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Brain Computing Interface - Applications and Challenges

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Abstract:
Brain Computing Interface (BCI) technology is a promising field to reinstate the information to patients suffering from Neurological Disorders. In this paper we will be taking a look at the signal acquisition techniques used in the BCI system, it suggests which technique is best to acquire the brain signals. The pre-processing methods that are used for feature extraction, the filters used to denoise to extract the required information by choosing the right Classifier algorithm. BCI technology has made a great impact on many applications, especially in the medical field by helping patients suffering from locked-in syndrome. It also extant in Neuro-ergonomics, Neuromarketing, Education, Security and authentication. Apart from the applications being benefitted there are many challenges faced in this technology till date. We talk about the Usability, Technical, Ethical and Legal issues faced. How misuse of this system may lead to problems, about the patients' privacy, the difficulty in training the user to use the device and low accuracy obtained due to noise and amplifiers used.

***Key Word**: Brain Computer Interface; Human-Computer Interface; Signal Processing; Feature Extractions; Classification.*

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I. Introduction

In 1970's, research at university of California about Brain Computer Interface (BCI) led to the development of expression BCI. The research on BCI is primarily based on neuroprosthetic applications that helps in restoring injured movements, sight etc. BCI or Mind-Machine Interface (MMI) is a communication pathway which helps to interact with the external devices through brain signals directly. BCI aides disabled people to interact with others just like communication between normal people. It helps in restoring human cognitive and sensory-motor functions. The signals are acquired through amplifiers and different filters, they are processed and then classified using algorithms. This paper gives the description about the basic and functional areas of the brain, various steps involved in BCI such as Signal Acquisition, Signal Preprocessing, Feature Extraction and Classification.

II. Material and Methods

In this paper, we conduct a literature survey by highlighting the details of various steps used in BCI. The processing methods are Signal acquisition, Preprocessing, Feature extraction and Classification. We discuss their applications in various fields. For this literature review, databases like Web of Science and google scholar were searched with keywords such as BCI, disabilities, techniques used for signal acquisition, processing and classification. Different technologies mentioned in the scientific literature in each stage has been reviewed. First, functional areas of brain are examined followed with signal acquisition: invasive and non-invasive methods are discussed. Then we discuss about preprocessing, feature extraction and classification. Lastly, the review provides an overview of various applications of BCI.

Functional areas of brain:
Brain is divided into six areas which perform different functions. The parts are Frontal lobe, Parietal lobe, Temporal lobe, Occipital lobe, Cerebellum and Brainstem.

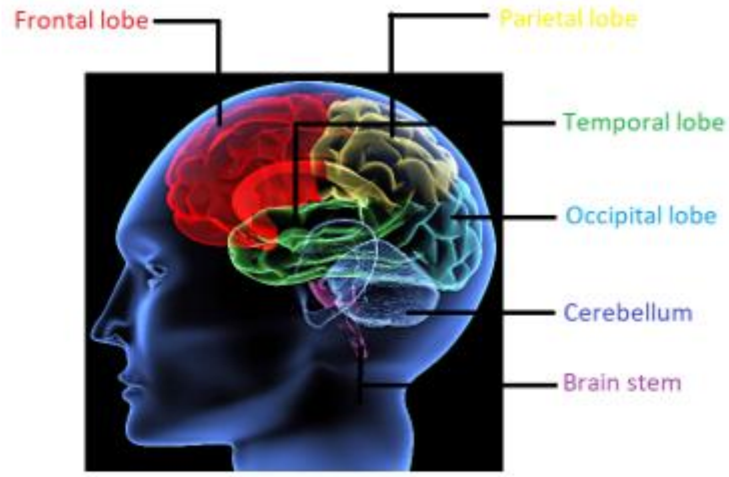

Fig 1: Brain-lobes[59]

Cerebral cortex is made up of Frontal, Parietal, Occipital and Temporal lobe. It is mainly responsible for thinking, voluntary movements, language, reasoning, and perception and has three functional areas – motor, sensory and arbitrary. Most important area to know in this paper is about the motor area which is responsible for voluntary movements.
There are four steps to follow for the brain signals to communicate with the device - signal acquisition, signal processing, feature extraction and classification.

