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REVIEW

Brain computer interfacing: Applications and challenges

Sarah N. Abdulkader *, Ayman Atia, Mostafa-Sami M. Mostafa

HCI-LAB, Department of Computer Science, Faculty of Computers and Information, Helwan University, Cairo, Egypt

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Abstract Brain computer interface technology represents a highly growing field of research with application systems. Its contributions in medical fields range from prevention to neuronal rehabilitation for serious injuries. Mind reading and remote communication have their unique fingerprint in numerous fields such as educational, self-regulation, production, marketing, security as well as games and entertainment. It creates a mutual understanding between users and the surrounding systems. This paper shows the application areas that could benefit from brain waves in facilitating or achieving their goals. We also discuss major usability and technical challenges that face brain signals utilization in various components of BCI system. Different solutions that aim to limit and decrease their effects have also been reviewed.

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* Corresponding author.
E-mail addresses: nabil.sarah@gmail.com (S.N. Abdulkader), drayman@fci.helwan.edu.eg (A. Atia), mostafa.sami@fci.helwan.edu.eg (M.-S.M. Mostafa).

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1. Introduction

Brain Computer Interface (BCI) technology is a powerful communication tool between users and systems. It does not require any external devices or muscle intervention to issue commands and complete the interaction [1]. The research community has initially developed BCIs with biomedical applications in mind, leading to the generation of assistive devices [2]. They have facilitated restoring the movement ability for physically challenged or locked-in users and replacing lost motor functionality [3]. The promising future predicted for BCI has encouraged research community to study the involvement of BCI in the life of non-paralyzed humans through medical applications.

However, the scope of research has been further widened to include non-medical applications. More recent studies have targeted normal individuals by exploring the use of BCIs as a novel input device and investigating the generation of hands-free applications [1,2]. The use of BCI interfaces for healthy users has been subject to some doubts as discussed in [4]. The problem of poor information transfer rate (ITR) of BCIs and its effect on reducing the commands user can give has been addressed as one of those issues. It has been claimed that this problem restricts BCI utilization for locked-in persons as it will not be able to keep up with ordinary communication ways or even existing human computer interfaces.

On the other hand, some of BCI advantages for able-bodied users have been enlightened in [5]. BCI could be helpful especially for safety applications or applications where it is instantaneously difficult to move and the response time is crucial. Besides they can also be used to increase the accuracy of the HCI systems, resulting in BCI contribution in various fields such as industry, educational, advertising, entertainment, and smart transportation. Despite its expected success, Brain computer interfacing needs to overcome technical difficulties as well as challenges posed by user acceptance to deal with such newly discovered technology.

The next sections will provide more information about BCI functions and associated applications. Various methods for acquiring brain signals are then explored along with the electrical changes reflected in the recorded brain waves. This paper will also discuss the issues facing BCI systems and some found solutions to their consequences in details.

2. BCI functions

Applications of Brain Computer Interface base its functionality on either observing the user state or allowing the user to deliver his\her ideas. BCI system records the brain waves and sends them to the computer system to complete the intended task. The transmitted waves are therefor used to express an idea or control an object.

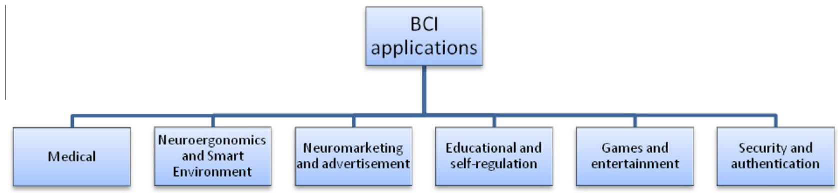

Figure 1 BCI application fields.

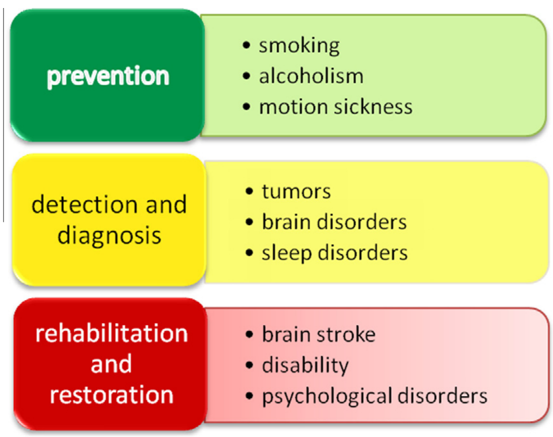

Figure 2 Usage of BCI in medical field phases.

The following subsections give a brief introduction to those BCI operations.

2.1. Communication and control

Brain computer interface (BCI) systems build a communication bridge between human brain and the external world eliminating the need for typical information delivery methods. They manage the sending of messages from human brains and decoding their silent thoughts. Thus they can help handicapped people to tell and write down their opinions and ideas via variety of methods such as in spelling applications [6], semantic categorization [7], or silent speech communication [8].

BCIs can also facilitate hands-free applications bringing the ease and comfort to human beings through mind-controlling of machines. They only require incorporating brain signals in order to accomplish a set of commands and no muscles intervention is needed [9,10,3]. BCI assistive robots can offer support for disabled users in daily and professional life, increasing their cooperation in building their community [11].

2.2. User state monitoring

Early BCI applications have targeted disabled users who have mobility or speaking issues. Their aim was to provide an alternative communication channel for those users. But later on, BCI enters the world of healthy people as well. It works as a physiological measuring tool that retrieves and uses information about an individual's emotional, cognitive or affectiveness state. The target of brain signals utilization has been extended beyond controlling some object or offering a substitution for specific functions, in what is called passive BCI [12]. According to Garcia-Molina et al. [13], the precise awareness of the current emotional or cognitive state can affect the recognition of the mental task associated with the recorded brain waves.

Another beneficial employment of such information is to determine the state itself and use that knowledge for enhancing various BCI systems. BCI User state monitoring function is considered a helpful hand in Human Computer Interfaces and adapts them according to the estimated user emotional or cognitive state [14,13]. It participates in a shared control environment and decides the best type of control that might be used in certain situations.

It also contributes in the development of smart environments and emotion controlling applications [4,15]. Working conditions' assessment and educational methods' evaluation are examples of other fields that could benefit from measuring user's brain state [16,17]. The next section highlights some applications that exploit brain computer interface.

3. BCI applications

Brain computer interfaces have contributed in various fields of research. As briefed in Fig. 1, they are involved in medical, neuroergonomics and smart environment, neuromarketing and advertisement, educational and self-regulation, games and entertainment, and Security and authentication fields.

3.1. Medical applications

Healthcare field has a variety of applications that could take advantage of brain signals in all associated phases including prevention, detection, diagnosis, rehabilitation and restoration as shown in Fig. 2.

