the many things governed by the brain. The brain receives information through different sensors such as sight, smell, touch, taste, and hearing. The brain constructs the received data from the different sensors and form a meaningful message. The brain controls our body movement of the arms and legs, thoughts, memory and speech. It also determines how a human respond to different situations such as stress by regulating our heart and breathing rate.

As it is known, the nervous system is another essential system in the human body. The nervous system divided into central and peripheral systems. The central nervous system is composed of two main parts which are the brain and spinal cord. The peripheral nervous system is composed of spinal nerves that branch from the spinal cord and cranial nerves that branch from the brain. The peripheral nervous system includes the autonomic nervous system, which controls vital functions such as breathing, digestion, heart rate, and secretion of hormones.

The brain skull represents the shield of the brain from injury. It is formed from 8 bones. These bones include the frontal, two parietal, two temporal, sphenoid, occipital and ethmoid. The face is formed from 14 paired bones including the maxilla, zygoma, nasal, palatine, lacrimal, inferior nasal conchae, mandible, and vomer [4].

Anatomically five basic parts of the brain can be distinguished including Cerebrum, Diencephalon, Cerebellum, Mesencephalon, and Medulla oblongata as shown in Fig. 2.1. The cerebrum, located directly under the skull surface, is the largest part of the brain. Its main functions are: (1) the initiation of complex movement, (2) speech and language understanding and production, (3) memory, and (4) reasoning. Brain monitoring techniques which make use of sensors placed

Fig. 2.1 Brain anatomy [8]
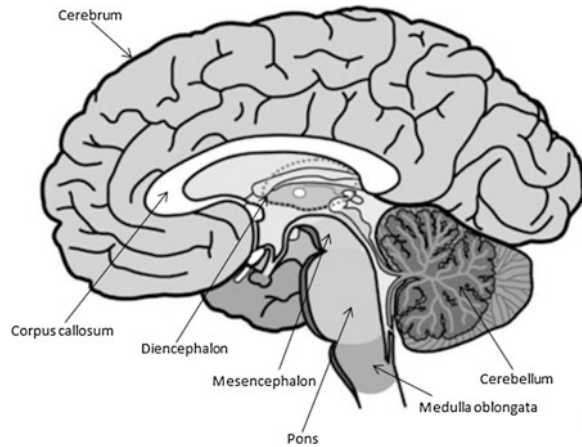
on the scalp mainly record activities from the outermost part of the cerebrum; the cortex. More inside the cerebrum the basal ganglions can be found which consists of a number of nuclei controlling the direction of slow movements [5]. Also the thalamus is located here which directs sensory information to appropriate parts of the cortex. The second part of the brain is the Diencephalon. One important function of the diencephalon is the forwarding of sensory information to other brain areas. Besides that, it contains the hypothalamus which controls the body temperature, the water balance and the ingestion to assure the state of homeostasis for the body, i.e. "good working conditions" for all body cells. The coordination of all kinds of movements is done in the third part which is the cerebellum. Therefore, it cooperates closely with structures from the cerebrum (e.g. the basal ganglions). Cerebellum and Cerebrum are connected via the Pons. However, the largest part of the reticular system is located in the Mesencephalon where it controls vigilance and the sleep-wake rhythm.

The Medulla Oblongata connects the brain with the spinal cord. Respiration and the cardiovascular system are controlled by that part of the central nervous system. Furthermore, a huge number of peripheral nerves pass through the medulla oblongata. Compared to the brains of other mammals, the human brain has the largest and best developed cortex. Neural processes related to abilities like complex reasoning, speech and language etc. which distinguish humans from other mammals take place in that part of the brain [6, 7].

Moreover, the cortex consists of two hemispheres which are connected via a beam called corpus callosum. Each hemisphere is dominant for specific abilities. For right handed persons, the right hemisphere is activated more during the recognition of geometric patterns, spatial orientation, the use nonverbal memory and the recognition of non-verbal noises [8]. More activity in the left hemisphere can be observed during the recognition of letters and words, the use verbal memory and auditory perception of words and language. Each hemisphere is partitioned into five anatomically well-defined regions, the so called lobes as given in Fig. 2.2.