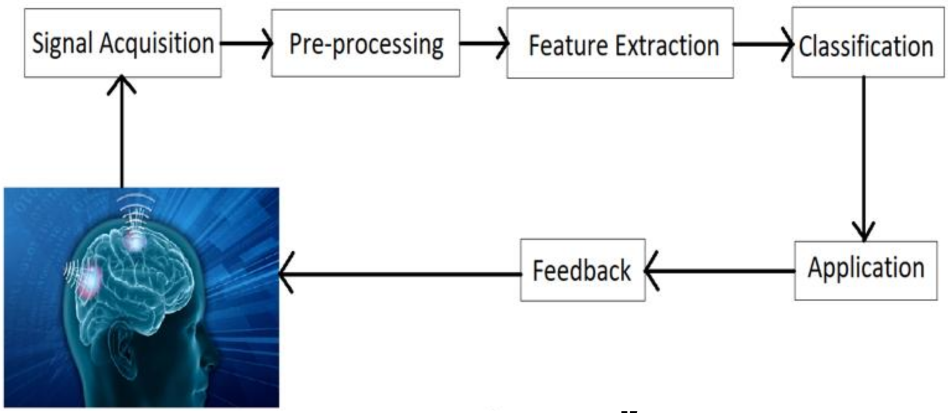

Fig 2: Block diagram of BCI[57]

Signal Acquisition:

Signal acquisition is used to acquire or record the brain signals and are further preprocessed to enhance the signal and reduce the noise. It mainly comprises two methods - invasive and non-invasive techniques. These techniques help in extracting magnetic, electrical or physical indication of brain action. In invasive technique, parameters are obtained by implanting the electrodes in the cortex. In non-invasive technique, these parameters are measured using external sensors.

Invasive methods:

1. Intra-cortical electrode array - To record the brain signals, an electrode or collection of electrodes are placed in the cortex. The electrode is to be positioned near the source and array of electrodes must be stable throughout the recording process. This method is loftier than other invasive techniques due to its high signal-to-noise ratio, large spatial resolution and temporal resolution. As per the research[1], people suffering from tetraplegia were able to control external prosthetic arms. Amyotrophic Lateral Sclerosis (ALS) is a disorder affecting the nerve cells in the brain and the spinal cord. In this paper, authors have explained on how intra-cortical electrode array can be used to shift the cursor and choose items on the monitor. A lot of experiments[2] have been done on monkeys which succeeded to move the cursor and also control robot arms in virtual reality.
2. Electrocorticography (ECoG) - In this method, an electrode grid is implanted over the cortex surface. It is superior to all other invasive methods but less superior than Intracortical electrode arrays as they have high

spatial resolution, signal-to-noise ratio and also bandwidth. It fails to give the same brain activity measurements as intracortical electrode array. Studies have shown that using ECoG provides solutions for seizure problems and reconstruct human limb motion in 3D space[3]. This has also helped tetraplegia patients to operate the cursor on their own and also control upper limb prosthesis[4].

Non-invasive methods:

1. EEG (Electroencephalography) – It records electrical potential by measuring the voltage fluctuations that occur in the brain along the scalp. The electrodes are placed in a wearable device like a cap. EEG is widely used to diagnose strokes, neurological disorders and tumors. When compared to other non-invasive techniques, it has better temporal resolution, but low spatial resolution. There are chances of signals getting corrupted due to the noises generated from the brain such as cephalic, parts of the heart, artifact movements etc. This technique is also used in controlling prosthesis, a robotic arm with high accuracy to perform desired tasks and also moving cursor. In addition, it is used in Meal Assistive robot[5], Exoskeleton control[6], Control of lower limb exoskeleton[7] and Foot Lifter Orthosis.

2. MEG (Magnetoencephalography) – This technique computes the magnetic potential radiated from electric currents occurring inside the brain. SQUID magnetometer is a quantum interference device made of superconductors. Portability is not possible because the brain's magnetic signals can interfere with earth's magnetic field so acquisition has to be carried out in a laboratory.

3. fNIRS (Functional near Infrared Spectroscopy) – This technique detects the brain activity by measuring the change in concentration of HBO (oxyhemoglobin) and HBD (deoxyhemoglobin) in cortex using light in the IR region. It has low temporal resolution but large spatial resolution. It is portable and used in Gait Rehabilitation and Hand rehabilitation with NIRS[8].