3.1.1. Prevention

Various consciousness level determination systems along with their brain-related studies have been developed. The attentiveness influences of smoking and alcohol on brain waves have been enlightened in [18–22]. The importance of such studies for medical prevention lies in the possible loss of function and decrease of alertness level resulting from smoking and\or alcohol drinking, while the authors of [23] have investigated the most responding brain parts to alcoholism.

Traffic accidents are considered the main cause for death or some serious injuries as claimed in [24,25]. Analyzing their causes for later prevention has been a concern for researches in various fields. Thus concentration level for those suffer from motion sickness, especially drivers, has been studied. Motion sickness, which occurs as a result of sending conflicted sensory information generated from body, inner ear and eye to the brain, is usually happening on moving transportation media.

It can cause traffic accidents as it declines in a person's ability to maintain self-control. And according to [26,27], a prediction of motion sickness could contribute in a driver-state monitoring and alertness system using a set of EEG power indicators. Its accompanying EEG signals from different five brain regions have been examined in [26]. The human hearing level, as part of sensory information gathering process, has been measured via auditory evoked potential BCI-based system in [28]. In another study [29], a virtual reality-based motion-sickness platform has been designed with a 32-channel EEG system and a joystick which is used to report the motion sickness level (MSL) in real time experiments. Consciousness level monitoring via brain waves has been expanded to include not only drivers but also stayed-alone sick people as suggested in [30].

3.1.2. Detection and diagnosis

Mental state monitoring function of BCI systems has also contributed in forecasting and detecting health issues such as abnormal brain structure (such as brain tumor), Seizure disorder (such as epilepsy), Sleep disorder (such as narcolepsy), and brain swelling (such as encephalitis). Tumor, which is generated from uncontrolled self-dividing of cells, could be discovered using EEG as a cheap secondary alternative for MRI and CT-SCAN. EEG-based Brain tumors detection systems have been the main subject of the researches in [31,32], while [33] has been concerned with identifying breast cancer using EEG signals.

Sharanreddy and Kulkarni have proposed a system in [34] that recognizes EEG abnormalities associated with brain tumors and epilepsy seizures. Early detection of epilepsy seizure, one of the most common neurological disorders, and controlling its effects are presented in [35,36].

Dyslexia, one of the brain disorders, can be diagnosed by measuring brain behavior as described in [37]. It influences the reading and learning ability making its discovery at an early stage saves the children from self-esteem and self-confidence issues and allows them to gain their basic skills and knowledge. Sleep disorders can be detected with BCI assistance as well as claimed in [38,39]. They demonstrate some methods for deploying EEG signals in noticing Idiopathic rapid eye-movement (REM) sleep behavior disorder (iRBD) as iRBD has been found to be a strong early predictor for Parkinson's disease (PD).

Wei et al. [40] have experimentally confirmed the relationship between human gait cycle and EEG signals through the use of plantar pressure measuring system. This relationship helps predicting diseases such as dyskinesia, peripheral neuropathy, and musculoskeletal disease.

3.1.3. Rehabilitation and restoration

Mobility rehabilitation is a form of physical rehabilitation used with patients who have mobility issues, to restore their lost functions and regain previous levels of mobility or at least help them adapt to their acquired disabilities [41]. People suffer from serious injuries or events such as strokes may also be able to fully recover.

Stroke is a condition in which the brain cells suddenly die because of the lack of oxygen. It can be caused by an obstruction in the blood flow. The patient may suddenly lose the ability to speak, there may be memory problems, or one side of the body can become paralyzed. Disabilities and brain strokes have been subject for many studies interested in solutions involving brain signals. It has been pointed out in [42] that brain structures associated with stroke injuries could be reorganized and the damaged motor functions could be restored via neuroplasticity [43,44].

Mobile robots can be used to help locked-in people completing daily life activities as discussed in [3,45]. For patients who cannot recover previous levels of mobility or communication, BCI based prosthetic limbs, also called neuroprosthetic devices, can be used to regain normal functionality [46–49].

Various reality approaches for BCI-based rehabilitation training such as real, virtual, and augmented approaches have been presented. Real rehabilitation approach exploits brain signals generated from healthy people along with the decoded kinematic parameters [50]. It assists stroke patients modifying their thinking behavior to resemble the recorded signals and retraining healthy areas of the brain to take over. Another approach for rehabilitation involves virtual reality through monitoring and controlling avatar movement generated from the outgoing brain waves [51]. Augmented reality represents the third approach in the reality based BCI treatment such as augmented mirror box system which appears as a development for Mirror Box Therapy (MBT). MBT uses brain signals generated from symmetrical movements that incorporate injured and healthy limbs [52].

Motor imagery signals also contribute in neurofeedback systems for poststroke motor therapy [53,54]. Classification of and Comparing the results of motor imageries and actions are shown in [55,56].

3.2. Neuroergonomics and smart environment

As previously mentioned, deploying brain signals is not exclusive to the medical field. Smart environments such as smart houses, workplaces or transportations could also exploit brain computer interfaces in offering further safety, luxury and physiological control to humans' daily life. They are also expected to witness cooperation between Internet Of Things (IOT) and BCI technologies as stated in [57].

Lin et al. [58,59] have proposed a cognitive controller system called Brain computer interface-based Smart Living Environmental Auto-adjustment Control System (BSLEACS). It monitors user's mental state and adapts the surrounding components accordingly. It has extended its functionality with the involvement of universal plug and play (UPnP) home networking. On the other hand, the surrounding environmental contribution in enhancing BCI based home applications via context awareness has been considered. Navarro et al. [4] have developed such an application that automatically changes the available options accessible by the user according to the current context. Also integration of both healthcare and smart house in gaining non-intrusive mental health care has been an existing approach in brain computer applications as shown in [60].

Brain signals also assist in improving workplace conditions by assessment of an operator's cognitive state [16]. They also analyze the impact of workload mental fatigue and task time on EEG features [61]. Operating room as well represents a candidate place for smart workplace BCI-based application as in

[62]. The system measures the stress level of a surgeon and alert according to the response type.

The field of intelligent transportation has also been benefitted from the cognitive state monitoring BCI function. Driver's behavior has been studied in numerous studies. It has been found that distraction and fatigue are two main sources for driver's inattention, which is considered as a strong cause for most traffic accidents [63]. Various types of measures have contributed in determining the driver's cognitive state [64–66]. Uses of EEG signals for fatigue detection have been widely studied in [67], while [68] has discussed the utilization of workload index to assess the driver's mental state. Several models for distinguishing distracted drivers have been examined in [69]. Kim et al. [70] have presented multimodal context recognition for smart driving system to predict concentration and stress by analyzing both ECG and EEG signals and controlling car speed by concentration value of brain signals.