Fig. 2.2 Hemisphere partitions [8]
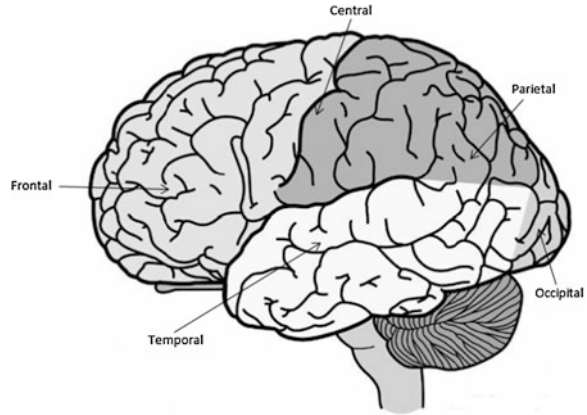
2.3 Brain Computer Interface Types

Brain computer interface can be classified into three main groups as shown in Fig. 2.3. Classification depends on the way that the electrical signal is obtained from neuron cells in the human brain.

2.3.1 Invasive BCI Acquisition Techniques

In invasive BCI techniques, special devices have to be used to capture the brain signals. Such devices are called Invasive BCI devices; devices that are based on detecting from single area of brain cells is called single unit while the detection from multiple areas is called multi-units [9]. Invasive BCI devices are inserted directly into the human brain by a critical surgery as can be seen in Fig. 2.4. The electro-corticogram (ECoG) are the obtained signals from these inserted electrodes [10]. These devices have the highest quality of human brain signals but have the risk of forming scar tissue.
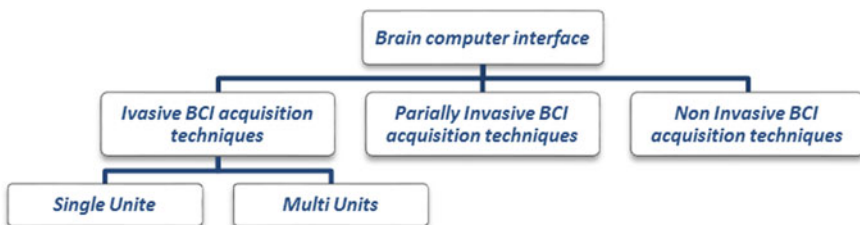

Fig. 2.3 Brain computer interface types

Fig. 2.4 Invasive BCI
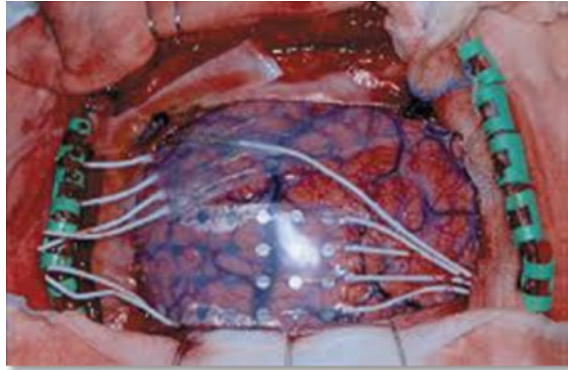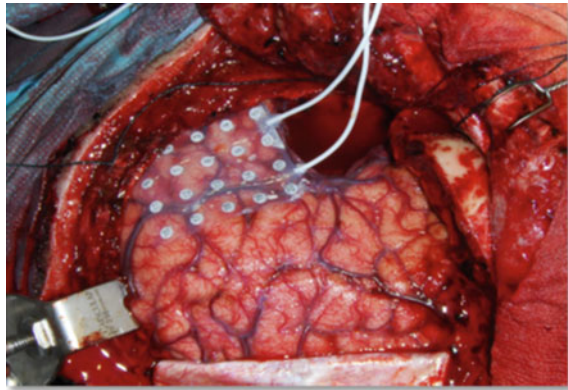electrodes [10]

Fig. 2.5 Partially invasive
BCI electrodes

2.3.2 Partially Invasive BCI Acquisition Techniques

Other devices that can capture the signal from the brain are the partially invasive
BCI devices. Devices are inserted in the skull on the top of human brain as depicted
in Fig. 2.5. These devices have bit weaker quality of human brain signals than
invasive BCIs and have less risk of forming scar tissue [11, 12].