4. fMIR (Functional Magnetic Resonance Imaging) - This measure neuronal activity by detecting the variations in blood flow. fMIR detects the changes in deoxy-hemoglobin, concentration resulting in neural metabolism. It has been widely established in clinical applications such as surgical, monitoring treatment results. The challenges include low contrast to noise ratio of blood oxygen level dependent signals, signal dropouts and image distortion.

5. PET (Positron Emission Tomography) – It computes the gamma rays released by a tracer which is radioactive substances such as radiotracers to measure changes in metabolic process and also changes in blood flow. A positron emission topography scan is an imaging test used to detect functioning of tissues and organs.

There are even hybrid variations in acquisition techniques which include the combination of fNIRS and EEG, EEG with EMG and electrooculography (EOG). Table 1 shows different acquisition techniques used in various articles.

Table 1. Overview of Signal Acquisition Techniques:

Acquisition Techniques	Method	Signal recorded	Portability	Spatial resolution	Temporal resolution	Reference
Intracortical electrode array	Invasive	Electrical signal	Portable	Highest	Highest	[9]
ECoG (Electrocorticography)	Invasive	Electrical signal	Portable	High	Mediate	[5]
EEG (Electroencephalography)	Non-Invasive	Electrical signal	Portable	Low	High	[8],[6],[7]
MEG (Magnetoencephalography)	Non-Invasive	Magnetic signal	Non-Portable	Mediate	High	[10]
fMRI (Functional Magnetic Resonance Imaging)	Non-Invasive	Blood flow	Non-Portable	High	Low	[11]
fNIRS (Near Infrared Spectroscopy)	Non-Invasive	Blood flow	Portable	Mediate	Low	[12]
PET (Positron Emission Tomography	Non-Invasive	Blood flow	Portable	High	Low	[13]

Signal pre-processing:
Extraction of information from brain signal is essential for which pre-processing of signals are necessary. The pre-processing has the following steps[58].

a. Referencing: Here, the brain activity is computed using a particular electrode and it is compared with a reference brain voltage. The recommended area must be selected in a way that the brain actions at that area is approximately equal to null. The three types of referencing are:

1. Common reference: This is a widely used technique which uses a same reference area for every electrode. The reference area is located at a greater distance from the electrodes[14]. The action at the reference area effects all electrodes uniformly.
2. Average reference: This technique uses the rule that the activity in the entire brain at each point is equal to zero. Here, the mean of the activity at every electrode obtained from the measurements is subtracted by the mean of the reference15. Subtracted this average produces a dereferenced solution.
3. Current source density (CSD): It is defined as the amount of current change per time flowing through the cortex. The CSD is evaluated by calculating the Laplacian which calculates by taking the sum of the differences between an electrode and its neighbors[16]. But the problem is that this estimation is valid only if the electrodes are in a 2-dimensional plane and uniformly spaced.

b. Temporal filtering: In general, the brain activity contains many unwanted signals. These signals must be removed using appropriate filters. Usually, brain signals will be less than 30Hz. Hence, signals greater than 50Hz must be removed using FIR lowpass filters.

c. Signal enhancement: Once the filtered signals are obtained, they must be enhanced so that they can be used for further applications. The various factors on which they are dependent are the number of electrodes, recording technology and neuro mechanism of the BCI[17]. Some of the enhancement techniques are:

i. Spatial filters: The position and area of the chosen brain signal and the different EEG and non-EEG noise sources decide the spatial filters to be used.

ii. Common Average Referencing (CAR): CAR records from a number of electrodes in a bipolar fashion. Then, the total average Electroencephalography waveform is calculated by taking mean across electrodes and subtracting each result from each electrode[18]. The observed activity is of equal magnitude in the average and individual electrode waveforms. Also, the result of the reference electrode should be removed from each electrode when the common mean waveform is deducted.

iii. Surface Laplacian (SL): It is the second order derivative of the surface potential. Due to its intrinsic spatial high pass filtering characteristics, the high spatial frequency components increase which in turn decreases the volume of conduction effect. Hence, when compared to surface potential, larger spatial resolution is achieved.