Alcoholic drivers, as a contributor to road accidents, could also be characterized through the use of EEG signals as mentioned in [71]. [72] has developed an audio-visual virtual environment in order to evaluate and analyze the driving responses along with the associated brain signals. [73] has suggested some driving specific tasks to the simulated driving model and explore the neural dynamics generated, while in [74], kawamura et al. have described the use of multiple stimulation methods when dealing with drowsy drivers to increase their attention level. [24] has investigated the feasibility of using driver's EEG signals to detect emergency conditions such as the sudden appearance of a pedestrian.

3.3. Neuromarketing and advertisement

Marketing field has also been an interest for BCI researches. The research in [75] has explained the benefits of using EEG evaluation for TV advertisements related to both commercial and political fields. BCI based assessment measures the generated attention accompanying watching activity [76]. On the other hand, the researchers of [77] have considered the impact of another cognitive function in neuromarketing field. They have been interested in estimating the memorization of TV advertisements thus providing another method for advertising evaluation.

3.4. Educational and self-regulation

Neurofeedback is a promising approach for enhancing brain performance via targeting human brain activity modulation. It invades the educational systems, which utilizes brain electrical signals to determine the degree of clearness of studied information. Personalized interaction to each learner is established according to the resultant response experienced [17].

Learning to self-regulate through noninvasive BCI has also been studied. It provides a mean for improving cognitive therapeutic approaches. The research in [78] has analyzed the feasibility fMRI for the emotional regulation, while [79] has suggested the use of hybrid rtfMRI–EEG BCI to fight the depression feeling as well as other neuropsychiatric disorders through training sessions. Furthermore, EEG based emotional intelligence has been applied in sport competitions to control the accompanying stress as examined in [80]. In [43], BCI technology has been elaborated in self-regulation and skill learning via functional Magnetic Resonance Imaging (fMRI) neurofeedback.

3.5. Games and entertainment

Entertainment and gaming applications have opened the market for nonmedical brain computer interfaces. Various games are presented like in [81] where helicopters are made to fly to any point in either a 2D or 3D virtual world.

Combining the features of existing games with brain controlling capabilities has been subject to many researches such as [82] which tend to provide a multi-brain entertainment experience. The video game is called BrainArena. The players can join a collaborative or competitive football game by means of two BCIs. They can score goals by imagining left or right hand movements.

On the other hand, some EEG serious games have been employed for emotional control and/or neuroprosthetic rehabilitation. They are containing either a new game idea or a modified one. In [5], Tan and Nijholt have described Brainball game which intends to drop the stress level. The users can only move the ball by relaxing; thus, the calmer player is more likely to be the winner and thus they would learn to control their stress while being amused.

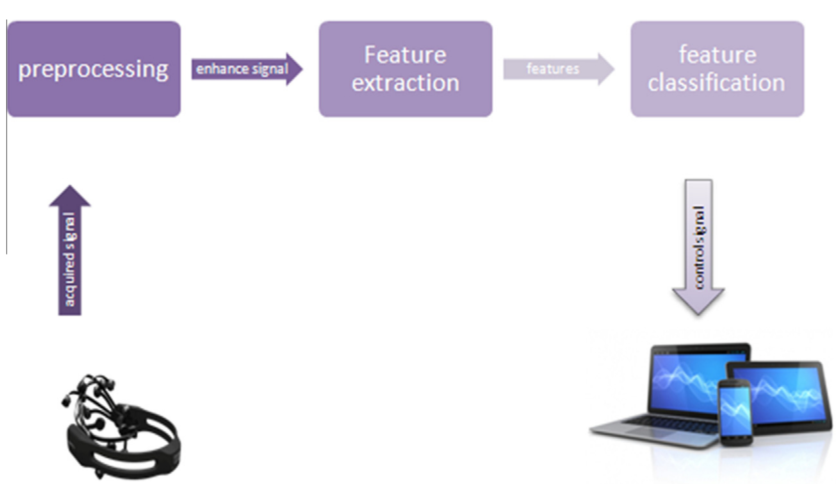

Figure 3 BCI system.

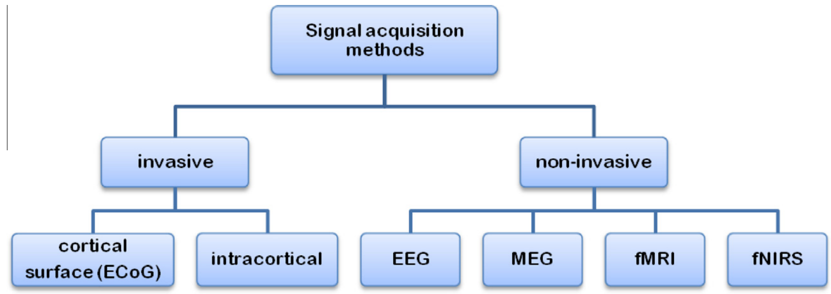

Figure 4 Signal acquisition methods.

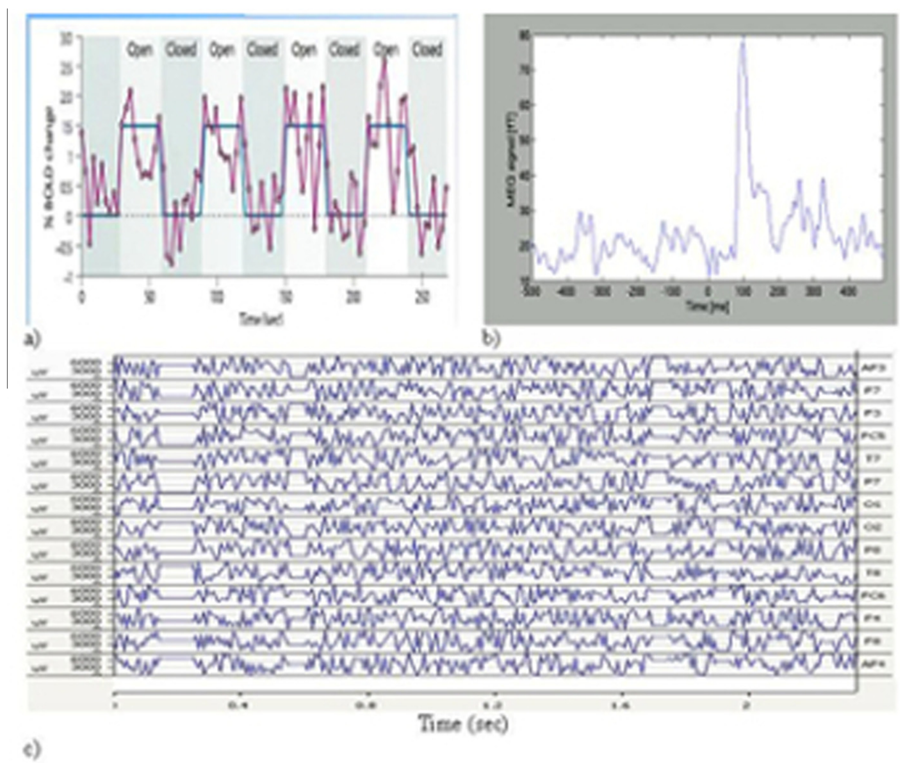

Figure 5 Examples of different types of recorded signals: (a) blood-oxygen-level-dependent (BOLD) change, (b) magnetic signals and (c) electrical signals.