2.3.3 Non Invasive BCI Acquisition Techniques

Non Invasive BCI devices are considered the safest type and low cost type of
devices. However, these devices have weaker human brain signals than other BCI
devices due to the skull. The detection of signals is done by some electrodes placed
on the scalp as given in Fig. 2.6. At the same time, placing such electrodes is easy
as well as portable. Most noninvasive techniques are constructed by recording
ElectroEncephaloGraphs (EEG) from the scalp. Recent EEG Non Invasive BCI

Fig. 2.6 A wireless non-invasive signal capturing device

devices have better temporal resolution due to use up to 256 electrodes on the whole area of the human scalp. While others, Non Invasive BCI devices, use functional Magneto-Resonance Imaging (fMRI), Positron Electron Tomography (PET), MagnetoEncephaloGraphy (MEG) and Single Photon Emission Computed Tomography (SPECT) [13, 14].

2.4 Types of BCI Signals

The brain generates an amount of neural activity. There are a plethora of signals, which can be used for BCI. These signals are divide into two classes: spikes and field potentials [11]. Spikes reflect the action potentials of individual neurons and acquired through microelectrodes implanted by invasive techniques. Field potentials are measure of combined synaptic, neuronal, and axonal activity of groups of neurons and can be measured by EEG or implanted electrodes. The following is the classification of EEG signals based on their frequencies/bands [15, 10].

- *Delta Signal*. It is captured within the frequency range of 0.5–3.5 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow wave sleep as well as in babies. A sample from the Delta signals is shown in Fig. 2.7.
- *Theta*. The frequency of this signals ranges from 3.5 to 7.5 Hz. Theta is linked to inefficiency and daydreaming. In fact, the very lowest waves of theta represent the fine line between being awake or in a sleep. However, as shown in Fig. 2.8, high levels of theta are considered abnormal in adults.

Fig. 2.7 Delta wave sample

Fig. 2.8 Theta wave sample
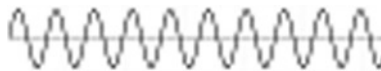

Fig. 2.9 Alpha wave sample

Fig. 2.10 Beta wave

Fig. 2.11 Gamma wave

- *Alpha*. As shown in Fig. 2.9, this signal frequency ranges from 7.5 to 12 Hz. Hans Berger [12] named the first rhythmic EEG activity he saw, the "alpha wave". Range seen in the posterior regions of the head on both sides, being higher in amplitude on the dominant side. It is brought out by closing the eyes and by relaxation. Several studies have found a rise in alpha power after smoking marijuana.
- *Beta*. Beta is another brain signal in which its frequency ranges from 12 Hz to about 30 Hz. It is seen usually on both sides in a symmetrical distribution and it is most evident frontally. Beta waves are often divided into β1 and β2 to get more specific range. The waves are small and fast when resisting or suppressing movement, or solving a math task. It has been noticed in these cases that there is an increase of beta activity. The shape of such signal is shown in Fig. 2.10.
- *Gamma*. It is a signal with frequency range of 31 Hz and up. It reflects the mechanism of consciousness. Figure 2.11 shows the shape of the Gamma signal.

2.5 Components of Interest

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

2.5.1 Oscillatory EEG Activity

Oscillatory EEG activity is caused by complex network of neurons that create feedback loops. The synchronized firing of the neurons in these feedback loops generates observable oscillations. There are two distinct oscillations of interest which are: (1) the Rolandic mu-rhythm, in the range 10–12 Hz, and (2) the central beta rhythm, in the range 14–18 Hz. This activity represents "idling" or rest state [10].

2.5.2 Event-Related Potentials

Event-Related Potentials (ERPs) are time-locked responses by the brain that occur at a fixed time after a particular external or internal event. These potentials occur when subjected to sensory, mental event, or the omission of a constantly occurring stimulus. Exogenous ERP components occur due to processing of the external event but independent of the role of the stimuli in the processing of information. On the other hand, Endogenous ERP components occur when an internal event is processed. It dependents on the role of the stimulus in the task and the relationship between the stimulus and the context in which it occurred [10]. The ERP events can be classified as follows:

- *Event-Related Synchronization/(De) synchronization*

  A particular type of ERP is characterized by the occurrence of an event-related desynchronization (ERD) and an event-related synchronization (ERS). A decrease in the synchronization of neurons causes decrease of power in specific frequency bands. This phenomenon is defined as an ERD and can be identified by a decrease in signal amplitude. ERS is characterized by an increase of power in specific frequency bands that is generated by an increase in the synchronization of neurons and/or in signal amplitude.