iv. Principal component analysis (PCA): It is the linear mapping that converts a number of possibly correlated variables into a small number of uncorrelated variables. The first principal component contains the changeability in the data and the following components contains the remaining variabilities[19].

v. Independent component analysis (ICA): In this case multivariate signals are separated into additive subcomponents by assuming the mutual statistical independence of the non-Gaussian source signals[20]. When the Electroencephalography and the artefacts have approximate amplitudes, ICA is efficient.

vi. Classical automatic methods: There are two types of classical automatic enhancement methods[21].
   a. Rejection methods: It discards corrupted EEG which is either based on automatic or visual detection. The quality of detection depends on correctness.
   b. Subtraction methods: It is based on the assumption that the corrupted Electroencephalography combines the artefact signals generated by the muscles and eyes blink with the original EEG. We can recover the original EEG either by taking the difference of recorded artefact signals and the measured EEG or by applying modern techniques of artefacts rejection.

vii. Common spatial patterns: This method is used to obtain same projection matrix by decomposing distinct categories of EEG datasets taken from a single trial. This common projection matrix increases the difference between the categories. The advantage of this process is that there is no need for prior selection of frequency bands. In some applications, more electrodes are required[22]. This method is used to identify spatial patterns in EEG and changes in the position of electrodes affects classification accuracy.

viii. Common spatial subspace decomposition (CSSD): This method is used to extract signal related components from many various datasets which are responsible for one condition. The spatial factors and corresponding spatial filters are divided into specific and common parts[23]. Finally, the particular signal components are improved using applicable spatial filters and spatial factors.

Feature extraction and methods:

Feature extraction is the process of reducing the number of resources or dimensions in order to obtain critical properties. These methods are used to reduce complexity and increases clarity while processing. The critical properties of brain signal features are unwanted signals and outliers which are the objects that differs from other objects, number of dimensions are high, varying brain signals, non-linear nature of brain signals and non-sufficient training sets. Following are the methods of Feature Extraction:

a. **Band powers:** The distribution of power in electroencephalography in predetermined frequency bands is called band powers. These band powers can be used for feature extraction[24].
b. **Cross correlation between EEG band powers:** By comparing different locations and frequency bands we can obtain the cross-correlation coefficients of the EEG activity[25].
c. **Frequency representation:** The properties of this method are feasibility in application, increased speed of calculation and direct explication of the results[26].
d. **Time frequency representation:** Since brain signals are not linear and stationary, the methods based on Fourier transforms are not efficient for feature extraction since they cannot analyze time varying spectral content[27]. Time-frequency methods decompose the signal into a series of frequency bands, and the instantaneous power is represented by the envelope of oscillatory activity that forms the spatial patterns for an electrode.

The two types of time frequency representation are:

i. **Wavelet based feature extraction algorithm:** Here, the selection of a specific wavelet called ‘mother wavelet’ is used for extraction. This choice can be made simpler by having suitable information about the physiological activity taking place inside the brain[28].
ii. **Empirical mode decomposition:** This method can be used for time-series data which are not linear and non-stationary. It is a data driven approach. It is used to split a signal into a countable number of components of components of high and low frequencies called intrinsic mode functions[29]. The advantage is that the extraction process is not linear, but the recoupling for performing reconstruction is linear.

e. **Hjorth parameters:** These parameters are used to specify the features of an EEG signal[30]. They are measured in time domain. The three parameters are:
   i. **Activity:** It is the process of measuring the average power of the signal. It is usually computed in terms of standard deviation.
   ii. **Mobility:** It is obtained by dividing standard deviation of the slope by the standard deviation of the amplitude. It represents mean frequency of the signal.
   iii. **Complexity:** It can be defined as the total count of standard slopes in the signal during the mean time required for a specific amplitude.
f. **Parametric models:** Are those models which denotes a group of distributions which can be described using a finite number of parameters. These parameters are analyzed together. This module assumes that the time series under analysis to be the output of the model. Some of the parameters used are:
   - Autoregressive parameters (AR)
   - Multivariate AR parameters (MVAR)
   - AR parameters with exogenous input (ARMAX)
   - Adaptive AR parameters (AAR)
g. **Inverse models:** These are one of the promising feature extraction algorithms which computes the activities in the brain volume using only EEG and head models[31]. These models represent the brain as a set of volume elements (voxels).
h. **Specific techniques:** The two types of specific techniques used;
   - Peak picking (PP) method finds a particular pattern based on its maximum value at a region containing a specific cognitive component. It recognizes a P300 component by subtracting the minimum and maximum amplitude in a trial[32].
   - Slow cortical potentials (SCPs) calculation methods: In this method, the slow cortical potentials’ voltage values are taken from the regular electroencephalogram, filtered for specific values, corrected for eye movement artefacts and given as a feedback to the patient via visual or auditory channel[33].