3.6. Security and authentication

Security systems involve knowledge based, object based and/or biometrics based authentication. They have shown to be vulnerable to several drawbacks such as simple insecure password, shoulder surfing, theft crime, and cancelable biometrics [83]. Cognitive Biometrics or electrophysiology, where only modalities using biosignals (such as brain signals) are used as sources of identity information, gives a solution for those vulnerabilities [84,85]. The motivation behind exploring the feasibility of electrophysiology is that biosignals cannot be casually acquired by external observers. They also can be of great value for disabled patients or users missing the associated physical trait [86]. This makes such signals difficult to synthesize and therefore improves the resistance of biometric systems to spoofing attacks. Besides electroencephalogram (EEG), as a biometric modality, could be used to send covert warning when the authorized user is under external forcing conditions, as implemented in [87].

Several researches have considered authenticating the EEG signal generated from driving behavior as part of smart driving systems. In [88,89], the authors have used a simplified driving simulator with mental-tasked condition to verify driver's identity on demand. Unconscious driver authentication has taken place in [90].

4. BCI system components

As shown in Fig. 3, BCI system consists of four basic components. They include signal acquisition, signal preprocessing, feature extraction, and classification. Signal acquisition component, described in details in the following section, is

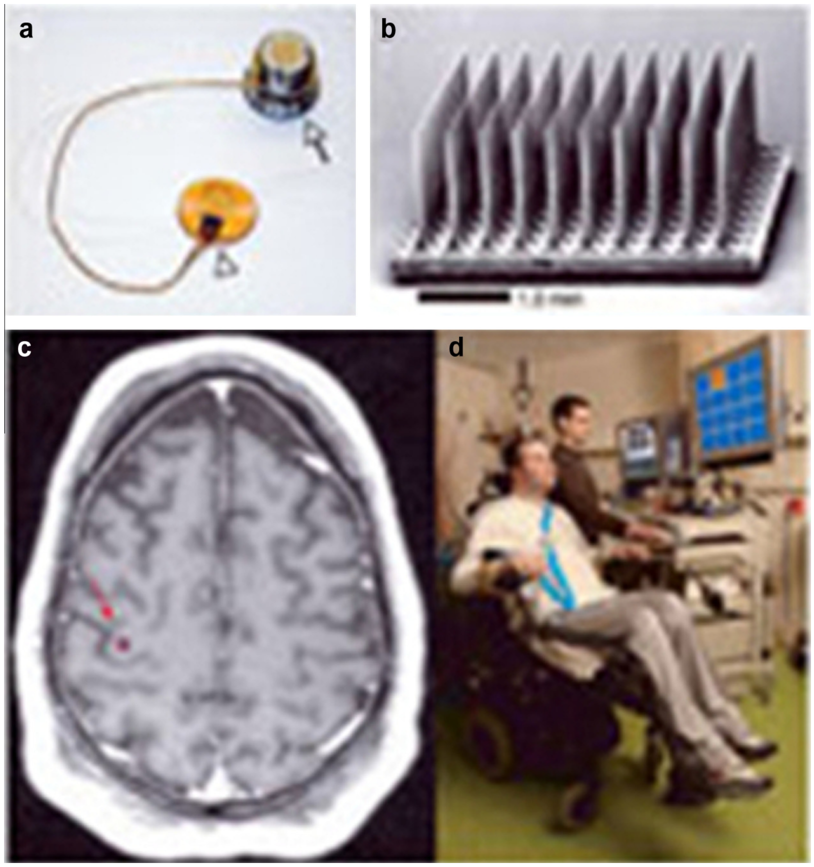

Figure 6 Intracortical acquistion.

responsible for recording the brain waves and sending them to the preprocessing component for signal enhancement and noise reduction. Feature extraction component generates the discriminative characteristics for the improved signal, decreasing the size of the data applied to the classification component. Classifiers are translating the produced features into device commands [3,91].

5. Signal acquisition

Measuring brain generated oscillations is one of the main components in any BCI based system. It reflects the voluntary neural actions generated by user's current activity. Various methods for signal acquisition have been studied. It is the BCI application and the category of its intended users that decides the proper signal acquisition method and its measured phenomena.

As shown in Fig. 4, there are two general classes of brain acquisition methods: invasive and non-invasive methods. In invasive technology, electrodes are neurosurgically implanted either inside the user's brain or over the surface of the brain, while in non-invasive technologies, the brain activity is measured using external sensors [5]. Examples of acquired signals are presented in Fig. 5. Fig. 5.a [92] presents the blood-oxygen-level-dependent (BOLD) changes. Fig. 5.b [93], shows magnetic signals generated from the brain while electrical brain signals are recorded in Fig. 5.c.

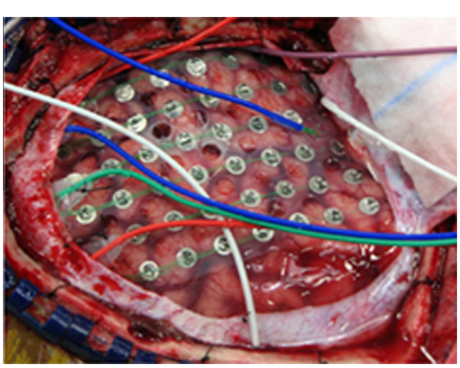

Figure 7 ECoG acquisition.

5.1. Invasive techniques

Invasive recording methods implant electrodes under the scalp. They measure the neural activity of the brain either intracortically from within the motor cortex or on the cortical surface (electrocorticography (ECoG)). Their greatest advantage is that they provide high temporal and spatial resolution, increasing the quality of the obtained signal and its signal to noise ratio.