- *Visual-Evoked Potentials*

  Another type of ERF commonly used in BCI is the visual-evoked potential (VEP), an EEG component that occurs in response to a visual stimulus. VEPs are dependent on the user's control of their gaze and thus require coherent muscular control [16]. P300 is ERP component elicited in the process of decision making. The P300 is thought to reflect processes involved in stimulus evaluation or categorization. It is usually elicited using the oddball paradigm, in which low-probability target items are mixed with high-probability non-target item [17]. The user is presented with a task that cannot be accomplished without categorization into both categories. When an event from the rare category is displayed, it elicits a P300 component, which is a large positive wave that occurs approximately 300 ms after event onset [10].

- *Slow Cortical Potential*

It is the slow cortical potential, which is caused by shifts in the depolarization levels of certain dendrites. Negative SCP indicates the sum of synchronized potentials, but positive SCP indicates the reduction of synchronized potentials from the dendrites.

- *Neuronal Potential*

Neuronal potential is a voltage spike from individual neurons. This potential can be measured for a particular neuron or a group of neurons. The signal is a measure of the average rate, correlation, and temporal pattern of the neuronal firing. Learning can be measured through changes in the average firing rate of neurons located in the cortical areas associated with the task [8].

2.6 Monitoring Brain Activity Using EEG

Several techniques have been used to monitor brain activities such as (1) Electroencephalography (EEG), (2) Magnetoencephalography (MEG), (3) Functional Magnetic Resonance Imaging (fMRI), (4) Functional Near-Infrared Spectroscopy (fNIRS), (5) Single Photon Emission Tomography (SPECT), and (6) Proton Emission Tomography (PET). Each method has its own characteristics as well as pros and cons. However, for several reasons the potential differences which can be measured between two points of the scalp are very different from those could be measured when electrodes were implanted directly in the brain. For instance, the activity of the potential generators could be measured directly by:

1. A superposition of potentials generated in different areas of the cortex is measured using scalp electrodes since brain tissue and the liquor are conductive.
2. The amplitude of the originally generated potential differences is attenuated because of the resistive properties of the tissue between the potential generators and the electrode (e.g. liquor, skin, bone of the skull).
3. Capacities caused by cell membranes and other inhomogeneities (e.g. liquor-skull, skull-skin) between potential generators and electrodes influence the amplitude of the EEG signals as a function of their frequency.

Therefore, the positions for EEG electrodes should be chosen in a way, which all cortex regions are covered. For most applications, this is usually the whole cortex. An internationally accepted standard for electrode placements is the 10–20 system (electrodes are placed at distances of 10 or 20 % of the length of several connections between some reference points) introduced in 1957 by the International EEG Federation [18]. Electrodes were placed according to the 10–20 system. Three anatomical reference points must be determined before the 10–20 system electrode positions which are:

1. Nasion: the onset of the nose on the skull, below the forehead.
2. Inion: the bony protuberance which marks the transition between skull and neck.
3. Pre-auricular reference point: located before the cartilaginous protrusion of the acoustic meatus (the auditory canal).

Figure 2.12 shows the electrode positions of the 10–20 system in their projection on the cortex. The name for a particular electrode position reflects the anatomical region of the cortex above which it is located. Fp stands for frontopolar, F stands for frontal, T stands for temporal, C stands for central, P stands for parietal, O stands for occipital and A stands for auricular while G denotes the ground electrode. Even numbers denote the right part of the head, odd numbers refer the left part.

