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Brain computer interface: control signals review

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A R T I C L E I N F O

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Future directions

A B S T R A C T

Brain Computer Interface (BCI) is defined as a combination of hardware and software that allows brain activities to control external devices or even computers. The research in this field has attracted academia and industry alike. The objective is to help severely disabled people to live their life as regular persons as much as possible. Some of these disabilities are categorized as neurological neuromuscular disorders. A BCI system goes through many phases including preprocessing, feature extraction, signal classifications, and finally control. Large body of research are found at each phase and this might confuse researchers and BCI developers. This article is a review to the state-of-the-art work in the field of BCI. The main focus of this review is on the Brain control signals, their types and classifications. In addition, this survey reviews the current BCI technology in terms of hardware and software where the most used BCI devices are described as well as the most utilized software platforms are explained. Finally, BCI challenges and future directions are stated. Due to the limited space and large body of literature in the field of BCI, another two review articles are planned. One of these articles reviews the up-to-date BCI algorithms and techniques for signal processing, feature extraction, signals classification, and control. Another article will be dedicated to BCI systems and applications. The three articles are written as base and guidelines for researchers and developers pursue the work in the field of BCI.

1. Introduction

For generations, humans dream about the interaction with computer through brain activities. It was a fantasy thing that the scientists and others dream about through science fiction movies and imagination. This dream comes true and currently we are able through advanced electronic devices to capture the brain signals and control the real world devices. Certainly, still there are some of the constraints and challenges but we believe that in the few coming years, there will be too much to do with brain signals and effective solutions for many of its current research problems.

Brain Computer Interface (BCI) is a complete system including the software and hardware that manipulate human signals to control Computers and different communication devices. However, some other definitions are presented in the literature as follows:

1. Donoghue et al. in [65] defined the BCI as Brain Machine Interface (BMI) in which its major goal is to provide a command signal from the cortex that controls disabled body parts or physical devices, such as computers or robotic limbs.
2. Wolpaw et al. in [69] defined the BCI as a device that provides the brain with a new, non-muscular communication and control channel.
3. Schwartz et al. in [2] defined the BCI as “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.”

Such definitions describe the overall functionalities of the BCI in terms of capturing the brain signals, processing the received signals, classifying them, and utilizing these signals for control. Therefore, the terms BMI and BCI could be used interchangeably describing the communication between the brain and the computer and/or external devices.

The direct effect of the BCI is on people having neuromuscular injuries and neurodegenerative diseases. Such disabilities include amyotrophic lateral sclerosis that affects nerve cells in the brain and the spinal cord which makes the persons’ cognitive function intact. The most severe disability is the locked-in syndrome (LiS). LiS is named after Plum and Posner where it means that a person is completely paralyzed [78]. In complete LiS, the person is lost control in every part of his/her body including eye movements while in incomplete LiS, a

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person can control the movement of some of the muscles such as head and toes [39]. In classical LiS, the vertical eye movements are possible as well. There are two causes of LiS which are lesion in the pons of the brainstem and neuro-degenerative diseases [118]. So, instead of direct contact with computer using for instance mouse and image processing, which it could not be possible in some cases, new software and hardware enable the recognition of people's thinking and their physiology. A continuous improvement to software and hardware is expected to add more accuracy and performance to the BCI systems.

In the near past, research in BCI was not that attractive to researchers due to the rejection of deciphering brain signals and thoughts. The brain activity research was limited to the clinic and laboratory exploring the brain functions. At the same time, signals deciphering technology and devices were not available or highly expensive. This led to only limited number of research groups to work in this field. However, in the last two decades a drastic change to the research in the BCI field has been occurred. Using sensors and brain signals, many research articles have come to a conclusion that the new technology would advance the BCI science [5,80,95,102,125]. In addition, instead of only 8 research groups were working on the BCI field in the last 10 years [68], currently, till writing this article, more than 116 groups are investigating different problems in the field [14]. In addition, more than 76 companies are working on BCI devices and systems around the world [13].

In fact, large body of research and publications of the BCI have been increased significantly in the last 10 years and different Universities have recognized the importance of the BCI and even funding agents. Fig. 1 shows the distribution of the BCI research groups around the world. As can be seen, the largest number of these groups are in USA with 33 research groups followed by Germany with 10 groups. Fig. 2 also shows the number and the distribution of BCI companies around the world. Again USA ranked the first by 26 companies working on the BCI field followed by Netherlands by 9 companies. Looking at the BCI devices, more than 50,000 assistive devices have been produced [9] for people daily activities and some others for assisting people with disabilities.

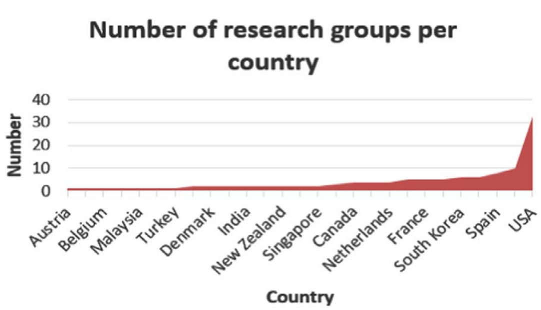


Fig. 1. BCI research groups distribution around the world.

The reason behind this large research activity is due to the advances of computers hardware and software as well as the social acceptance to the devices that serve disabled people. In addition, new companies have been specialized in production of BCI devices which encouraged new researchers to direct their research interest to the field. This is just indicators to the witnessed research activities in the field BCI in the last few years.

This paper is one of the three survey papers prepared to introduce the field of BCI to academia and industry alike. The paper gives a complete view to BCI along with simplifying and organizing the ideas to the readers. The contributions of the paper in hand are: 1) identifying Brain signals, their types, and their classifications, 2) surveying the current BCI technology in terms of hardware and software and 3) stating the challenges and future directions of BCI research. It also direct the BCI research towards the open problems and challenges.

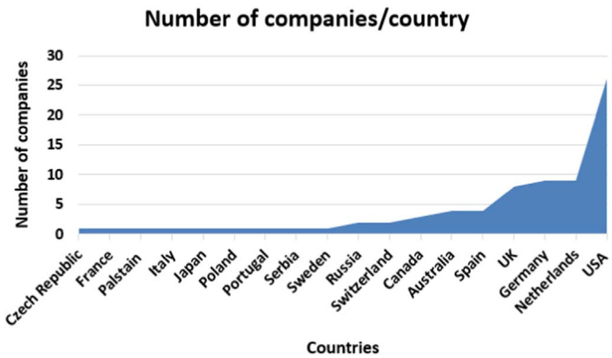


Fig. 2. BCI companies distribution around the world.

Moreover, this paper lists all of the most used hardware and software tools for new as well as experienced researchers and summarized their features. The second paper focuses on the algorithms and techniques used for BCI signal detection, feature extraction, classification, and control. The Third paper is targeting current BCI systems and applications in some details.

The paper roadmap is as follows: Section 2 introduces the brain architecture; Section 3 classifies the BCI; Neuroimaging Methods are introduced in Section 4; mental control signals are classified in Section 5, BCI technologies in terms of hardware and software platforms are summarized in Section 6; Section 7 elaborates on the BCI challenges and open problems; future directions are stated in Section 8; finally the paper concludes in Section 9.

2. Brain architecture

The common concept about the brain is that it is a general purpose computer. This concept is far beyond the truth. In fact, the brain is more complex than a general purpose computer. It is a set of subsystems that cooperate together to control the whole human body and its functionalities. Through external devices such as sight, touch, taste, hearing, and smell, the brain is able to receive information from the external environment. There are also some other information that is received by the brain from the body internal systems. This three-pound organ is able to analyze all of the received information and accurately control the body parts such as hands, legs, eyes, etc. Based on the recent topographical maps of the brain, it was discovered that the brain parts are associated with distinct cognitive functions.

The brain could be generally divided into two main parts which are the cerebral cortex and sub-cortical regions. Sub-cortical regions are those the areas that control the basic and vital functions such as heart rates, body temperature respiration,

and emotional responses including fear, reflexes, learning, and memory. On the other hand, the cerebral cortex is considered newer in terms of evolutionarily. It is the largest and the most complicated part of the brain. This part is the focus on most of BCI research where it controls the sensory and motor processing and higher level functions such as language processing, pattern recognition, planning, and reasoning.

Cerebral cortex is divided into two hemispheres, as shown Fig. 3, in which each hemisphere is portioned to four lobes which are: frontal, partial, occipital and temporal lobes. The partial lobe is responsible for several functions such as spelling, perception, objects manipulating, and spatial awareness. The basic functions of the temporal lobe are the language, recognizing faces, memory, and generating emotions. The third lob is the Frontal lobe in which it is linked with organizing, planning, social skills, flexible thinking, conscious movement, problem solving, attention, and emotional and behavioral control. The final lobe is the Occipital lobe in which it is related to interpreting visual stimuli.

The nervous system is another important system of human body. It

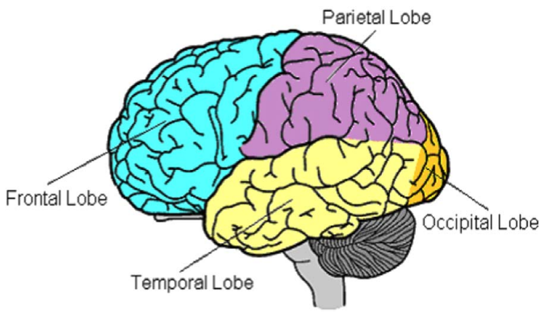


Fig. 3. Lobes of cerebral cortex.

is divided into two main parts which are central and peripheral systems. Spinal cord and the brain are the two components of the central nervous system. The peripheral nervous system involves the autonomic nervous system in which it controls functions such as digestion, secretion of hormones, breathing and heart rate.