However, these techniques suffer from a lot of issues. Aside from Usability issues rising from the involvement of surgical procedure, problems related to the system's output have occurred. The small size of the monitored brain regions by those implants is considered one of them. Once implanted, they cannot be shifted to measure brain activity in another area. Besides, the body adaptation to the new object, which may fail, can cause medical complications. Problems regarding the stability of implants and protection from infection can arise as well. Thus the usage of invasive recording in real world has been usually restricted to the BCI based medical applications for a few disabled users [94,5].

According to [95], the invasive systems have mostly been tried in BCI systems' experiments that use monkeys. A few patients with tetraplegia have used implanted electrodes. The next subsection provides more details about these invasive methods.

5.1.1. Intracortical

Intracortical acquisition technique represents the most invasive method shown in Fig. 6 [96]. It is planted under the cortex surface of the brain. It can be achieved using single electrode, or array of electrodes that measure the action signals out of individual neurons. Electrode tips are placed very close to the signal source and the arrays have to be stable over a long period of time. Due to its relatively high spatial resolution, its usage in source localization problem is extensively recommended. But intracortical acquisition could encounter long term signal variability. This could happen as a result of neuronal cell death or increased tissue resistance. Besides, if the system involves a stimulus to activate the disabled limb, this additional stimulus might also generate a significant noise effect [95].

Monkeys and rats have been involved deeply in BCI research studies that employ intracortical invasive acquisition. Movement has been analyzed with animals using implanted electrodes. Monkeys have learnt first to move a cursor into eight targets located at the corners of an imaginary cube in a research aiming to minimize the number of used electrodes. The extracted information has helped in the estimation of the movement intention and has been used to train an adaptive movement prediction algorithm. Monkeys have been used to move a brain-controlled robot arm in virtual reality. Researchers have also succeeded in assisting them to eat with a real robot arm [94].

Figure 8 MEG acquisition.

Figure 9 fMRI acquisition.

Studies using invasive recording techniques with human subjects have been limited to some severely disabled peoples. Amyotrophic lateral sclerosis (ALS) is a progressive neurodegenerative disease that affects nerve cells in the brain and the spinal cord. Motor neurons reach from the brain to the spinal cord and from the spinal cord to the muscles throughout the body. An ALS patient has been able to move a cursor on a computer screen to select presented items after implanting a single electrode into the motor cortex [94]. Another study in [97] has aimed to show that the classification accuracy increases with the gradual rising of the number of electrodes. On the other hand, several researches concerned with reducing the number of electrodes to decrease the features' size or enhance user's acceptability have taken place in [98–100].

5.1.2. Cortical surface

Electrocorticography (ECoG) is a recording method that brings a less invasive option while at the same time preserves the advantages of invasive approach. It involves implanting electrode grids or strips over the cortex surface through a surgical operation shown in Fig. 7 [101]. It records the electrical activity of neurons at the embracing area [102]. [94] has considered the number of electrodes as measurement for invasiveness degree.

Figure 10 fNIRS acquisition.

Figure 11 EEG acquisition.

ECoG recording is located in the middle between invasiveness accuracy and the safety of non-invasiveness. As a result of its relative closure to signal sources, it offers a higher spatial resolution and signal amplitude than those provided by non-invasive techniques such as EEG. Proposing a better amplitude signal makes it less affected by the noise and artifacts generated from muscle engagement. These advantages make ECoG a good candidate solution for seizure localization problem. Thus it has been used by epilepsy patients before surgery [103].

Researchers have exploited the over-cortex recording in multiple studies concerned with motor tasks and speech process classification. [104] has used ECoG signals for the prediction of kinematic parameters for five-class finger flexion, while [105] has distinguished multiple motor-imagery task pairs such as left versus right hand and finger versus tongue imagery movement with ECoG brain signals for both paralyzed and non-paralyzed epileptic patients. It has been found that non-paralyzed subjects' activities could have been categorized and understood by the system. ECoG has also been very beneficial especially in speech and language processing where animals could not be helpful in assessment of brain signals related to vocal actions and language semantics. The feasibility of decoding semantic information, associated with various pictures categories, has been analyzed in [7]. They have requested the subjects to apply different language related tasks, such as picture naming, on the presented pictures.

5.2. Noninvasive techniques

These recording methods follow the approach that does not require implanting of external objects into subject's brain. Thus it avoids the surgical procedures or permanent device attachment needed by invasive acquisition. Various assessment methods for different types of measured signals such as functional magnetic resonance imaging (fMRI), functional nearinfrared spectroscopy (fNIRS), magnetoencephalography (MEG), and electroencephalogram (EEG) are presented next.

5.2.1. Magnetoencephalography (MEG)

It is a non-invasive method that measures magnetic fields produced by electrical currents occurring naturally in the brain. The magnetic signal outside of the head is currently acquired only using the superconducting quantum interference device (SQUID). MEG signals could interfere with other magnetic signals such as the earth's magnetic field so this recording method requires laboratory configuration with shields and specific equipments [106,95] as shown in Fig. 8 [107]. Despite its portability and cost issues, MEG signals are less distorted by the skull layer compared to electric fields. But this advantage does not lead to huge improvement either in performance or in training times over noninvasive electronic acquiring techniques [95].

5.2.2. Functional magnetic resonance imaging (fMRI)

fMRI detects the changes in blood flow which are related to neural activity in the brain using the device shown in Fig. 9 [108]. Thus it helps mapping activities to the corresponding used brain areas which is known as source localization problem. It depends on the fact that any usage of brain part requires the increase of incoming blood flow. It uses blood-oxygen-level-dependent (BOLD) contrast, which is sensitive to the hemodynamic response [109]. The intensities of BOLD contrast reflect the changes in the deoxyhemoglobin concentration in the brain tissue. Although fMRI temporal resolution is low, it provides a high spatial resolution and captures information from deep parts of the brain that cannot be gathered by electrical or magnetic measuring [95].

5.2.3. Functional near-infrared spectroscopy (fNIRS)

fNIRS is a noninvasive technique that measures blood dynamic in the brain in order to detect the neuronal activity. It uses light in the near-infrared range to determine the blood flow [110]. It has the advantage of providing high spatial resolution signals. But regarding the temporal resolution, fNIRS recording is likely to be less effective than that based on electromagnetic signals. Compared to fMRI, fNIRS is portable as shown in Fig. 10 [111] and less expensive but provides less imaging capabilities. Its advantages present a viable alternative for clinical studies and possibly for practical use [95].

5.2.4. Electroencephalogram (EEG)

Electroencephalography (EEG) is the recording of electrical activity along the scalp through measuring voltage fluctuations accompanying neurotransmission activity within the brain. The electrodes are attached in a cap-like device as shown in Fig. 11 [112]. It has unique usability advantages over other types of brain signal recording that recommend it for commercial use. It is easy to use, portable and inexpensive. EEG recording also provides high temporal resolution. However its signal to noise ratio and spatial resolution represent a limitation compared to other methods.