Generally, there are two categories of artifacts can be distinguished in EEG measurements which are biological and technical. The biological artifacts are caused by the recorded subject and technical artifacts are caused by the EEG recording device. The sources of many biological artifacts are dipoles originating for example from muscular activities which are much stronger than the EEG related
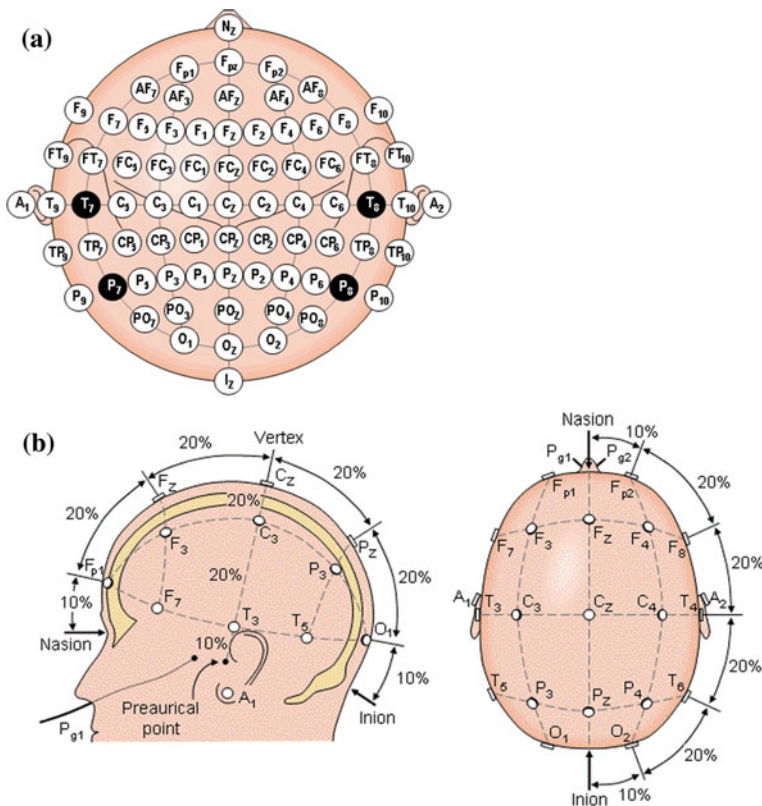

Fig. 2.12 Electrode position. **a** Brain electrods. **b** top view of the brain and electrods positions [12]

dipoles. A superposition of both types of dipoles causes artifacts in the signal which are often characterized by large peaks or fluctuations of a particular morphology. Sometimes, however, they can hardly be distinguished from the actual EEG. Other biological artifacts influence the contact between skin and electrode or the electrical properties of the medium between potential generators and electrodes.

2.7 BCI System

Forming a BCI system requires following three main steps as shown in Fig. 2.13:

Step 1 is the signal acquistion, *Step 2* is the signal processing, and *Step 3* is the data manipulation.

Step 3: Using these obtained signals to control in external devices or computer depending on the application.

Step 1: Signal Acquisition

Signal acquisition process is required to capture the brain electric signals. The electric signals could be recorded from the scalp, the surface of the brain, or from the neural activity. Since the capture signals strength are usually low, they need to be amplified. Then, to be used by computer applications, they need to be digitized.

Step 2: Signal Processing

In this step, obtained signals in step 1 are analyze to get the control signals. Signal processing could be done through some other sub operations as follows:

- *Preprocessing*

The first part of signal processing is preparing the recording electric signal for processing like enhancement to make the features clear for detection. Some filtering techniques could be used in the preprocessing operation.

- *Feature extraction*

Simply, feature extraction means extracting specific signal features. EEG recordings not only contain electrical signals from the brain, but also several
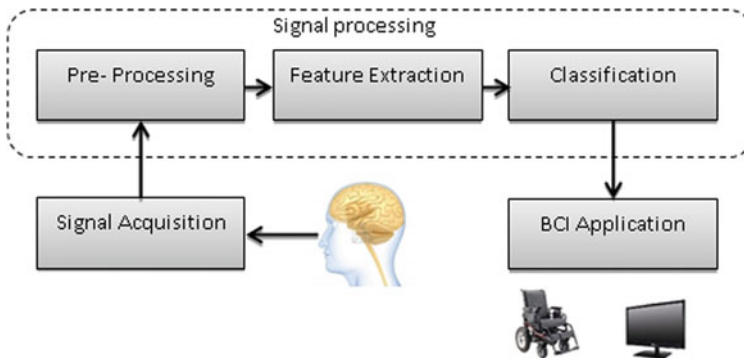

Fig. 2.13 BCI signal processing

unwanted signals. Those unwanted signals may bias the analysis of the EEG and may lead to wrong conclusions. Therefore, the digitized signals are subjected to feature extraction procedures.

- *Signal Classification: translation algorithm*

The next stage, the translation algorithm, in which it translates the extracted signal features into device commands orders that carry out the user's intent. The signals are classified on both frequency and on their shape; the classification algorithm might use linear methods or nonlinear methods.