In reality, most of the BCI designs mainly attempt to map the direct relationship between the neural cortical recordings and movements, they do not use a feature-extraction algorithm.

Classification

The signal patterns in the brain are considered to be dynamic stochastic processes because of various biological factors such as lack of attention, a rapid spread of the disease and also due to technical issues which includes amplifier noise and changes in the electrode impedances. Different types of classification algorithms are used to implement BCI systems. Before choosing the right classifier, knowing its properties is very important.
There are four classifier taxonomies in contrast to each other.

a. **Generative/Informative and Discriminative classifiers**:

   Informative classifier finds the likelihood of each class and chooses the best among them. Example- Bayes Quadratic

   Discriminative classifiers discriminate the classes in order to find the best feature vector directly. Example - Support Vector Machine (SVM)

b. **Static and Dynamic classifiers:**

   It is used to classify only a single vector feature and therefore it doesn't take temporal data into consideration. Example - Multilayer perceptron (MP)

   Dynamic classifier, classifies a series of feature vectors and also takes in transient information. Example - Hidden Markov model (HMM), FIR filters multilayer perceptron (FIR-MLP), Tree based neural network (TBNN) etc.

c. **Stable and Unstable classifiers:**

   Performance is not affected by small variations in the training data and they are less complex. Example - Linear Discriminant Analysis (LDA)

   Unstable classifiers performance is affected even due to minor changes in training set and it is highly complex. Example - Multilayer Perceptron (MP)

d. **Regularized classifier:**

Overfitting of training sets is taken care of by regularized classifiers. It helps in limiting the noise and complexity of the classifier. It is robust to outliers and generalization performance is good.

Types of classifiers:

1. **Linear Discriminant Classifier:**
   - Linear Discriminant Analysis (LDA): LDA is one of the most famous classification algorithms used for BCI application. The main intention of LDA (also known as Fisher's LDA)[34] is to classify the data denoting to different classes by using hyperplanes. If there are more than two classes (N>2), many hyperplanes must be used. The technique which can be used for this condition is the "One Versus the Rest" (OVR) strategy where a particular class is separated from the rest of the classes. On-line BCIs uses this method since its requirements for computation are very less. It provides good results and it is simple to use.
   - Support Vector Machine Classifier: This classifier was outlined for performing classification between two classes. SVM clustering is a state-of-the-art learning machine that utilizes statistical learning theory. Its aim is to search out the maximum margin hyperplane between two classes. We can expand the capabilities by increasing the hyperplane margins. By adjusting the parameters, better classification rate can be achieved. The Gaussian or RBF Support Vector Machine are the resultant SVM's [35]. They have also given excellent outcomes for various applications of BCI.
2. **k-Nearest neighbor Classifier:** k-NN classifier is an algorithm based on supervised learning. This model is used to describe memory-based learning which helps the model to memorize the training datasets. It is a non-linear classifier and assuming the number of voting neighbors to be k = k1 + k2 …. kn. To estimate the class, a training data and predefined k value is required. Based on the similarity measure, the classifier finds out the k-most similar samples from the training sample space[36]. The output of this classification can be affected by the value of the distance and also by the k value. k-NN is efficient when used in low-dimensional feature vector of BCI system.
3. **Nonlinear Bayesian Classifiers**: Bayes quadratic and Hidden Markov Model (HMM) are the two Bayesian classifiers used. Bayesian Graphical Network (BGN) is not very efficient in real time applications of BCI as they are not very fast. Discarding uncertain samples is done better using Bayesian classifier when compared to discriminative classifier. This classifier produces non-linear decision boundaries.