3. BCI classifications

According to Fabien [37], the BCI could be classified according to dependability, invasiveness, and synchronization as shown in Fig. 4. In terms of dependability, the BCI is categorized as dependent and independent while in terms of invasiveness it could be divided into invasive BCI, non-invasive, and semi-invasive BCI. In the final category, the BCI could be synchronous or asynchronous (self-paced). These three categories are briefed as follows.

3.1. Dependent BCI and independent BCI

The dependent BCI requires certain level of motor control from the subject while independent BCI does not require any control [10]. Dependent BCI could help the subject to do things more easily such as playing video games and moving wheelchair. On the other hand, subject with severe disabilities would need an independent BCI where no motor control is needed.

3.2. Invasive BCI, non-invasive, and semi-invasive BCI

BCI is classified to invasive, non-invasive, and semi-invasive according to the way of the brain activity is measured. In invasive BCI, the microelectrodes are implanted in the brain, under the skull, during neurosurgery [52]. In this case, the signal might be produced with high quality but prone to scar tissue build-up over time and the signal might get lost. In addition, once the invasive technologies have been planted, it is not possible to move it to measure other parts of the brain [30]. On the other hand, in non-invasive BCI, the signals are recorded without any penetration in the scalp [77]. The signals in this case could be in low quality; however, non-invasive BCI is still preferable due to avoiding surgery. In the semi-invasive BCI, the electrodes are implanted underneath the skull and the brain signals are recorded using Electrocardiography (ECoG). For instance, Pfurtscheller group in [93] implanted macroelectrodes for epileptic patients over frontal regions. The patient tried to perform imagery tasks for hand, mouth and tongue and the BCI system with able to classify the imagery tasks ECoG through a single session.

3.3. Synchronous and asynchronous (self-paced) BCI

BCI system is called a synchronous when the user interaction with the system is done at certain period of time. In other words, the system has to impose the subject to interact with it at certain period of time. Otherwise, the system will not be able to receive the subject signals. On the other hand, in asynchronous BCI, also named as “self-paced” [3,112], the subject is able to perform its mental tasks at any period of time and the system will react to his/her mental activities. Therefore, the subject is free to have his/her activity at any period of time.

4. Neuroimaging methods

Many brain activities could be generated by potential actions of the subject or by changing in the blood flow. Recording such activities could be done directly by monitoring electrophysiological signals. The most used methods are: 1) electroencephalography (EEG), 2) electrocorticography (ECoG), 3) single-neuron recordings, 4) magnetoencephalography (MEG), 5) positron emission tomography (PET), 6) functional magnetic resonance imaging (fMRI), and 7) optical imaging (i.e., functional Near InfraRed (fNIR)). Table 1 summarizes the advantages and disadvantages of each method and Table 2 provides a comparison between these methods. However, MEG, PET, fMRI, and fNIR are not used as other methods because they depend on metabolic process that are less responsive to rapid communication. At the same time they are expensive and technically demanding.

Based on the recent BCI research activities [1,7,8,25,87,113], it seems that only electroencephalography (EEG), electrocorticography (ECoG), and single-neuron recordings are the three valid methods, so far, for BCI systems. They use inexpensive equipment and offer good communication and control channels.

4.1. Electroencephalography (EEG)

EEG is the recording of electrical activity through the scalp due to firing some of the neurons in the brain. These electrical activities is recorded over a short period of time through multiple electrodes located on the scalp directly on the cortex. EEG is considered as the most common method for brain signals recording because it has high temporal resolution, easy to use, safe, and affordable.

The used electrodes could be one of two types which are active electrodes or passive electrodes. Passive electrodes require an external amplifier to amplify the measured signals; on the other hand, active electrodes usually have an embedded amplifiers.

The main purpose of using either embedded or external amplifiers

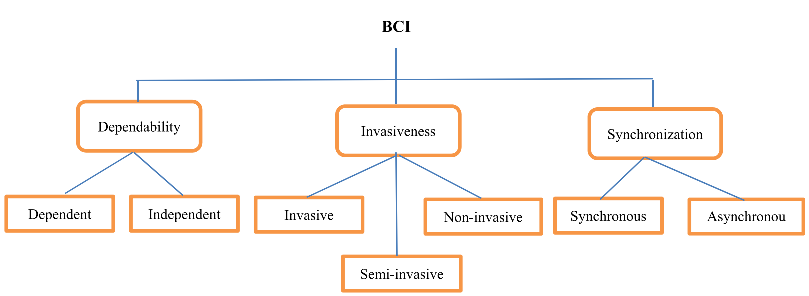


Fig. 4. BCI classifications.

Table 1
Neuroimaging methods comparison [30,124].

Neuroimaging Method	Advantages	Disadvantages
Electroencephalography (EEG)	1. Provides most of the required information about the brain activity. 2. Efficient in diagnosing some brain diseases, disorders, coma, encephalopathies, and brain death. 3. inexpensive 4. No harmful side effect 7. 5. There is no need for injecting any electrical signal. 6. The voltage is restricted to the measuring device.	1. Doesn't help in brain imaging or location determination of tumor, injuries, etc. 2. Does not provide the image of the brain cross sections.
Electrocorticography (ECoG)	1. Flexible to place the electrodes during recording 2. Direct measurement 3. The measurement could be before, during, or after the surgery. 4. Has better precision and sensitivity than EEG. 5. Due to the closer proximity to the brain, ECoG has lower signal-to-noise ratio and high spatial resolution.	1. Recording and electrode placement are limited by the time available during surgery and exposed cortex area and. 2. The Recording might be affected by anesthetics, narcotic analgesics, and the surgery itself. 3. Due to recording limited sampling time—seizures (ictal events) may not be recorded.
Magnetoencephalography (MEG)	1. Has an excellent temporal resolution and better spatial resolution than EEG. 2. MEG the magnetic fields are less influenced than electrical currents. 3. MEG helps in identifying the seizure focus in patients with epilepsy and it helps the surgeon in facilitating the planning of surgery.	1. Only detects magnetic fields oriented in parallel to the surface of the skull (neurons in cerebral sulcus). 2. MEG equipment is very expensive 3. Location of the brain activity on the surface or deep beneath the surface of the brain cannot be well identified. 4. Sensitive to external noise.
Positron emission tomography (PET) and single photon emission computed tomography (SPECT or SPET)	1. Most of the brain activities can be detected. 2. Efficient in diagnosing some brain diseases, disorders, coma, encephalopathies, and brain death. 3. Inexpensive 4. Has no side effect. 5. No need for injecting any electrical signal. 6. The voltage is restricted to the measuring device.	1. No brain image or brain cross section can be retrieved. 2. Does not provide location determination of tumor, injuries, etc.
Functional magnetic resonance imaging (fMRI)	1. Has relatively good spatial and temporal resolution. 2. Relatively inexpensive compared to PET 3. MRI procedure is very noisy; 4. Very sensitive to motion. 5. Relatively inexpensive compared to EEG	1. temporal resolution is poor 2. Gives little information about the temporal dynamics of their responses.
Optical imaging (functional Near InfraRed (fNIR))	1. Easy to measure 2. Involves no radioactivity	1. Low temporal resolution 2. Needs time to be measured (> 2–5 s)

(continued on next page)

Table 1 (continued)

is to reduce the effect of the environment noise as well as the weakness of the signals due to cable movement. One of the problems of EEG is that it needs gel or saline liquid to reduce the impedance of skin-electrode contact [37].

The problem with the gel or the liquid is that it dries with time. However, currently there are some of the dry electrode that are invented which might solve the problem of old electrodes [121,127]. For reliable signals, it is assumed that the distance between the electrode have to be between 1 cm and 2 cm for low signal-to-noise-ratio. In addition, EEG is able to detect changes in the brain signals within millisecond where an action requires almost 0.5–130 ms to propagate across a neuron.

With more experience with EEG recoding, 10–20 system [114], shown in Fig. 5, it is recommended as a standard layout. 10–20 refers to specific anatomic landmarks or inter-electrode distance, such that it is 10–20% of the front-to-back or right-to-left head perimeters. This standard has been revisited by the authors of [128] and they concluded that 10-10 and 10-5 systems could be a valid standard as well. EEG is also digitized by 12-bit Analog to Digital Converter (ADC) with sampling frequency ranging from 100 Hz to several hundreds. Fig. 6 is Block diagram of one of the recording setup of a single EEG channel where low and high pass filters are used prior to signals amplifications. The low pass filter is used for anti-aliasing filtering and high pass filter is used for low frequency artifact elimination. EEG is usually described in terms of activity types which are rhythmic activity and transients. The rhythmic activities are divided into certain frequency bands. These bands are proved to have certain biological significant or certain distribution over the scalp [26]. In addition, it becomes a kind of nomenclature that EEG signals that falls below 1 Hz and above 20 Hz are considered as artifactual. Table 3 compares between all of the EEG bands in terms of frequency, shape, properties, and mental activities. As stated in the table, there are six types of signals which are Delta (Δ), Theta (Θ), Alpha (α), Mu (μ), Beta (β), and Gamma (γ). Delta (Δ) has a variable amplitude and falls in the range of 1–4 Hz [104].