Step 3: Data Manipulation

Once the signals are classified, the output is manipulated to suite the output devices (e.g. computer screen).

2.8 BCI Monitoring Hardware and Software

BCI signals are very week signals that need special treatments to be handled correctly. The strength of the measured signals is usually between 1 μV and 100 mV along with the scalp impedance and other noises. In order to receive such signals and display them on digital formats, suitable amplifiers should be used. Therefore, the BCI hardware can be divided into three classes; the first class is the electrodes while the second class is the signal amplifiers. The third class is the real time signal handling. Throughout this section, a brief description to each class is provided.

The EEG measurement electors are usually made of gold or Ag/AgCl. The gold electrodes are effective in measuring EEG, EMG or ECG signals as well. However, the Ag/AgCl electrodes proved to be more effective when the EEG frequencies below 0.1 Hz. In addition, there are two types of electrodes which are active and passive electrodes. The active electrodes contain an amplifier with gain 1–10 inside it in which it reduces the noise and cable interferences. On the other hand, passive electrodes do not include any amplifiers in electrodes service. Such electrodes are usually distributed on the scalp from 10 to 20 electrodes in most of the cases (Fig. 2.14).
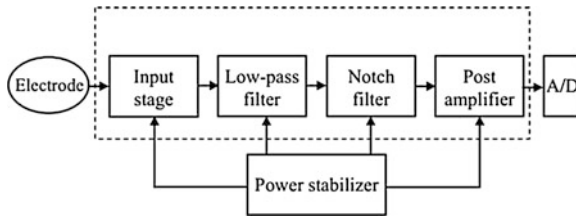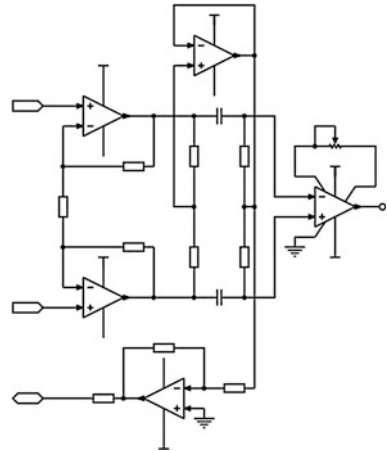
Fig. 2.14 Gold electrodes [13]

Fig. 2.15 Electrode's signal filters

Fig. 2.16 Electrode's amplifier

The other part of the BCI hardware is the biological signal amplifier. It is one of the important parts of physiological recording and analysis in which the brain signals are very weak and it is used to amplify them. Figure 2.15 [19] is a sample of BCI amplifier. As can be seen in the Figure, signals captured by electrodes are amplified through handling by the input stage component to remove the possible noise produced from electrode-skin interfaces. In fact, it is a pre-amplified circuit that could be simply based on simple op-amp OPA2277 devices as shown in Fig. 2.16. The signal is also passed through two filters which are Low-pass filter and Notch filter. After all, the signal is post amplified.

Real time signal recording and analysis is managed on different Operating Systems including windows and Linux as well as Mac OS. C++ is one of the most used language for analysis over C++ LabVIEW (National Instruments Corp., Austin, TX, USA) and MATLAB (The MathWorks Inc., Natick, USA) are mostly used as programming languages. Different signals are utilized to control many applications. There is some commercial software and hardware kits are already used in some of the BCI applications. One of the software kits is the neurobci [8] in which it allows users to develop their own Brain Computer Interface (BCI), bio- or neurofeedback application, as created in Html/Jscript, C++, or Matlab. FieldTrip

Fig. 2.17 Emotive headset

[20] is a MATLAB toolbox that is used for analysis. It utilizes TCP connections for multiple clients as at the same time.

DataSuite [21] is another software tool for data acquisition. The DataSuite consists of two parts including the DataRiver and MatRiver. DataRiver is a data management and synchronization real time engine while MatRiver is a MATLAB client toolbox for DataRiver. The following Figure shows the data flow of DataSuite. For more details about other BCI tools, the reader is encouraged to read the survey by Arnaud et al. [22] Fig. 2.17: DataSuite data flow. Two computers each running an instance of DataRiver are represented. One acquires data (left); the other (right) uses MatRiver to perform data classification and feedback visualization. Dashed lines indicate control signals.