- Bayes Quadratic: For the highest probability, this classifier allocates the feature vector to the respective class. The posteriori probability belonging to a given class is calculated using the Bayes rule. The estimation of the feature vector is obtained using Maximum A Posteriori (MAP) rule and their probabilities[37]. Bayes quadratic is used by making assumptions of different normal distribution of information. It is named as Bayes Quadratic since it has quadratic decision boundaries.
- Hidden Markov Model: Time series can be efficiently classified using HMMs which is a nonlinear technique[38]. HMMs are widely used in the field of speech recognition and they can provide the probability of observing a feature vector for a given sequence. HMM are used for classification of temporal sequence of BCI features and for classification of raw Electroencephalography. INPUT-OUTPUT HMM (IOHMM) has been used for BCI application. IOHMM is a discriminative classifier.

4. **Neural networks:** These are very commonly used classifiers in BCI along with linear classifiers[39]. Non-linear decision boundaries are produced by assembling several artificial neurons. The most widely used neural network is Multilayer Perceptron (MLP) and it is made up of various layers of neurons which includes an input layer, one or more hidden layers and an output layer. The class of the input vector is determined by the output layer neurons. Neurons are linked to the same inputs but with distinct outputs. MLP is basically used to classify as many numbers of classes which helps the neural network to be more flexible. MLP is also called as universal approximators as it can approximate any continuous function and it is built using several numbers of neurons and layers. Since they are called as universal approximators they can be applied to most of the Brain Computing Interface problems such as binary or multiclass BCI and synchronous or asynchronous BCI.

III. Results and Discussion

In this section, we discuss about various applications of BCI and discuss the challenges faced during their establishments. Figure 3 shows the various Brain Computer Interface applications.

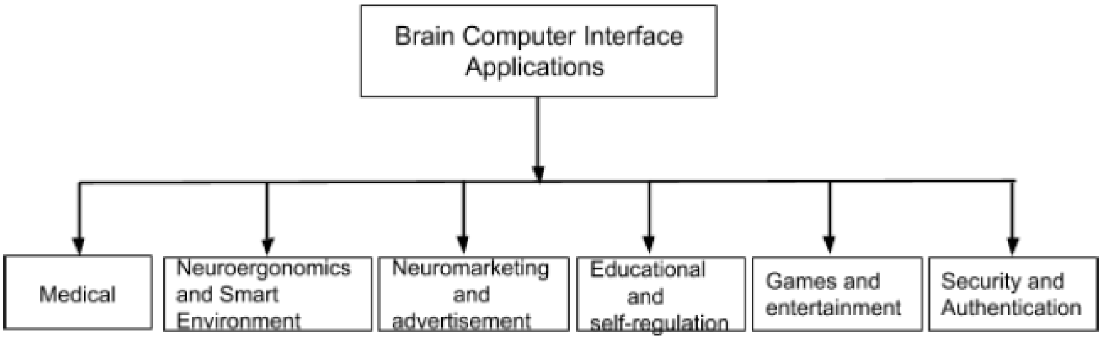

Fig 3: BCI Applications[60]

1. Medical applications

One of the main applications in brain computing is in the medical field[40]. The advantages of brain signals in three different phases are explained below:

Prevention: Many consciousness levels determining systems analyze the impact of smoking and drinking alcohol on brain waves have been developed[41]. Recent studies show that traffic accidents are the major causes for deaths and serious injuries. Motion sickness occurs by transmitting conflicted sensory data generated from inner ear, eyes and the body. Due to traffic accidents a person loses his self-control. As per the study, the prediction of motion sickness can help in driver state monitoring. Even sick people can be monitored by observing their brain signals.