Delta seems to be the highest in amplitude and the slowest wave that associated with deep sleep and wakeup states. Theta (Θ) has an amplitude that greater than 20 μ V and fall within the range of 4–7 Hz. Theta is generated with idling, creative inspiration, unconscious material, drowsiness, and deep meditation. Alpha (α) is a wave with amplitude of 30–50 μV and change rate between 8 and 13 Hz. It is usually associated with relaxation, concentration, and sometimes in attention. Mu (μ), is found in the alpha wave frequency range where the recorded amplitude over motor cortex is maximum. It is usually associated with suppression indicates that motor neurons are working. Beta (β) is associated with alert, thinking and active concentration and falls in the range between 12 and 30 Hz. Finally Gamma (γ) could be detected at somatosensory cortex with frequency greater than 30. It is also shown during short term memory matching of recognized objects, sounds, or tactile sensations.

Table 2
Neuroimaging methods comparison.

Neuroimaging Method	Activity Measured	Risk	Spatial Resolution	Temporal Resolution	Portability
Electroencephalography (EEG)	Electrical	Non-invasive	~10 mm	~0.001 s	Portable
Electrocorticography (ECoG)	Electrical	Semi-invasive	~1 mm	~0.003 s	Portable
Magnetoencephalography (MEG)	Magnetic	Non-invasive	~5 mm	~0.05 s	Non-portable
Positron emission tomography (PET)	Metabolic	Non-invasive	~1 mm	~0.2 s	Non-portable
single photon emission computed tomography (SPECT or SPET)	Metabolic	Non-invasive	~1 cm	~10 s–30 min	Non-portable
Functional magnetic resonance imaging (fMRI),	Metabolic	Non-invasive	~1 mm	~1 s	Non-portable
Optical imaging (functional Near InfraRed (fNIR))	Metabolic	Non-invasive	~2 cm	~1 s	Portable

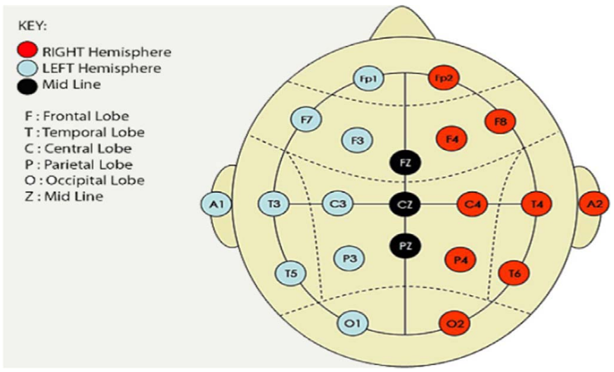


Fig. 5. 10–20 system and electrodes positions.

4.2. Electrocorticography (ECoG)

Electrocorticography (ECoG) [33] is used to measure the electrical activities of the brain through an invasive procedure. In other words, the skull of the subject has to be removed and the electrodes are placed directly on the service of the brain. Therefore, since the electrodes are placed directly on the skull, the special resolution of the measured signals are much better than EEG and signal-to-noise ratio is superior due to greater vicinity to neural activity. However, the usage of ECoG is very limited to the exposed brain area and it is almost impossible to be used outside of a surgery room [6].

4.3. Magnetoencephalography (MEG)

Magnetoencephalography (MEG) is used to identify and analyze the magnetic field of the brain using a functional neuroimaging technique. MEG works from the outside of the head and it became daily routine of the clinical practice. It was first invited by David Choen in 1968 [28,91] and started by using a detector made of conduction cooper inside a shielded room reducing the background noise. Recently, more sensitive sensors such as superconducting quantum interference devices, such as (SQUID) devices [58,86], are used to produce improved MEG signals. MEG becomes very important especially for patients with epilepsy and patients with brain tumors in which it could help in identifying regions with normal brain function in patients with epilepsy or tumor or other mass lesion. At the same time, MEG works on the magnetic waves instead of electrical waves; therefore, it could provide a complementary information to EEG. MEG also captures signals with good temporal resolution and very good spatial resolution. However, the scanners have to be close to the brain surface to detect neural activity that generates very small magnetic fields. Therefore, MEG needs special type of sensors such as superconducting quantum interference (SQUID) sensor [57].

4.4. Single Photon Emission Computed Tomography (SPECT)

SPECT is also named as SPET [123] which is a nuclear tomographic imaging that it is based on gamma rays. The desirable image is generated based on tracking the gamma rays injected in the blood-stream of the patient and emitted by radionuclides. It needs specific chemicals to be bind with certain brain tissue which allows concentration on the radionuclides in the region of interest of the body. SPECT devices can produce 3D information that later can be constructed as 3D image of the monitored part of the brain. In addition, it has spatial resolution of about 1 cm and several seconds as time resolutions.

4.5. Positron Emission Tomography (PET)

Positron Emission Tomography (PET) [123] is used to observe metabolic processes in the body and it is similar to SPECT; however, in PET a pair of gamma rays is emitted due to radionuclides injection in the patients. In other words, this radionuclides emits positrons that interacts with the electrons located in the monitored/canned area. This interaction generates the gamma rays. Using these gamma rays, an image can be constructed. Unfortunately PET has high operating cost which makes it not preferable to be used.

4.6. Functional Magnetic Resonance Imaging (fMRI)

fMRI is one of the non-invasive techniques that is used to measure the variation of blood oxygen level during the brain activities. fMRI produces high spatial resolution that makes it suitable for identifying the active regions in the brain. However, the fMRI time resolution is very poor, ranges from 1 s to 2 s. In addition, it suffers from poor resolution with head movements and might produces artifacts.

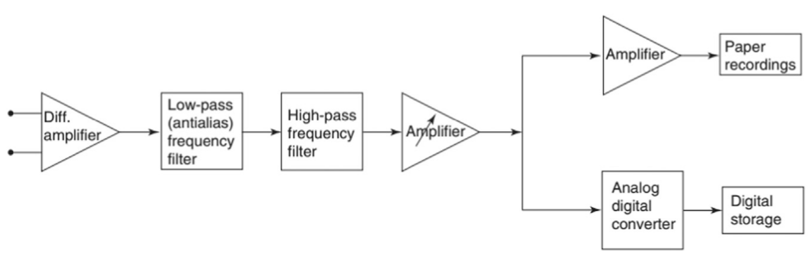
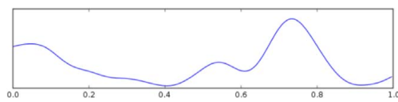
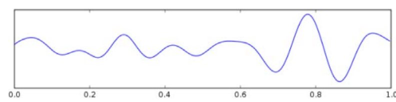
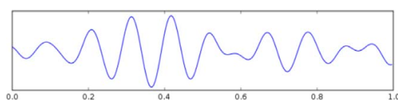
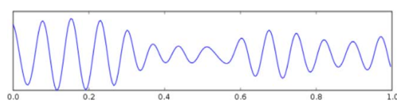
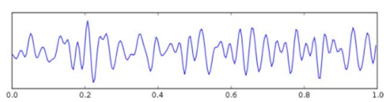
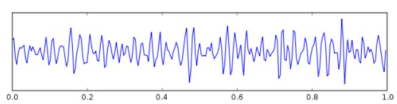


Fig. 6. Block diagram of recording of a single EEG channel.

Table 3
Brain signals comparisons.

Type	Frequency range (Hz)	Signal Shape	Properties	Mental Activity
Delta (Δ)	1–3		Frontally in adults, posteriorly in children; high amplitude waves	1. Slow-wave (deep) sleep 2. in babies
Theta (Θ)	4–7		Frontal midline (Fz to Cz)	Idling, unconscious, meditation and drowsiness
Alpha (α)	7–12		Posterior regions of head, both sides, higher in amplitude on dominant side.	Relaxation and concentration
Mu (μ)	8–13		Sensorimotor cortex	Suppression indicates that motor neurons are working
Beta (β)	12–30		sensorimotor cortex, between C3 and C4, symmetrical distribution, most evident frontally; low amplitude waves	Alert, thinking and active concentration.
Gamma (γ)	> 30		Somatosensory cortex	1. Somatosensory processing 2. shown during short term memory matching of recognized objects, sounds, or tactile sensations

4.7. Optical imaging (functional Near InfraRed (fNIR))

fNIRS technology [42,74,105] projects the infrared light into the brain to measure the changes at various wavelengths as the light is reflected back out. Usually, the fNIRS detects the localized blood volume and oxygenation changes. In fact, fNIRS is used to shape the function maps of the brain activities since the fluctuations in tissue oxygenation modulate the scattering and absorption of the infrared light photons to varying amounts [116]. Therefore, images similar to the traditional Functional Magnetic Resonance Imaging could be generated with high spatial resolution (< 1 cm) at the expense of lower temporal resolution (> 2–5 s). Unfortunately, due to the low temporal resolution, fNIRS is not preferred to be used by most of the researchers [71].

5. Mental control signals classifications

BCI is based on control signals that are taking directly from the brain. Some of these signals are relatively easy to be extracted and some others are hard and need some extra preprocessing. These control signals can be categorized into three categories which are: 1) Evoked signals 2) Spontaneous signals, and 3) Hybrid signals. The following is a brief description to the three types. Fig. 7 shows the control singles classification and Table 4 summarizes their features.

5.1. Evoked signals

Evoked signals, also referred to as Visual Evoked Signal (VEP), are the signals generated unconsciously by the subject when he/she receives external stimuli. The most well-known evoked signals are Steady State Evoked Potentials (SSEP) and P300. Evoked signals depend on the external stimulation which could be uncomfortable, clumsy and tiring for the subject.

5.1.1. State Evoked Potentials (SSEP)

SSEP signals are brain signals that are generated when the subject perceives periodic stimulus such as flickering image, modulated sound, and even when the subject feel some vibrations [73,124]. As a subject, in general, when you feel a certain change at certain frequency your brain respond. In other words, the EEG signals power in the brain will increase to reach the stimulus frequency. Thus, based on the sensation process, signals at different brain areas are observed. Various types of SSEP signals are detected such as Steady-state visual potentials (SSVEPs) and somatosensory SSEP or auditory SSEP. SSVEP is commonly used in many applications.