Emotiv EEG neuroheadset [23] is a wireless BCI set; this set is a neuro-signal acquisition and processing wireless neuroheadset. The set can be wirelessly connected to a computer. One advantage of the set is it has 14 saline sensors offer optimal positioning for accurate spatial resolution.

ModularEEG [24] is another EEG hardware created by the OpenEEG hardware developers. The modularEEG has two or more EEG amplifiers, and a 6-channel signal capture board that connects to a PC via a standard serial cable. The modularEEG has two types of electrodes which are active and passive electrodes. Some skin preparation is required while there is no preparation is required when active electrodes are used. Figure 2.18 shows the modularEEG board and the active electrodes.

2.9 Brain Computer Interface Applications

BCI is interesting area to researchers because it can solve many problems which seem to be impossible. The essential target of BCI applications is to convert the user's intent or thoughts to an action in external device or computer and control to
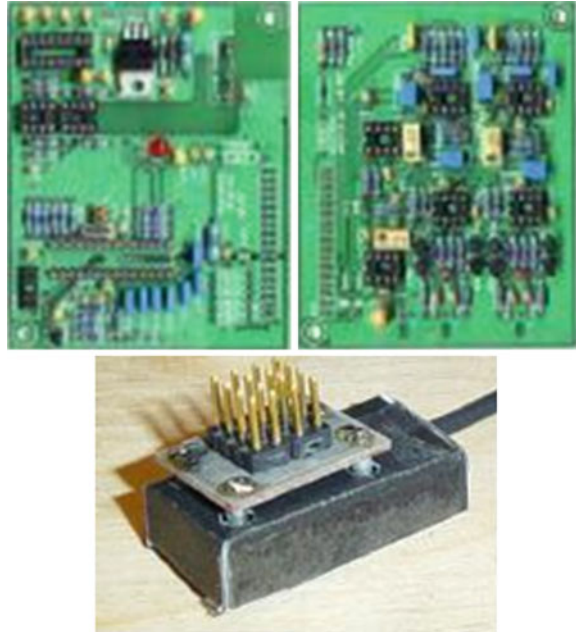
these devices. Many applications of BCI concerned on patients suffer from disorders of consciousness (DOC).These patients unable to make communication with their around world [25].

By using BCI, these patients can control some devices to perform basic and important jobs they need without helping like moving with wheelchair, getting something for eating or drinking by using robotic legs or arms controlled by brain. BCI technologies are used to restore the vision to blinds by connecting an external camera with brain [26]. Applications on device control not include patients only, but also healthy users like whose needs to perform many jobs at the same time like divers, astronauts and drivers where they keep their hands on swimming, operate equipment and the steering wheel [27].

Rabie et al. [28] developed a BCI based system that can help disabled persons to use the web through their brains only. The authors developed a technique that captures the eye signals through the brain to select the appropriate letters as well as words to be written on the web browser. Another application that has been developed is the wheelchair simulator that is controlled also by the BCI signals.

BCI used also on User-state monitoring which make alert to sleepy drivers or students. Also, it extended physically to measure the heart beats for users. Many applications focused in entertainment and playing games especially after using 3D monitors, certain glasses and an EEG headset where the control on the game by thoughts. EEG combined sometimes with eye movement on some applications for security and safety where the system can monitor suspicious objects, deviant behavior or arousal state. A common BCI application is neurofeedback training to

improve working, attention, executive functions and memory. Neuroergonomics is an evaluation application used to estimate how well human abilities match a technology. BCI used also in education and training techniques [25]. By sing BCI based on EEG, patient can control or move the cursor by mental thoughts where the patient can select words or letters [26].

2.10 BCI Trends

The BCI technology has achieved many goals in different working areas of medical and nonmedical during the last ten decades. Researchers in this filed are looking in the future for more development in trends and applications. Since the current trends are focused on utilizing of motor system which is related to: (1) the electroencephalogram (EEG) signals for neurorehabilitation, (2) controlling of robot and exoskeleton based on EEG signal, (3) implementation of BCI component on field programmable and reconfigurable computing system, and (4) solving the interoperability and standardization issues of BCI software platforms. Researchers looking for developing a common file format for BCI data exchange and introducing an accurate and robust pre-processing and feature extraction techniques of BCI signals.