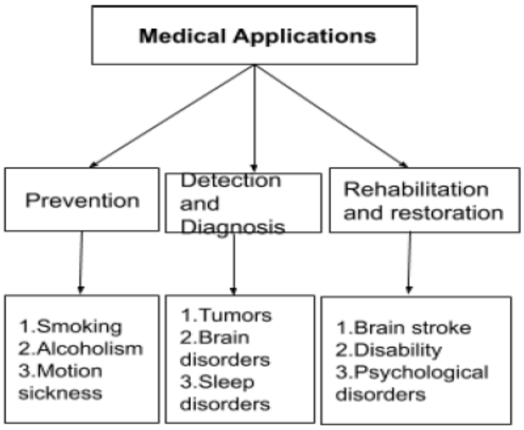

Fig 4: Medical Applications of BCI[60]

Detection and diagnosis: Many abnormalities which include improper brain formation (brain tumor), seizure disorder (epilepsy), sleep disorder (narcolepsy) and brain swelling (encephalitis) and many more can be determined using BCI systems. EEG is an inexpensive technology which can be used to detect brain tumors which are caused by uncontrollable cell division. A disorder called Dyslexia can be diagnosed by computing brain behavior[42]. Similarly, sleep disorders can also be detected. Experiments have validated the relation between human gait cycle (manner of walking) and EEG signals by using a plantar pressure measuring system.

Rehabilitation and restoration: A physical rehabilitation such as mobility rehabilitation is used to treat patients with mobility issues. It can bring back their functions which were lost and help them recover their previous mobility actions[43]. Even people suffering from stroke or serious injury can be recovered. Other problems such as losing speaking ability, memory problems, paralysis of body parts and disabilities can be cured. Neuro-prosthetic devices can be used in assisting patients who have lost some power of mobility or communication.

2. Neuro-ergonomics and Smart environment

BCI has a huge application other than medical field including smart homes, transportations collectively known as Smart environment. It has control over the surrounding elements by monitoring mentally is one of the key factors for smart homes. Based on EEG features[44], we can analyze the mental status of the person in the workplace. Application based on transportation which can be monitored using brain signals and found the reasons for accidents are distraction and fatigue. Fatigue is detected using EEG signals.

3. Neuromarketing and advertisement

Marketing is one of the important fields in BCI research[45]. There are advantages in both political and commercial fields in evaluating TV advertisements using EEG. Also, researchers have considered the effects of different cognitive functions in neuromarketing. Advertising evaluation can be performed by estimating the memorization of TV advertisements.

4. Educational and self-regulation

Enhancing the performance of the brain by modulating the activities of the brain is called Neuro feedback[46]. To determine the degree of clearness it utilizes the brain electrical signals which occupies the educational systems. Noninvasive BCIs such as fMRI and hybrid rtfMRI EEG can be used for emotional regulation and to fight against depression. fMRI neurofeedback has a huge impact on self-regulation and skill learning.

5. Games and entertainment

Applications related to gaming and entertainment have provided a market for people who are non-therapeutic. Various games are designed to be played in 2D, 3D or virtual worlds. There are many researches who combine the features of already existing games with brain computing capabilities (the game is Brain Arena) [47]. Some games related to EEG are also designed for controlling one's emotions and neuro-prosthetic recovery.

6. Security and authentication

Authentication is present in the security systems found on the basis of object, biometrics and knowledge[48]. The different challenges involved in this domain are insecure password, theft crime, shoulder surfing and cancelable biometrics. A technology called electrophysiology (cognitive biometrics) gives a solution for facing these challenges. The main advantage of this technology is that third party observer cannot extract bio signals. These are some of the application domains where BCI systems are used. Many more applications can be derived from these.

Challenges faced during implementation of BCI:

Even in recent times people are not deploying BCI in an effective way due to various obstacles faced such as ethical, legal, usability and technical challenges. Challenges are also caused due to the signals received from brain activity are liable for intrusion, can also cause harm to patients controlling the device or an issue of protecting the data of the patient. In this paper let's discuss the challenges that affect the advancement in this technology.

1. Usability Challenge:

It talks about the issue of acceptance by patients to use BCI technology. We use ITR (Information Transfer Rate) system for acceptance and permission of the user. Patients undergo training period during preliminary phase or classifier phase, they are taught how to use the device and also control their feedback signals. This training process is tedious and time consuming. We can tackle this problem by using a single trial rather than using multi-trial analysis and adaptive and zero training classifiers are also used[49]. ITR (Information Transfer Rate) is a criterion used in brain computing interface devices for determining the amount of information given as output by the system[50]. The evaluating metric is captivating because it is acquired using information theory principle and it incorporates speed and accuracy.