SSVEPs signals are provoked by usually repetitive visual stimuli. The visual stimuli such image flickering generates SSVEP at the visual cortex that has the same frequency of the flickering image (usually between 6 and 30 Hz) [40] [76]. SSVEP could be further classified based on the type of modulation into time modulated VEP (*t*-VEP) BCIs, frequency modulated VEP (*f*-VEP) BCIs, and pseudorandom code modulated VEP (*c*-VEP). In t-VEP, the flash sequences of the different

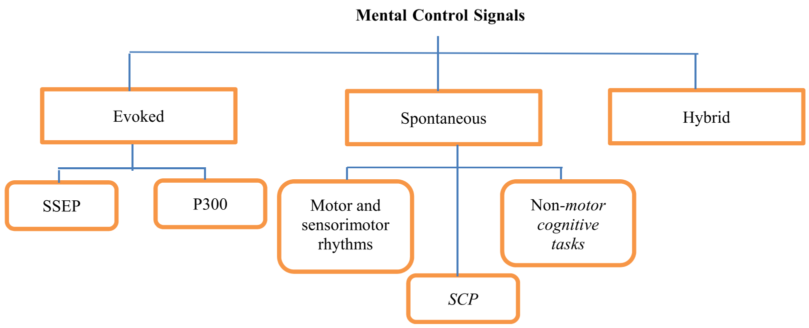


Fig. 7. Mental control signals classification.

targets to different stimulus should be orthogonal or near orthogonal to each other to ensure reliable identification of the target. T-VEP has a low information transfer rate which is almost less than 30bits/min. However, there is no need for user training. f-VEP depends on flashing each target with unique frequency; this generates evoked responses with the same frequency. f-VEP has high information transfer rate; generally (30–60 bits/min). Again, f-VEP does not require any kind of training. Lastly, c-VEP uses pseudo-random sequences that determine the duration of ON and OFF. Here, the information transfer rate is very high in which it could be more than 100 bits/min. However, the subject has to be trained first. One of the common application of the SSVEP is the graphical user interface with some buttons on it where each button is having certain frequency. When the subject focuses on one of the buttons the brain generates the equivalent frequency that can be used, for instance, to control the button click.

5.1.2. P300

It is an EEG signal that appears after almost 300 ms when the subject is exposed to infrequent or surprising task. This signal is usually generated through “odd-ball” paradigm where the user is requested to attend a random sequence of stimuli with one is less frequent than the others [66]. When this rare stimuli is relevant to the subject, it triggers the P300 EEG signals. Again P300 does not require any subject training; however, it requires repetitive stimuli which might lead to tiring and inconsistency to the subject. A typical P300 signal could be as shown in Fig. 8.

5.2. Spontaneous signals

Spontaneous signals are the signals generated by subject voluntarily without any external stimulations. Most of the well-known spontaneous signals are the Motor and sensorimotor rhythms, Slow Cortical Potentials (SCP), and Non-motor cognitive tasks.

5.2.1. Motor and sensorimotor rhythms

Motor and sensorimotor rhythms [85] are those rhythms related to motor actions such as moving arms. These rhythms are coming from over the motor cortex with frequency bands located at μ (≃8–13 Hz) and β (≃13–30 Hz). The amplitude of these rhythms could be controlled by the subject. However, the control of these sensorimotor rhythms are done by one of two different methods which are operant conditioning and Motor imagery.

In operant conditioning, the subject can voluntarily change the amplitude of his/her sensorimotor rhythms through long training. It is up to the subject to choose his/her mental strategy that suites him/her. However, the training could last for weeks or months. After all, the μ and β rhythms at different positions can build up as a control signal.

Motor imagery, is the translation of the subject motor intention into control signals through motor imagery states. For instance, the left hand movement may generate EEG signals accompany with in the μ and β rhythms, (μ 8–12 Hz) and (β 18–26 Hz) decrease in specific motor cortex area. Different applications could be used according to the motor imagery rhythms such as controlling a mouse or playing a computer game. With new Artificial Intelligence techniques, the subject might not need any training; however, it is always better to have some training before using the motor imagery systems.

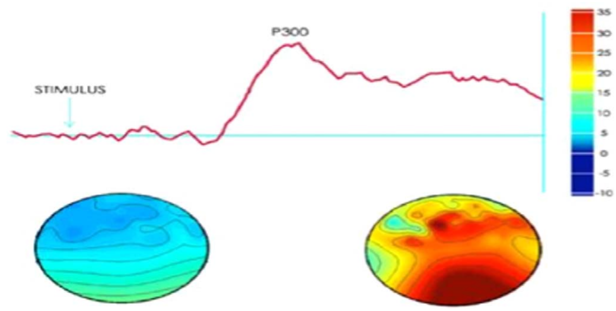


Fig. 8. P300 evoked signal.

Table 4
Control signals summary.

Signal	Characteristics	Transfer rate (bits/min)	Training	Advantages	Disadvantages
VEP	It is based on signal modulations in the visual cortex	60–100	No	1. Need very little training 2. High bit rate	1. Permanent attention to 2. external stimuli
P300	It is the positive peaks due to infrequent stimulus	20–25	No	3. single EEG channel is required	3. Some subjects might get tired
SCP	It is the slow voltages shift in the brain signals	5–12	Yes	1. does not depend on any stimulation	1. needs very long time training 2. some subjects might not be able to generate the signals
Sensorimotor rhythms	It is based on modulations synchronized to motor activities	3–35	Yes	2. Subject use it voluntarily 3. Suitable for control applications	3. needs multiple EEG channels for recordings for good performance

Table 5
Hybrid control signals.

Reference	Signals Type	Purpose
[79]	EMG and SSVEP	Enhance the BCI system performance. It uses the speller application as a case study.
[32]	SSVEP and P300	Enhances the classification accuracy and increases the transfer rate.
[138]	SSVEP and P300	Improving the performance of the BCI system in terms of detection accuracy and response time. A wheelchair control system is used for testing.
[135]	SSVEP and alpha rhythm	Studying the accuracy of the BCI system during fatigue state. A wheelchair control system is used for testing.
[11]	EOG and P300	Enhancing the classification accuracy and the system response time.
[81]	ERD, SSVEP	Improvement of FES triggering application.
[19]	ERD, SSVEP	Adding feedback to BCI applications.
[106]	P300, SSVEP	Improving ITR
[43]	P300, SSVEP	Used for smart home control
[137]	P300, ERD	Expand the control function for virtual environment
[53]	P300, ERD	Enhancing reliability
[117]	ERD, NIRS	Enhancing the classification accuracy
[108]	EEG, EMG	Enhancing BCI application performance.
[136]	ERD, EOG	Enhancing the classification accuracy and reducing the training time.
[131]	ERD, EOG	Performance enhancement.

5.2.2. Slow cortical potentials (SCP)

SCP is an EEG signal that belongs to a frequency below 1 Hz [61]. It is a low frequency potential detected in the frontal and central parts of the cortex; it is also the results of the depolarization level shifts in the upper cortical dendrites. SCP is a very slow variation, positive or negative, of the cortical activity that may last from milliseconds to several seconds. The subject can control generation of such signals using operant conditioning. Therefore, subject long training might be required even more than the required for motor rhythms. Currently, SCP is not preferred by many of the researchers and replaced by Motor and sensorimotor rhythms.

5.2.3. Non-motor cognitive tasks

Non-motor cognitive tasks mean that cognitive tasks are used to drive the BCI. Many of the tasks could be performed such as music imagination, visual counting, mental rotation, and mathematical computation [90]. Pattern classifier used by Penny et al. [130] is one of the examples on the non-motor cognitive tasks where pattern classifier was used with uncertain parameters while the subject was doing some subtraction.

5.3. Hybrid signals

Hybrid signals mean that a combination of brain generated signals are used for control. Therefore, instead of only one type of signals is measured and used in the BCI system, a hybrid of signals are utilized. The main purpose behind using two or more types of brain signals as input to a BCI system is the reliability and to avoid the disadvantages of each type of signals. Table 5 is a review to the state-of –the-art of hybrid systems. The reader is also referred to [115] for more information on some of these systems.

6. BCI technology

Any research field to be advanced, it requires two things which are a killer application and advanced technology. This section briefly reviews some of the current BCI technologies in terms of hardware and software. The hardware devices are used to capture the signals either through an invasive or noninvasive methods. However, BCI software platforms through intelligent algorithms are responsible for preprocessing and analyzing the signals provided by the hardware as well as generating the control commends for the external environment.

6.1. BCI hardware technology

As can be seen in the previous sections, there are different signals to be recorded out of the brain. In addition, there are number of channels that are recorded as well; these channels differ based on the type of signals to be measured. For instance, EEG deals with 8–64 channels, ECoG works with 32–192 channels, and the single unit recording might work with 100–300 channels [110]. Therefore, there is no yet a generic device or a platform that can handle all of the brain signals at once. Nevertheless, since BCI is dealing with human as well as animals brains, different regularity organization around the world including Ministry of Health, Labor, and Welfare (MHLW) in Japan, Food and Drug Administration (FDA) in the US, and European Commission (CE) in Europe allowing only certain devices for safety reasons. Therefore, laboratories and researchers around the world might implement their own devices to do their experimentations. Currently, the major investment in BCI devices has been directed towards invasive technology especially in North America; few commercial companies in Europe are interested in invasive technology; however, it is a major concern. In the other part of the world, Europe and Asia, most of the companies are interested in developing non-invasive EEG devices with minimum cost.