Several solutions have been provided to enhance EEG spatial resolution issue and improve signal localization. The increased use of electrodes up to 256 has been suggested. An international electrode positioning system has been revealed. It makes the distance between adjacent pair of electrodes to be either 10% or 20% of the scalp diameter [3], according to the assignment demonstrated in Fig. 12 [113]. This configuration has been commonly used across different EEG systems. [114] has reviewed sensors that allow less obtrusiveness and high portability option for extensive market use such as NeuroSky and Emotiv. Another EEG acquiring method is shown in [115]. It presents an unobtrusive in-the-ear EEG recording. It has been tested against on-scalp EEG and proven feasibility. This approach's gain appears in fixing electrode position, comforting user and robustness to electromagnetic interference. A Lot of researches regarding BCI based applications have begun concerning with reducing the number of used electrodes, while maintaining signal to noise ratio.

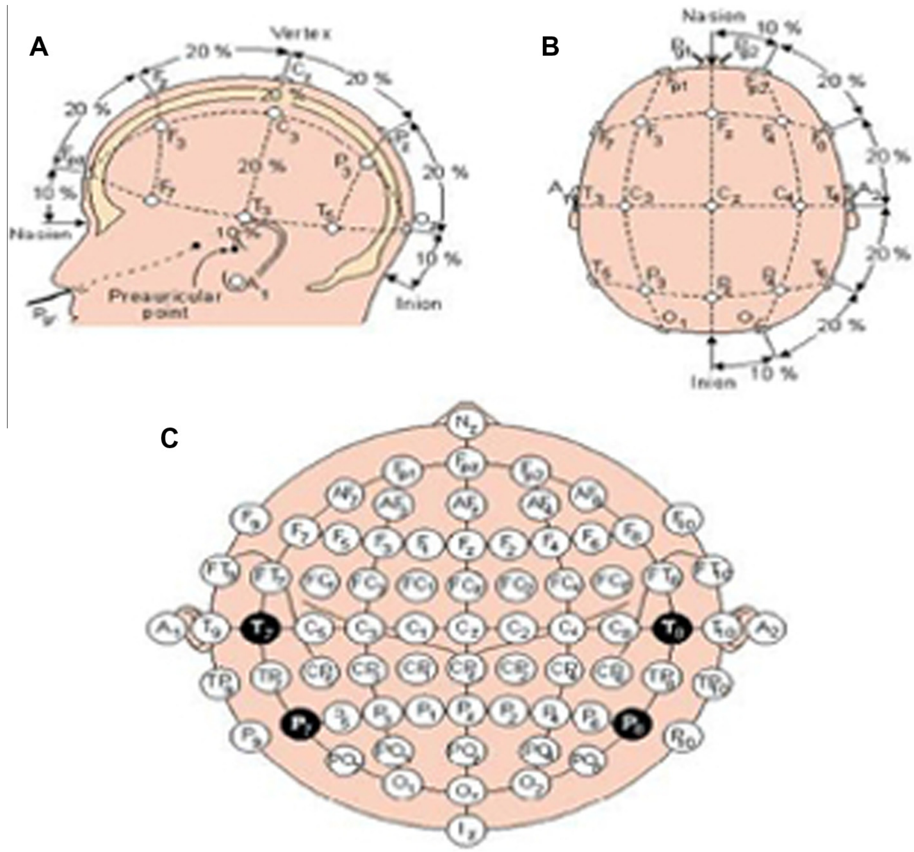

Figure 12 The 10–20 international system.

Table 1 Summary of acquisition method characteristics.

	Cortical surface	Intracortical	EEG	MEG	fMRI	fNIRS
Invasiveness and medical issues	Invasive	Invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive
Spatial resolution	High	Very high	Low	Mediate	High	Mediate
Temporal resolution	High	High	Mediate	Mediate	Low	Low
Portability	Portable	Portable	Portable	Non-portable	Non-portable	Portable
Recorded signal	Electrical	Electrical	Electrical	Magnetic	Metabolic	Metabolic

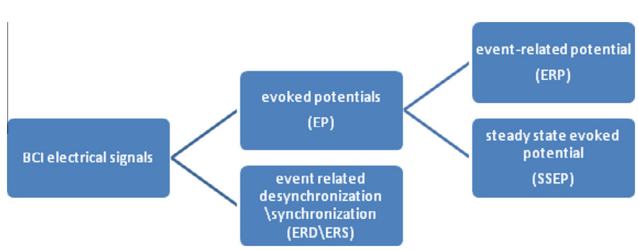

Figure 13 BCI electrical signals.

Further studies concerning EEG signal acquisition method have taken place. Discriminating numerous types of actions are considered such as mental and motor actions [116], knee and ankle contractions [117], Hand grasping [118,119], and imagined writing [120,121]. Analyzing the classification results of motor actions of both paralyzed and non-paralyzed people using EEG and ECoG signals is presented in [105]. Also the presence of speech in the classification of motor imagery has been examined [122] and it has been found that speech existence does not notably affect the accuracy results.

Table 1 [123] gives a summary for brain acquisition methods along with their advantages and disadvantages.

6. BCI electrical signals

Researches considering electrical signals generated from brain activities have revealed two main approaches [2] for studying these signals as shown in Fig. 13. The first approach is concerned with exploring the effect of various triggering conditions on them like in evoked potentials (EP), while the other aimed to detect the brain oscillatory that is not necessarily associated with external stimulation like in event related desynchronization\synchronization (ERD\ERS).

6.1. Evoked potential or evoked response (EP)

It is an electrical response recorded from the nervous system after the presentation of a stimulus. It can be further divided into steady state evoked potential (SSEP) and event-related potential (ERP) [124]. EP components are labeled either exogenous or endogenous [125]. Exogenous components are influenced by physical attributes of stimuli such as intensity, modality, and presentation rate. On the other hand, the psychological or cognitive significance of the stimulus, that is, the psychological or cognitive demands of the situation determines the endogenous components. They are not influenced by the physical attributes of the stimuli. Endogenous components vary in amplitude, latency, and scalp distribution with strategies, expectancies, and other mental activities triggered by the event [126].

Steady State Evoked Potentials (SSEP) [127] are evoked by a stimulus modulated at a fixed frequency and occur as an increase in EEG activity at the stimulation frequency. The stimulation could be either visual as in Steady State Visually Evoked Potentials (SSVEP) [128], auditory as in steady-state auditory evoked potentials (SSAEP) [129] or even somatosensory as in Steady-state somatosensory evoked potential (SSSEP) [130].