2. Technical Challenges:

It mainly deals with the problems associated with the electrical properties of brain signal. It includes Non-linearity, Non-stationarity, Noise, Small training sets and High Dimensionality Curse.

- **Non-linearity**: Brain activities are chaotic and unpredictable. For better characterization of EEG signals, nonlinear dynamic methods are used.
- **Non-stationarity**: It's found that there is continuous change in the brain signals during recording sessions[51]. The variations in EEG signals are caused due to mental and emotional state. Noise, Fatigue and concentration levels are considered to be the factors of non-stationarity.
- **Noise**: There are unwanted signals produced while changing the electrode positions and also noise from the surroundings. It found that there is a difficulty in finding out the actual pattern due to the artifacts movement which combines the electrophysiological activity produced during Electromyography (EMG) and signals formed while performing Electrooculogram (EOG)[52].
- **Small Training Set**: As it's said training the user is time consuming, they are adapting by providing a small training set. The challenge here is that they are still trying to compromise between the complexity with the advancing technology used to capture the brain activity and the amount of training required for optimal result.
- **High Dimensionality Curse**: To maintain high spatial accuracy, the brain signals are captured and recorded using various channels. Dimensionality of the vector is increased with respect to the amount of information required to measure various brain signals. Small number of distinctive characteristics affects the classifier performance. It's required to use at least 10 times of the training set for each class but using a large dataset doesn't support in dimensional environment[53].

3. Ethical Challenge:

Ethics in healthcare refers to the way the patients are treated and interacted by the doctors and to make proper healthcare decisions[61]. The principles of medical ethics are

1. Autonomy means self-rule, it's about providing the right to the patient to involve in clinical decisions and educating them about the entire process about BCI but there is lack of autonomy as few patients are unable to communicate and doctors fail to get consent to carry out the interface process[54].
2. Non-Maleficence, concerned to provide enough benefit to the patient with harmless treatment. If this technology is misused or carried out in a wrong way then it's causing mental harm to the patient and it may also lead them to death. Just like cybercrime, scientist have reported neuro crime, mishandling of neural devices[55]. Any disruptions or modifications in the device used without informing the patient about the same and still using the device for brain computations is reported as neuro crime. The invasive methods like electrocorticography (ECoG), an electrode grid implanted over the cortex surface or epidurally in the brain may result in infections, hemorrhage and cranial smearing and also the patient could be harmed mentally if the process fails in getting the required output. This is one of the biggest challenges to overcome and use the technology fearless.
3. The cost to procure BCI devices is high.
4. The information related to data obtained by BCI is not exchangeable or uses the information by the patient as there is no common file format to exchange the data between the patient and doctor.

5. The reliability issue talks about the poor BCI systems used. The brain signals have to be amplified as the extracted signals from the brain have low strength but the amplifiers used are not good and it also leads to high error rate.

4. Legal Challenge:
The legal challenges include Freedom of privacy and thought.
Freedom of privacy - Confronting with the use of BCI has a lot to do with securing patients' information but still the information can be leaked due to eavesdropping where the attacker passively overhears the information shared over network and attains rights to access personal data, interception of active data, contradiction of service and modifying the information[56].
Freedom of thought - can be a threat for the patient, as the BCI system allows the user to operate the artificial limb, wheelchairs and mouse cursor with their thoughts can become a violation of their right by limiting their thought to control only a few devices.

IV. Conclusion

This paper explains about the importance of brain computer interfacing. Initially, the structure of the brain is introduced schematically. Then the four steps involved in the communication of brain signals with the device are explained in detail. The first step is signal acquisition where the brain signal is captured and further sent for preprocessing. The two methods namely invasive and non-invasive methods are explained with different technologies. Finally, the results obtained are tabulated for different features. The next step is signal preprocessing. Here, the signal to be analyzed is preprocessed. There are three main steps namely referencing, temporal filtering and signal enhancement. There are different methods to enhance the signal. The succeeding step is feature extraction where the essential features of the signals are captured. Based on the features, the final step i.e., classification is performed. The different classifier taxonomies and types of classifiers are explained. Then, the application domains related to brain computing interfaces are elaborated. Finally, the different challenges associated with brain computing interfaces are narrated. This literature review highlights that there are lot of applications for BCI but there are lot of implementation challenges.

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