Electrodes are the enabling technologies that allows brain information to be encoded by different techniques and algorithms providing input to control devices. These electrodes are very important for brain data transfer and without such technology, it is impossible to acquire brain signals. Unfortunately, the current electrodes still not up to the applications requirements. There is a great opportunities and large space for signal acquisition devices. These electrodes could be wired or wireless [63].

Most of the wired electrodes are formed by sealing metal wire such as tungsten, gold, platinum, iridium, platinum-iridium, stainless steel in insulating material. In addition, the length of such wires are determined by the desirable BCI, usually from 13 to 200 μm. These electrodes consist of four layers which are: 1) substrate, 2) insulating, 3) adhesion, and 4) screen printing layer. The substrate layer is usually composed of ceramic, polyimide, silica/glass or silicon. The insulating a layer is also called doping layer where other material(s) covers the substrate. For instance, if silicon is used as a substrate, the silicon nitride could be used as a doping materials.

In the third layer, adhesion layer, titanium or chromium might be added allowing active metal to adhere to the substrate surface. Finally, Photolithography or is used to connect lines, lay out the electrodes recording sites, and bonding pads are used to lay out the microelectrode recording sites, connecting lines, and bonding. There are different types of electrodes classified based on the used materials such as Silicon, Ceramic, and Polyimide based electrodes. Some others are classified based on the neuroimaging method such as ECoG and EEG. In this paper, we cover only the most used types of electrodes. The reader is directed to a good survey on electrodes technology made by *Greg at al.* in [38].

Passive electrodes are used to measure EEG signals; most of these electrodes are in a shape of disc or ring that are made of Ag/AgCl alloy [129]. Although these electrodes are small but they are very sensitive to noise and sensitive to cable variations. Therefore gels or glues treatments are used for better conductivity. For these reasons passive electrodes might not be feasible for very sensitive applications [75]. More advanced electrodes have been investigated such as dry electrodes. Dry electrodes became one of the recent active research where there is no need for gels or glues. Special materials are used in dry electrodes including conductive foams, spring-loaded fingers, and micro-machined structures, conductive rubber, conductive carbon nanotubes, and bristle structures. A sample of the miniature passive

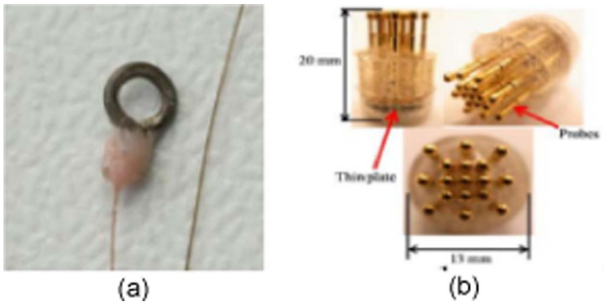


Fig. 9. EEG electrode types, (a) a miniature passive ring electrode (b) a spring-loaded dry electrode [119].

ring electrode is shown in Fig. 9(a) and a spring-loaded dry electrodes is shown in Fig. 9(b) [22,25,27,44,133]. Unfortunately, dry electrodes are still not up to the requirement base. Therefore, other active electrodes are investigated. Active electrodes come with amplifiers integrated into them [56,133]. Certainly, the active electrodes are used with the dry electrodes type without any conductive gel or glue [51]. Recently, wireless electrodes came to place in which they are combined with active and the dry electrodes technology. Wireless electrodes made the wireless BCI systems easier.

Table 6 summarizes all of the recent EEG devices and their specifications. The decision on which set or device to be used is based on the type of BCI applications.

6.2. BCI Software platforms and tools

This section briefly review some of the current BCI platforms and tools that are available and used in research. The review tries to identify the key points, development language, and operating system of each tool. However, the BCI requires many of the algorithms for signal acquisition, artifact removal, feature extraction, classification, and post processing to be included in the tool. Table 7 summarizes the major BCI platforms and tools in terms of their programming languages, supported platforms, and characteristics. The reader is encouraged to read the survey of Brunner et al. [20] for more details on some of these platforms.

6.2.1. BCI2000

BCI2000 is one of the general purpose non-profit software platforms for BCI started in 2000. As the name suggest the development of BCI2000 started in 2000 by Brain-Computer Interface R & D Program at the Wadsworth Center of the New York State Department of Health in Albany, New York, USA. In addition, one of the main contributors to the BCI2000 is the Institute of Medical Psychology and Behavioral Neurobiology. Many other contributors are from around the world. The platform has been maintained by a team of the developers and scientists that are trying to expand it to include all of the contributions and add new hardware devices. It has been designed to cover multiple tasks and applications such as data acquisition, brain monitoring, and stimulus presentation.

BCI2000 is a modular tool that consists of four main modules which are source module, signal processing module, user application module, and operator module, shown in Fig. 10. The source module is responsible for handling the acquisition of the brain signal while the signal processing module is responsible of the processing of the brain received signals. The user application module is responsible for generating the feedback for the user while operator module is responsible for the interface to the investigator. Fig. 10 shows the flow of information among the modules.

BCI2000 is a flexible software in which it allows other programs written in any language to be interacted with. It also runs on cross platform, windows, OS X, and Linux, and it is written in C++. Therefore, it could be compiled using Borland C++ Builder 6.0 or Borland/CodeGear Development Studio 2007/2009 (all BCI2000 versions), VisualStudio, and MinGW. It supports different filters such as spatial filter, Fast Fourier Transform, Normalizer, Random Filter, and simple low-pass filter.

It also supports more than a dozen of data acquisition systems, evoked potentials, appropriate processing of EEG oscillations, single-unit action potentials, and ECoG activity. For a complete guide to BCI2000, the reader is referred to Gerwin and Jürgen book [48]. Many research have been using BCI2000 platform including [49,82,132].

6.2.2. OpenViBE

OpenViBE is another open source software platform for design, test, and use for BCI. It has a generic acquisition server and supports large number of acquisition devices. It is also designed in a modular way that includes a graphical user interface for developers. This graphical user interface makes it easy for developers to drag and drop items building their applications. It comes with many signal processing algorithms used to extract signals characteristics. In addition, it includes three classification methods which are Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Classifier combinations for multiclass. Moreover, OpenViBE includes many paradigms including Speller Applications using P300, Spaceship for feet motor imagery, Handball for hand motor imagery, and SSVEP shooting game. A 3D graphical interface is enabled in OpenViBE powered by the open source Ogre 3D engine. OpenViBE can be programmed using LUA and Python languages in addition to its capability of connecting with Matlab for further signal processing.

OpenViBE involves an elementary component in the processing pipeline in which it allows to use some of the already created components which reduces the development time and helps to quickly extend functionality. It also runs on Windows, Ubuntu Linux, Fedora Linux, and some other Linux distribution. In addition, it supports vast selection of hardware EEG devices. Moreover, the platform has an excellent documentation including video tutorials that could help researchers, developers, and clinicians. Nevertheless, many of the research work already based on OpenViBE platform including [23,24,36,59,60,70,107,122].

6.2.3. TOBI: Common Implementation Platform (CIP)

The TOBI Common Implementation Platform (CIP) is European project to develop practical technology for BCI started in 2008. In fact, TOBI is not a platform, it is a cross-platform with multiple interfaces that connect different parts of other BCI systems. It is based on the model shown in Fig. 11. As can be seen in the Figure, data is intercepted by the data acquisition system then forwarded to the data processing module. The CIP has three interfaces which are TiA, TiB, and TiC. Another interface (TiD) is used for events and markers transfer within the CIP. The TiA interface is used to transmit different kind of signals such as raw biosignals, supporting multirate and block-oriented transmission at the same time [18]. The TiB is responsible for signal features transmission. TiC is another interface for detected classes and labels within the BCI. Tic messages might consist of different classifiers and class encoded in XML format. Therefore, other modules will receive the messages in a standardized way.

6.2.4. BCILAB

BCILAB [16] is an open source toolbox for BCI research. It is based on a plugin concept where different components are added through plugin. BCILAB involves different components including signal processing, feature extraction, machine learning, and BCI paradigms, as shown in Fig. 12. The toolbox depends mainly on some of the parameters that need to be known for adapting the toolbox as needed. It is also compatible with some other platforms such as BCI2000 and OpenViBE. BCILAB involves different methods such as machine learning, signal processing, statistical modeling, and electrophysiolo-

Table 6
Electrodes technology.

Device name	Communication	Number of channels	Sample Photo
Emotiv EPOC (www.emotiv.com)[54,92,54,109]	wireless	14	
Emotiv Insight (www.emotiv.com)	wireless	5	
PLX XWave Sonic (www.plxdevices.com)	wireless	1	
Neurosky Mindwave (www.neurosky.com)	wireless	4	
MyndPlay BrainBandXL EEG Headset - BrainBandXL (www.myndplay.com)	wireless	1	
InteraXon Muse (www.choosemuse.com)	wireless	4	
Melon EEG headband (www.thinkmelon.com)	Wireless	3	
Neuroscan MicoMagLink (www.neuroscan.com) [64,126]	Wired	64, 128, and 256	
BrainControl (http://www.braincontrol.it/?lang=en) [97,98]	Wireless	Not known	
OxyMon (http://www.artinis.com/)	Wired	1 to 112	
B-Alert X series (http://www.advancedbrainmonitoring.com/xseries/) [17,111]	Wireless	10 and 24	
Quasar – ECG: PSM (http://www.quasarusa.com/) [67,94]	Wireless	8	
Enobio (http://neuroelectrics.com/)	Wireless	8, 20, and 32	
MOBIlab+ (http://www.gtec.at/Products/Hardware-and-Accessories/g.MOBIlab-Specs-Features)	Wireless	8. 16. And 32	

(continued on next page)

Table 6 *(continued)*

Device name	Communication	Number of channels	Sample Photo
			
iWinks' Aurora (not ready yet) (https://iwinks.org/aurora)	Wireless	Not known	
Lycra Cap – Biopac https://www.biopac.com/products/)	Wired	Not known	
The BioSemi "Pin-type" (http://www.biosemi.com/)	Wired	16, 32, and 128	

Table 7
BCI software tools and platforms.