One of the most future trends is introducing a new kind of sensory modality that is more accurate and safe [29]. The revolution in nanotechnology will contribute in the progress of BCI by producing a smaller and far superior chips that can implant safely in the brain to yield high quality signals. The target is to increase the BCI reliability and accuracy to be clinically useful. Moreover, a wireless brain implant is an important technology today that lets people with mobility problems control a computer or wheelchair with their thoughts. The wireless brain sensor can record the activity of dozens of neurons in freely moving subjects [30]. Even though wireless BCI systems may provide a number of advantages. There are still many issues that need to be resolved including improving signal quality, more compact and stylish system designs, and implementation of useful applications [31].

BCIs driven by auditory stimuli are a relatively new phenomenon. With some key publications over the last 5 years, the auditory BCI approach has gained and continues to gain momentum. It is underpinned by the BCI community's efforts to find alternatives to the traditional BCI paradigms to meet the needs of end users who require a non-visual communication system. The trends now are seeking to study the effect of BCI auditory not only in communication field but also in attention monitoring and neurofeedback training to improve performance. In addition, how BCI auditory can contribute in diagnosis and treatment of disorders that have an auditory component is another issue to be handled.

Another trend now is Tactile and Bone-Conduction based BCI Paradigms. It has been proposed to offer alternative ways to deliver sensory stimulation inputs which could be crucial for patients suffering from weak or lost eye-sight or hearing. Already several preliminary techniques have been developed to connect the BCI to a traditional haptic interface or to utilize those interfaces as stimulation sources.

Vibrotactile stimulation brings also a possibility to create bone-conduction sensory effect in case of the head area exciters application. This point is still very preliminary yet relative to the existing applications. It brings a very interesting possibility to deliver multimodal stimuli (somatosensory and auditory combined) to TLS/ALS subjects with a very fast information transfer rate.

Currently, the field of BCI requires deeper insights on how to capture the right signals and then process them suitably. Efforts are being made to recognize the objects as they are seen by the brain. These efforts will bring in newer dimensions in the understanding of brain functioning, damage and repair. It is possible to recognize the thoughts of the human brain by capturing the right signals from the brain in future [8].

The P300 is an event related potential, a measurable electrical charge that is directly related with impulse. Therefore, by capturing the P300, a BCI can directly translate a person's intent into electrical commands that control artificial devices. A P300 speller is based on this principle, where the detection of P300 waves allows the user to write characters [26]. The trend now is solving the P300 speller classification problems such as, the detection of the presence of a P300 in the electroencephalogram (EEG) and the combination of different P300 responses for determining the right character to spell.

Over the past 20 years, Brain-Computer Interfaces (BCI) have been shown to be very promising for numerous applications, such as rehabilitation or entertainment, among many others. Despite this potential, most BCI applications remain prototypes that are not used in practice, outside laboratories. The main reason is the widely acknowledged low reliability of current BCI systems that are based on the translation of the spontaneous non-invasive electroencephalogram (EEG); mental tasks performed by the user are being too often incorrectly recognized by the BCI. Poor recognition performances are due in part to "imperfect" signal processing algorithms used to analyze EEG signals. However, another component in the BCI loop may also be deficient such as the signal generator, i.e., the user him/herself who may not be able to reliably produce EEG patterns. Indeed, it is widely acknowledged that BCI use is a skill, which means the user must be properly trained to achieve successful BCI control. So the main trend now is improving reliability of BCI by teaching and training the users to the BCI skills.

2.11 Conclusion

The BCI reads the waves produced from the brain at different locations in the human head, translates these signals into actions, and commands that can control the computer(s). Brain computer interface can be classified into three main groups which depend on the way that the electrical signal is obtained from neuron cells in the human brain. The brain generates an amount of neural activity. There are a plethora of signals, which can be used for BCI. These signals divide into two classes: spikes and field potentials, Components of particular interest to BCI can be

divided into four categories which are oscillatory EEG activity, event-related potentials (ERP), slow cortical potentials (SCP), and neuronal potentials. Several techniques have been used to monitor brain activities; each technique has its own characteristics as well as pros and cons. BCI is interesting area to researchers because it can solve many problems which seem to be impossible, Many applications focused in entertainment and playing games especially after using 3D monitors, certain glasses and an EEG headset where the control on the game by thoughts. Researchers in this filed are looking in the future for more development in trends and applications. Since the current trends are focused on utilizing of motor system.

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