Event-related potential (ERP) is elicited by a stimulus change. It is a time-locked deflection on the ongoing brain activity after exposed to the random occurrence of a desired target event. The event could be a sensory stimulus, a cognitive event, or the execution of a motor response. ERPs include somatosensory evoked potential (SSEP), visual evoked potentials (VEP) [131,132], and auditory evoked potentials (AEP) [28].

ERP amplitudes have values that range from less than a microvolt to several microvolts, compared to tens of microvolts for EEG, millivolts for EMG, and often close to a volt for ECG. Different methods such as sampling, averaging, filtering and eye-artifact removal are proposed to isolate the ERP signal buried in the EEG recorded specifically during the brain's response to any internal or external events.

The components of ERP such as P300, N100 and N400 are described with amplitude and latency. The amplitude is either positive, represented by the letter P, or negative, represented by the letter N, whereas the latency is indicated in terms of milliseconds after the stimuli.

6.2. Event related desynchronization\synchronization (ERD\ERS)

It has been found that changes caused by some events can block or decrease the power of the ongoing EEG signal. They are time-locked to the event but not phase-locked, and thus cannot be extracted by a simple linear method, such as averaging. The decreases or increases of power in given frequency bands can be used to detect these changes. This may be related to the synchrony level of the underlying neuronal populations. The power decrease is called event-related desynchronization or ERD while the power increased is called event-related synchronization (ERS) [133]. Although the ERD\ERS BCI systems do not need external stimulation, they require extensive training that may take many weeks, their performance is quite variable between users and their accuracy is not high. They can be induced by performing mental tasks, such as motor imagery, mental arithmetic, or mental rotation.

7. Challenges and proposed solutions

Establishing the communication interface using brain signals has faced a lot of challenges. They can be categorized as technical and usability. Technical challenges are concerned with the system obstacles specially those regarding EEG features characteristics. Usability challenges describe the limitations affecting the level of human acceptance [134].

7.1. Challenges

7.1.1. Usability challenges

They express the limitations facing the user acceptance of BCI technology utilization [1]. They include the issues related to the training process necessary for classes' discrimination. Information transfer rate (ITR) is one of the system evaluation metrics that combines both performance and acceptance aspects.

7.1.1.1. Training process. Training the user is a time-consuming activity either in guiding the user through the process or in the number of recorded sessions. It takes place either in preliminary phase or in the classifier calibration phase [135]. The user is taught to deal with the system as well as to control his\her brain feedback signals in the preliminary phase, while in the calibration phase, trained subject's signal has been used to learn the used classifier.

One of the commonly investigated solutions to this time-consumption problem is to employ single trial instead of multi-trial analysis, which is used for enhancing signal to noise ration [133], and placing the burden of small training size on subsequent BCI system components to handle. Various Adaptive and zero training classifiers have been examined as solutions as mentioned in [126].

7.1.1.2. Information transfer rate. It is the widely used evaluation metric for command BCI systems. It depends on the number of choices, the accuracy of target detection, and the average time for a selection. Thus compared to imagery BCI, selective attention strategies achieve higher ITR as their offered choices are larger [5].

7.1.2. Technical challenges

They are issues related to the recorded electrophysiological properties of the brain signals which include non-linearity, non-stationarity and noise, small training sets and the accompanying dimensionality curse.

7.1.2.1. Non-linearity. The brain is a highly complex nonlinear system in which chaotic behavior of neural ensembles can be detected. Thus EEG signals can be better characterized by nonlinear dynamic methods than linear methods.

7.1.2.2. Nonstationarity and noise. Nonstationarity attribute of electrophysiological brain signals represents a major issue in developing a BCI system [2,136]. It originates a continuous change of the used signals over time either between or within the recording sessions. The mental and emotional state

Table 2 Examples of BCI systems.

Application (and/or) stimulation type	Preprocessing	Feature extraction	Classifier	Results (%)
Subjects identification with imagined speech [142]	Autoregressive coefficients (AR)		SVM	99.76
Subjects identification with VEPs [142]	Autoregressive coefficients (AR)		SVM	98.96
Subjects identification with imagined speech [142]	Autoregressive coefficients (AR)		KNN	99.41
Person identification [143,144]	Autoregressive coefficients (AR) + Power Spectrum Density (PSD)		KNN + Fisher's linear discriminant analysis(FDA)	97.5
	Autoregressive coefficients (AR) + Power Spectrum Density (PSD)		KNN	70.7
	Autoregressive coefficients (AR) + Power Spectrum Density (PSD)		SVM	79.6
Effect of image stimulus type on neural control of a smart TV [145]	Bandpass filtering		SVM	95.1
Effect of video stimulus type on neural control of a smart TV [145]	Bandpass filtering		SVM	93.3
Classification of Go/NoGo tasks [146]	Bandpass filtering	Wavelet transform and Short Time Fourier Transform (STFT)	SVM	91
Recognize familiar objects [147]	Independent component analysis (ICA)		SVM	87
Detecting reading intention [148]	Bandpass filtering	PCA	KNN	86.49
BCI arousal detection [149]	Band pass filtering	Asymmetric spatial pattern (ASP)	KNN	82.25
	Band pass filtering	common spatial pattern (CSP)	KNN	76.98
	Band pass filtering	Asymmetric features (AF)	KNN	62.52
BCI arousal detection [149]	Band pass filtering	Asymmetric spatial pattern (ASP)	SVM	82.03
	Band pass filtering	Common spatial pattern (CSP)	SVM	77.72
	Band pass filtering	Asymmetric features (AF)	SVM	69.42
Choice/no choice task [150]	Bandpass filtering	CSP	LDA	80
Imagined movement of left and right hand [151]	Stationary Subspace Analysis (SSA)	CSP	LDA	79.9
Moving sound P300 speller [6]	Bandpass filter		SVM	71.4
	Bandpass filter		LDA	28.6
Motor imagery classification [152]	Bandpass filtering	CSP + Common Spatial Patterns Patches (CSPP)	LDA	70
Detect emergency situations from driver's mental states [24]	Power-line notch filter + Bandpass filtering	Mean power spectrum	LDA	70
Intended movement direction [153]	ICA	Canonical correlation analysis (CCA) + EEG spectral power modulations in alpha and theta bands	SVM	69.7
	ICA	Canonical correlation analysis (CCA)	SVM	65.6
	ICA	EEG spectral power modulations in alpha and theta bands	SVM	65.4
BCI valence detection [149]	Bandpass filtering	Asymmetric spatial pattern (ASP)	KNN	66.51
	Band pass filtering	Asymmetric features (AF)	KNN	62.01
	Band pass filtering	Common spatial pattern (CSP)	KNN	58.23
BCI valence detection [149]	Band pass filtering	Asymmetric spatial pattern (ASP)	SVM	65.39
	Band pass filtering	Asymmetric features (AF)	SVM	61.89
	Band pass filtering	Common spatial pattern (CSP)	SVM	57.54
Motor and mental activity discrimination [116]	Low pass filter	Power spectral density (PSD)	SVM	64.18
	Low pass filter	Power spectral density (PSD)	LDA	52.76
Static sound P300 speller [6]	Bandpass filter		SVM	62.9
	Bandpass filter		LDA	20