Platform	Programming language	Operating System			Characteristics
		Windows	Linux	OS X	
BCI2000	C++	✓	✓	✓	1. Good documentation 2. Simple setup and deployment 3. Includes tool for timing behavior 4. Has good impact on research
OpenViBE	LUA and Python	✓	✓		1. Modular software 2. Reusable components 3. Suitable for different users (developers, researchers, and clinicians.**)** 4. Based on free and portable software such as GTK+8, IT++9, VRPN10, and GCC. 5. Includes the acquisition server, the designer, 2D visualization tools, and sample scenarios for BCIs or neurofeedback applications
TOBI	C++		✓	✓	1. The cross-platform 2. Able to integrates different BCI tools 3. Server that can handle data devices at the same time
BCILAB	MATLAB	✓	✓		1. Emphasis on principled evaluation strategies. 2. Features number of algorithms and techniques 3. Supports real time and offline applications 4. Ease of use due to GUI 5. Extensible due to integration of plug-ins
BCI++	C++	✓			1. System simplifies interfacing 2. Supports different kinds of acquisition devices, which could be used by both the end-user in their daily activities (for example, home automation control) 3. Very flexible 4. Xbox 360, Windows Phone or Windows 7 Tablet platforms
xBCI	GNU C/C++	✓	✓	✓	1. High extendibility and flexibility 2. Multi-threaded parallel processing 3. Easy-to-use 4. High speed data processing 5. Multi-OS support
BF++	Python	✓	✓	✓	1. Provides a unique and reliable performance metric. 2. suitable for the description, 3. Simulation, and more importantly, optimization of the systems. 4. Usability.
Pyff	Python	✓	✓	✓	1. Foster a fruitful exchange of experimental paradigms between research groups 2. Decrease the need of reprogramming standard paradigms, 3. Facilitate the reproducibility of published results, 4. Promote standardization of feedback and stimulus presentation.
OpenBCI	C++	✓	✓		1. Centralized system with multiplexer server 2. Supports parallel hybridBCI 3. facilitates communication between the OpenBCI and external modules

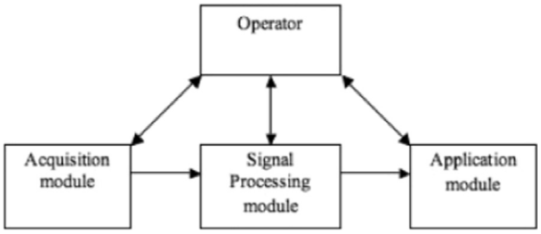


Fig. 10. BCI2000 block diagram.

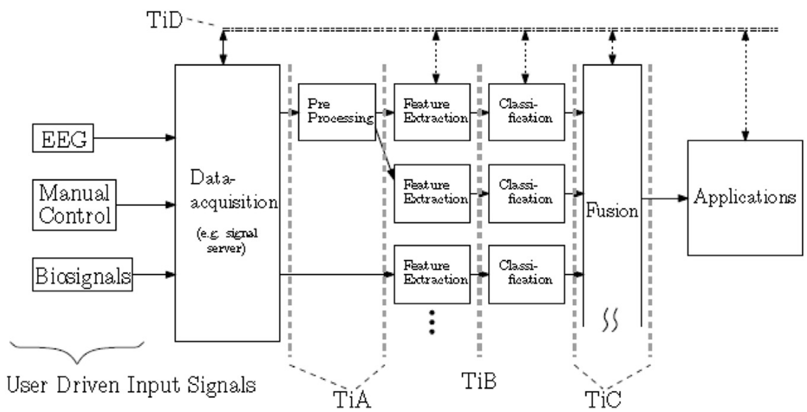


Fig. 11. TOBI Implementation Platform.

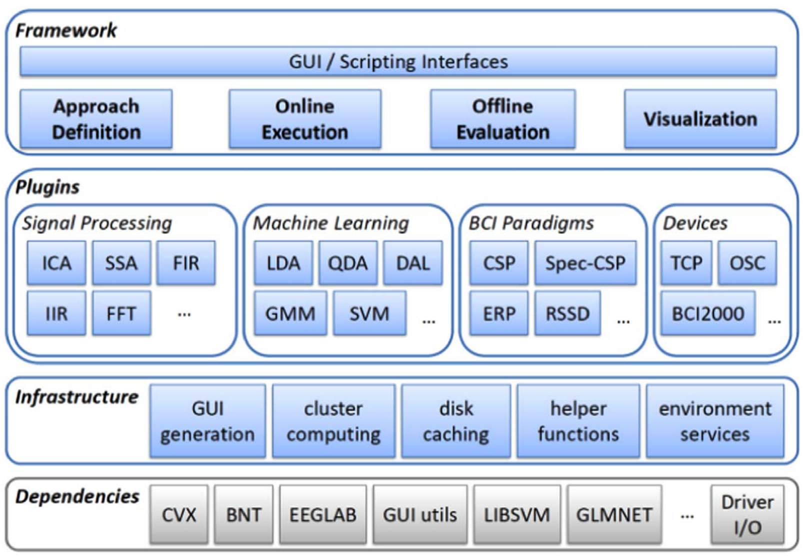


Fig. 12. BCILAB's architecture [15].

gical imaging and other plugins, given in Table ccc, which make it suitable towards research [4,15]. In addition, it has a graphical user interface that simplifies its operation. Fig. 13 shows the BCILAB interface.

6.2.5. BCI++

BCI++ [101] is another open source framework BCI that has two main modules which are Hardware Interface Module (HIM) and Graphics User Interface (AEnima). These two modules communicate through TCP/IP connection as shown in Fig. 14. The HIM module is dedicated to signal acquisition, storage and visualization, real-time execution and management of algorithms while the second module is responsible for creating and managing pc-driven protocols based on a high level 2D/3D Graphic Engine. BCI++ is compatible with devices such as 1) Kimera II (Sensibilab prototype), 2) G.Mobilab (G.Tec – Austria), 3) Neuroscan (Compumedics), and 4) Brain Products.

6.2.6. xBCI

xBCI [55] is an open source platform for BCI that is based on sophisticated graphical engine. This engine makes it easy on the BCI developers to build their applications. It contains three main components which are source component, processing component, and sink component. The source component function is related to acquiring data from hardware, generating data for simulation, and receiving data through network. Some other configurations are defined in the source component such as sampling frequency, data unit, and block length. The data received from the source component is manipulated in the processing component. Some functions such as digital filters, arithmetic operation and classifiers are done in the processing component. The final component, sink component, represents the user view to the data in addition to storing the data. BC++ is a rich platform that is designed based on the concept of multithread application, extensible modules, and portability.

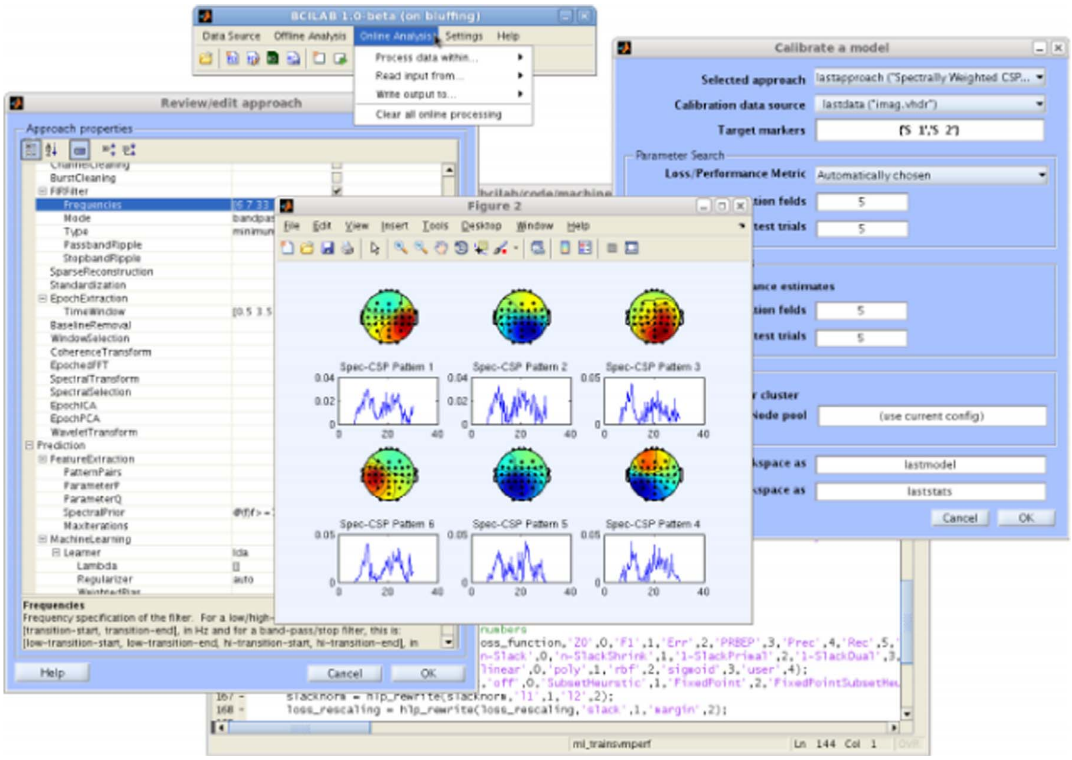


Fig. 13. BCILAB's graphical user interface.

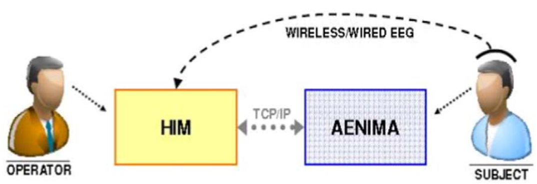


Fig. 14. Structure of BCI++.

6.2.7. BF++

BF++, body language framework, is a collection of different software modules, libraries and tools for brain computer interface applications. It consists of two main modules, as shown in Fig. 15, which are the NPX Lab suite and the BF++ Toys. The NPX Lab suite is a set of tools used for the analysis, editing and reviewing of EEG, MEG, ERP, EMG, ICA, CSP, etc. In addition, it contains many of the filters, file conversion, and many other tools. NPX Lab suite is also used to convert many different file formats (EDF, BCI2000, GDF, Neuroscan, NPX, Brain Vision Analyzer, EBNeuro, Micromed, CTF MEG, ASCII, Microsoft Wave, etc.) from NPX format. The second module is BF++ Toys in which it consists of many small applications for analysis, evaluation, simulation and optimization of BCIs. It is responsible for creating logical and semantic alphabets for your Bio-Feedback and BCI applications. Large body of research work was based on BF++ including [29,35,47,72].

6.2.8. OpenBCI

OpenBCI [99] is an open platform in which it is dedicated to be used as clinical applications, possibly in home setup. It is a Multilanguage and multiplatform that contains a multiplexer server, see Fig. 16. Such server allows new modules to be connected; it allows multiple paradigms base on different kind of stimuli and OpenBCI can switch among them without any change. However, the linear data flow is replaced centralized data flow model. The centralized communication is supposed to facilitate easy communication among the modules. It also facilitates communication between the OpenBCI and modules written in Python, Java, and C++. In addition, it supports the straightforward implementation of parallel hybridBCI.

7. BCI challenges

This section states some of the BCI challenges; these challenges could be classified into: *A) standards, B) participants and stable classifications, C) electrophysiological, D) information transfer rate (ITR), E) sensors, F) real-life applications, G) ethical issues, J) privacy and security, and H) agreement of the future directions.*

7.1. BCI standards

There is a lack in the BCI community in developing standards for the BCI systems. For instance, EEG practice involves tedious procedure for capturing the brain signals including using gel/liquid on electrodes for accurate measurements. Although the new dry electrodes might be a solution, but still the procedure is not standardized and might differ from subject to subject. In addition, there are thousands of devices already developed for BCI applications. Unfortunately, these devices are developed in separate islands where most of the devices are not compatible with each other.

7.2. Participants and stable classifications

Participants are the core of any BCI system; these participants could be independent or specific. In participants' independent, training might be required each time a subject uses the system which might lead to unstable signal classifications. In addition, BCI systems that require long time training are difficult to be used where the subject might got tired and unwilling to participate in the system. Moreover, the subjects

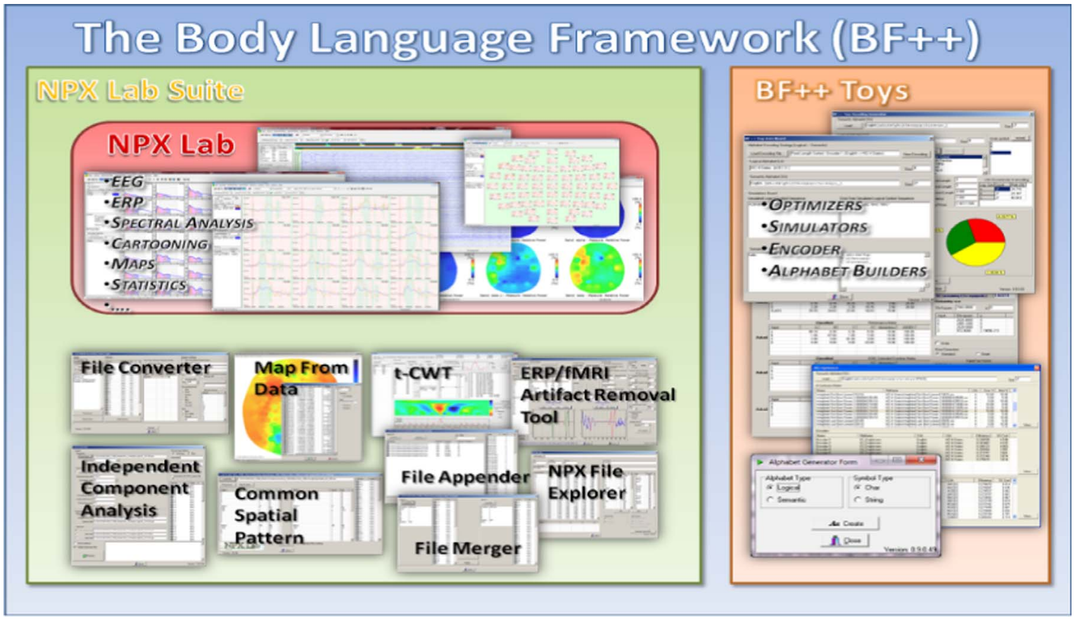


Fig. 15. Components of BF++.

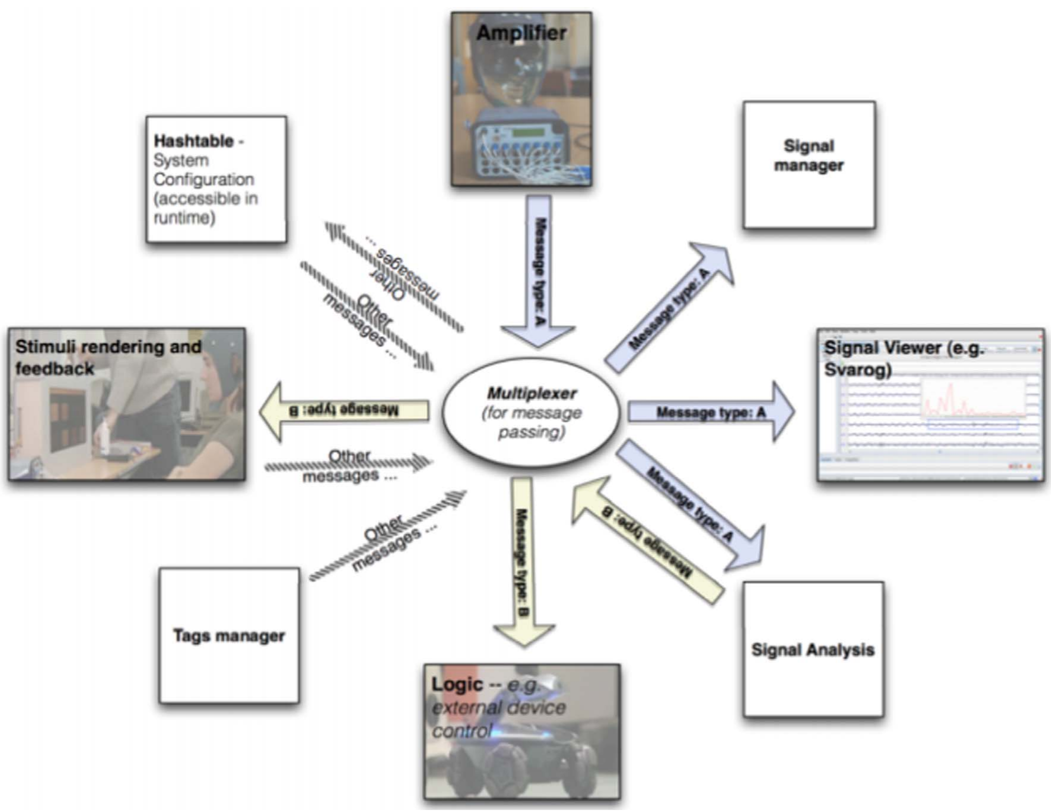


Fig. 16. OpenBCI centralized multiplexer server.

image of BCI, in most of the cases, either negative or unrealistic. Certainly, this affect the funding and society perception to the BCI.

7.3. Electrophysiological issues

The current BCI research tries to simplify the operation and data transfer from the brain to the control system by considering it as a communication system. This simplification is not completely true in which the brain and its signals are more complex than any communication system. Therefore, there are two main issues that are related to electrophysiological which are *Non-linearity and Non-stationarity in EEG.*

7.3.1. Non-linearity in EEG

Since the brain itself is a non-linear system, then its signals should be classified as non-linear dynamic signals and utilized by non-linear classification methods. Such consideration will lead to better performance than using linear methods. This is important in multitask brain operations where if two stimuli are used together, the first one might be received faster than the second one. SSVEPs signals for instance are characterized by three frequencies which are identical, harmonic, and subharmonic. So, combining the harmonic components with the identical enhances detecting the stimulus frequency.

7.3.2. Non-stationarity in EEG

The brain by nature is a non-stationary system where its states might change based on some internal mental activities or by some external factors such as electrodes movements. This clearly appears in online sessions as well as during inter-sessions. Certain non-stationary activities degrades the performance of the overall BCI system. Therefore, adaptive techniques and methods are required to adjust the acquired signals.

7.4. Information transfer rate (ITR)

ITR is one of the most used performance measure for BCI systems. According to [69], there are three effective factors for ITR which are target detection accuracy, number of classes, and target detection time.