background through different sessions can contribute in EEG signals variability. Also fatigue and concentration levels are considered part of internal nonstationarity factors. Noise is also a big contributor in the challenges facing the BCI technology and causing the nonstationarity issue. It includes unwanted signals caused by alterations in electrode placement, and environmental noise [106]. A combination of movement artifacts, such as electrical activity produced by skeletal muscles electromyogram (EMG) and signals created by eye movements and blinking Electrooculogram (EOG) [131], is also reflected in the acquired signals resulting in difficulties in distinguishing the underlying pattern.

7.1.2.3. Small training sets. The training sets are relatively small, since the training process is influenced by usability issues. Although heavily training sessions are considered time consuming and demanding for the subjects, they provide the user with necessary experience to deal with the system and learn to control his\her neurophysiological signals. Thus a significant challenge in designing a BCI is to balance the trade-off between the technological complexity of interpreting the user's brain signals and the amount of training needed for successful operation of the interface [124].

7.1.2.4. High dimensionality curse. In BCI systems, the signals are recorded from multiple channels to preserve high spatial accuracy. As the amount of data needed to properly describe different signals increases exponentially with the dimensionality of the vectors, various feature extraction methods have been proposed. They play an important role in identifying distinguishing characteristics. Thus the classifier performance will be affected only by the small number of distinctive traits instead of the whole recorded signals that may contain redundancy.

Generally, it is recommended to use, at least, five to ten times as many training samples per class as the number of dimensions [134]. But this solution cannot be sustained in a highly dimensional environment as the BCI system, causing the expanding of the dimensionality curse [137].

7.2. Proposed solutions

Several solutions have been investigated to confront and limit the influence of the previously mentioned technical issues. They are spread over various BCI system components. The following sections explain some employed methods for improving the performance of BCI based systems.

7.2.1. Noise removal

Preprocessing in either spatial, time or frequency domains has contributed in enhancing the signal caused especially by external factors. Improving the signal to noise ration (SNR) [138] of EEG signals is done by increasing the signal level and/or decreasing the noise level.

A widely used spatial filtering method is Independent Component Analysis (ICA) [139]. ICA accomplishes spatial filtering in an unsupervised manner by decomposing the observed EEG into statistically independent components (ICs). It aims at increasing the SNR of EEG signals via separating task-related EEG components from the task-irrelevant EEG components and the artifactual components.

Temporal based preprocessing can contribute in removing artifacts [140] from the signal using linear combination of the EOG-contaminated EEG signal and the EOG signal recorded using eye movement recording electrodes. The combination factors are determined via linear regression methods. Although it represents the most common technique for removing ocular artifacts from EEG signals, it does not meet the same success with removing EMG signals because of the difficulty of placing muscular detection electrodes.

Frequency-band filtering assists in removing noise and artifact. It can also provide a significant help with handling the internal nonstationarity factors. The task related frequencies can be selected to be used for further analysis in BCI systems. This filtering type does not require extra electrodes to detect the eye or muscle movement. The advantage of using filtering is its simplicity. However the effect for this method degrades if the unrelated signal overlaps or lies in the same frequency band as the signal of interest [131,132].

7.2.2. Separability of multiple classes

Machine learning techniques are employed to translate user's intent into a valid choice. They discriminate and identify the selected class. They have been used, for example, to overcome some limitations associated with small training sets, single trial, and also the variability between sessions and within individual sessions. They also aim to achieve higher performance and accordingly, higher ITR results. Next we demonstrate three different machine learning algorithms such as linear discriminant analysis (LDA), support vector machine (SVM), and k nearest neighbors (KNN).

7.2.2.1. Linear discriminant analysis. LDA is deployed to find the linear combinations of feature vectors which describe the characteristics of the corresponding signal. LDA seeks to separate two or more classes of objects or events representing different classes. It utilizes hyperplanes to accomplish this mission. Separating hyperplane is obtained by searching for the projection that maximizes the distance between the classes' means and minimizes the interclass variance.

This technique has a very low computational requirement and it is simple to use. LDA has been used with success in various types of BCI systems such as motor imagery based BCI, P300 speller, multiclass or asynchronous BCI. But although it generally provides good results due to its immunity to nonstationarity problem, its linearity can cause performance degradation in some situations having complex nonlinear EEG data.

7.2.2.2. Support vector machine. SVM is an algorithm that belongs to a category of classification methods which use supervised learning to separate two different classes of data. It exploits a discriminant hyperplane to identify classes like does LDA. However in SVM case, the selected hyperplane is the one that maximizes the distance from the nearest training points. This optimal hyperplane is described by the vectors which lie on the margin which are called support vectors.

SVM has several advantages. It is known to have good generalization properties, to be insensitive to overtraining and to the curse-of-dimensionality [141]. Finally, SVM shows good performance results in both Evoked potential and ERD/ERS BCI.

7.2.2.3. K nearest neighbors. It is labeled as one of the unsupervised nearest neighbor classifiers in which the feature vector is assigned to its closest class among k neighbors. KNN algorithms' main advantage is simplicity. However their sensitivity to the curse-of-dimensionality is considered the main drawback that affects their performance regarding BCI systems. Thus it can provide good results with efficient feature selection and reduction algorithms.

Some examples for using these classifiers for increasing separability between classes in BCI systems along with the deployed preprocessing and feature extraction methods are shown in Table 2.

8. Conclusion

Brain signals reflect the handled activities and controlling behavior of the brain or the influence of the received information from other body parts either sensing or internal organs. Brain Computer Interfacing provides a channeling facility between brain and external equipment.

BCI applications have attracted the research community. Several studies have been presented in this paper regarding the growing interest in BCI application fields such as medical, organizational, transportation, games and entertainment, and security and authentication fields. It also demonstrates the various devices used for capturing brain signals.

These recording devices are divided into two main categories: invasive and non-invasive. Invasive category, which requires implanting surgery, is usually needed for critical paralyzed situations because of their higher accuracy rates achieved either spatially or temporally. On the other hand, the non-invasive category, as mentioned previously, has been widely spread in other application fields due to its advantages over the invasive one. Other challenges and issues posed as a result of utilizing brain signals have also been discussed along with some solutions offered by different algorithms at various BCI processing components.

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