7.4.1. Target detection accuracy

The target detection accuracy can be improved through enhancing Signal-to-Noise Ratio (SNR) and separability of multiple classes. For reducing the SNR, several methods are used in the preprocessing phase such as trial averaging, Spatial filtering, and eliciting enhanced task-related EEG signals. Trail averaging is used in many applications to average across subjects to enhance the performance of individual BCI. Spatial filtering converts multi-channel EEG data into a low-dimensional spatial subspace eliminating task-irrelevant components. task-related EEG signals is associated with cognitive states such as emotions and attention. These cognitive states could be used to reduce the SNR.

7.4.2. Number of classes

With high ITR, the number of classes will be increased and more complex applications will be developed. Several stimulus coding methods including TDMA, FDMA and CDMA have been adapted for BCI systems [41,62,83]. TDMA, for instance, is used with P300 to code the target stimuli. FDMA and CDMA have been adopted in the VEP-based BCI systems.

7.4.3. Target detection time

Reducing the target detection time is one of the objectives of BCI systems to enhance the ITR. To do so, adaptive methods could be a solution to reduce the target detection time such as ‘dynamic stopping’ method. In addition, machine learning methods based single-trail classifications. Moreover, optimized stimulus presentation by reducing the duration of the ISI between two flashes in stimulus presentation [88].

7.5. Sensors issues

Another BCI challenge is the development of invasive and non-invasive sensors. Unfortunately, electrodes arrays made of silicon, ceramic, or polyimide-based were not practical in brain signal acquisition. Dry electrodes are invited to overcome the disadvantages of the current electrodes. However, dry electrodes with minimum SNR and high ITR are still required.

In addition, BCI sensing technology is not that attractive to many of the researchers due to social acceptance to the science itself and BCI sensors design complexity. The complexity of the brain sensors comes from the limited resolution comes from the captured information, reliability of the sensed signals and their variability, high error rate, and the real time data acquisition. Moreover, human cortex has almost 30,000 neurons/mm^3 in which the distance between these neurons is very small, in a range of μm. Therefore, designing an electrode or a set of sensors to capture these neurons signals poses another sensing technology challenge.

One more issue of the sensing technology comes from the invasive systems where electrodes have to be planted into the subject's brain. It requires the subject to be carefully evaluated and the electrodes positions have to be precisely identified. In addition, sensors materials have to be chosen with extreme caution to avoid their side effect on the subject's brain.

7.6. Real-life applications

Another challenge in BCI is the real-life applications. In other words, for any technology to be advanced, killer applications are required. Therefore, to move the research and the BCI applications out of the labs to the real-life applications, there are some issues need to be tackled. For instance, the cost of the BCI hardware and software plays an important role in developing effective applications in which it allows more researchers and companies to be involved. In addition, robust system performance is expected to encourage developing of killer BCI applications.

Moreover, designing mobile platforms, fatigues, and asynchronous system design are three challenges that hinder developing of real time applications. With mobile platforms including hardware and software, it is expected that with mobile platforms, a rapid progress in the real-life applications are possible. Wireless EEG amplifier and dry electrode are examples on such mobile platforms [22,96,134]. Fatigues are the temporary inability to maintain optimal cognitive performance. Reducing such fatigues is important for the system to remain practical. The solution for fatigues reduction is by optimizing the physical properties of the stimulus by, for example, different types stimulus patterns such as high-frequency stimulus [96], high duty-cycle stimulus [103], and image-based stimulus [50]. Asynchronous system design allows the subject to communicate with BCI system based on its own time and comfortability. Designing such systems is not an easy task where detecting idle states is a challenge by itself. Some of the systems try to simplify such issue by displaying a button to the subject to activate/deactivate the stimuli [12][46].

7.7. Ethical and security

With growing of some of BCI applications, two other issues came to floor which are ethical and security. It is well known that federal law protects medical information against deceptive practices. However, few rules govern access to BCI information. We believe that privacy is a concern of engineers and neuroscientists, lawyers and ethicists, government and industry. Therefore, standards and regulations are needed to mitigate the privacy and ethical issues.

Another issue which is the security since the BCI applications are moving towards ubiquities applications. We can imagine a hacking application that could be developed for accessing neuroscience results. Private information might be extracted targeting users’ memories, prejudices, religious and political beliefs. In fact, there is an ongoing research on both privacy and security of BCI including [31] [100][31].

7.8. Agreement of the future directions of BCI

There is a little agreement among the key players of BCI. It is obvious that there are many players are currently involved in the field of BCI including companies, engineers, researchers, policy makers, decision makers, and patients. However, it is difficult to identify a common vision among all on the future directions and polices of BCI. This challenge may affect the progress of the BCI.

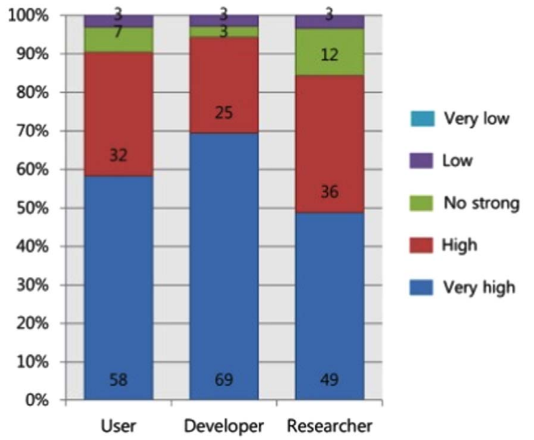


Fig. 17. Respondents' evaluations of the influence of BCI [84].

8. Future directions and recommendations for enhancing the results of the current systems

The future directions of BCI can be viewed in terms of three main key players which are user, industry, and research [21]. The vision to the BCI is to have seamless ubiquities applications connecting various brain signals. In addition, integrating brain applications with games, health, and education is long term vision of BCI. Rehabilitation is expected to benefit from BCI-based treatments in the coming years. Plug and play devices are expected to be available in the next few years. Using decoded brain signals, it is expected to have treatments for some disease such as for epilepsy, depression, Parkinson's disease, and schizophrenia. The following are our expectation for the near future of BCI.

8.1. User centric applications

It is expected to move the BCI application from device centric to user centric in which the users' needs, wants, and limitations will be taking into consideration in all of the BCI design and implementation process [45]. The design and implementation of a BCI application should take into consideration the validity of the assumptions about users' behavior and reactions in all stages. Current applications focus only on the utilization of the devices without putting the user into focus. Long time training for example and the effort that the user has to do is not practical. Therefore, putting the needs of the users as a center of the design and implementation process of the BCI applications is expected to lead to better and more effective applications. In fact, the users' acceptance problem to the BCI will be almost solved. It also encourages more research into the BCI issues due to social acceptance to the BCI application which it is one of the issues of the BCI systems.

8.2. Smart electrodes

Currently we have different types of electrodes including dry electrodes where some amplifiers are used as well as wireless electrodes. With the advances in sensing technologies, it is expected in the next few years to see smart electrodes involving computational intelligence techniques that can adapt automatically based on the users' behaviors and positions. Different kinds of filters are expected to be included in the electrodes with multi-channel acquisition. In addition, wide range wireless electrodes will be an adds-on to the current electrodes. It is also expected to have very tiny electrodes with high capabilities in capturing a very sensitive brain signals. We believe that including the field of Artificial Intelligence into the sensing technologies will lead to very advanced sensors with high sensing capabilities.

8.3. Users' confidence

The users' confidence means that the users believe in the BCI and its future. Looking at the confidence chart presented in Fig. 17 [84] where a survey has been done for users about BCI future, as can be seen, the users expectation is very high. As stated before, users are one of the key players in BCI. Therefore, it is expected that more users will be willing to participate in BCI activities and applications.

8.4. Beyond medical applications

Nowadays, BCI applications are going further than medical applications. We can see some of the applications that are related to spelling control and prototypes for gaming. In addition, a survey done by Jan et al. [120] indicates that there are some BCI applications are directed beyond the medical applications including control, training and education, gaming and entertainment, and safety and security. Therefore, it is expected to have more advanced BCI non-medical applications in the next few years. In fact, BCI killer applications are required to be the force towards standardization and enhancement of the current systems.

8.5. Cloudy BCI

Currently, we are in the era of cloud computing and most of the computer applications especially the ones with heavy computation are moving towards cloud computing. Although, the BCI computation still light, but with heavy applications such as games, it is expected to have heavy load and processing for effective application. Therefore, moving BCI to cloud is not that far from reality. As a proof of concept, Maria et al. in [89] designed an EEG based system on a mobile cloud. The cloud has been used for long term data analysis. Therefore, relating the BCI with the new technology such as cloud will make it very attractive to the researchers. In addition, BCI cloud play an essential role in Internet of Things (IoT) including people with disabilities into the new era of IoT.

8.6. BCI in a box

One of the leading factors in any field is the readymade applications where the user/researcher can use with minimum effort. This is one of the directions that we expect in the next few years to have great impact on the field of BCI research. Few of the readymade applications are now commercially sold such as EMOTIV [34]. However, it is far from the BCI community expectations. So, we propose to the reader is to simplify the BCI systems to be easy to install and use by putting everything in a box. Certainly, many applications will be developed based on this type of systems.

9. Conclusion

The field of BCI is one of the important fields that deals with brain activities. It is expected that BCI applications will have great effect on our daily life. To extend the work in this field, this paper is one of the three survey papers towards simplifying the field and providing state-of-the-art to the reader. This paper focuses on defining the BCI. It also classifies and compares the brain signals. In addition, it surveys the current BCI hardware and software. Moreover, it explains the current challenges of the field. Nevertheless, it draws some road maps for the future of BCI. The second paper will be an extensive survey on the current techniques and algorithms used for BCI while the third paper will discuss the current applications of BCI and their impacts on the society.

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