A Study on Brain Computer Interface

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Abstract
Brain computer interface technology characterizes a highly emergent field of research with application systems. Its influences in medical fields range from avoidance to neuronal rehabilitation from severe damages. Mind interpretation and remote communication have their distinctive fingerprintin several fields such as educational, self-regulation, production, marketing, security as well asgames and entertainment. It produces a related understanding between users and the adjacent systems. This paper demonstrates the application areas that could value from brain waves in assisting orrealizing their aims or objectives. This paper also discusseschief usability and technical challenges that face brain signals consumption in various components of BCI system.

Keyword
Brain Computer Interfaces, Brain signal acquisition, BCI applications, Mind commands, Brain Monitoring

I. Introduction

Brain Computer Interface (BCI) technology [13] is a powerful communication tool between users and systems. It does not need any external gadgets/devicesor muscle intervention to concern commands and concludes the interaction. The research community has primarily established BCIs with biomedical usesin mind, leading to the generation of assistive devices. They have simplified renovating the movement skill for physically challenged or locked-in clients and substituting lost motor functionality. Theencouraging future forecast for BCI has encouraged research community to study the participationof BCI in the life of non-paralyzed beings through medical applications.

On the other hand, the scope of research has been additional widened tocomprise non-medical applications. More recent readings have targeted normal individuals by discovering the use of BCIs as a novel input device and examining the generation of hands-free applications.

Applications [12-13] of Brain Computer Interface base its functionality on either perceiving the user state or permitting the user to convey his/her ideas. BCI system records the waves generated by brain and directs them to the computer system to complete the projected task. The transmitted waves are consequently used to direct an idea or regulate an object.

Brain Computer Interface (BCI) systems build a communication link between human brain and the external world eradicating the necessity for typical information delivery approaches. They achieve the distribution of messages from human brains and translating their silent opinions. Thus they can support handicapped persons to tell and write down their thoughts and ideas via variety of methods such as in spelling applications, semantic categorization, or silent speech communication [13].

BCIs can also assist hands-free applications carrying the luxury and ease to human beings through mind-controlling of machines. They only requireintegrating brain signals in order to accomplish a set of guidelines and no muscles participation is required. BCI assistive robots can offer provisionfor disabled users in daily and professional life, developing their relationship in building their community[11].

Early BCI applications have focused towards disabled users who havemotion or speaking worries. Their determination was to convey additional communication channel for individual users. But later on, BCI move into the world of fitand healthy people as well. It works as a physiological assessing tool that improves and uses statistics about an individual's emotional, intellectual or usefulness state. The target of brain signals deployment has been strained beyond observing some object or proposing a replacement for precise functions, in what is called passive BCI.

Brain computer interfaces have promoted in different fields of scientific research. BCI are involved in medical, neuroergonomics and smart environment, neuromarketing and advertisement, educational and self-regulation, games and entertainment, security and authentication fields.

II. Classification of BCI Technique

Brain computer interface can be classified into three main groups, as described below [10], based on the technique that the electrical signal is achieved from neuron cells in the human brain.

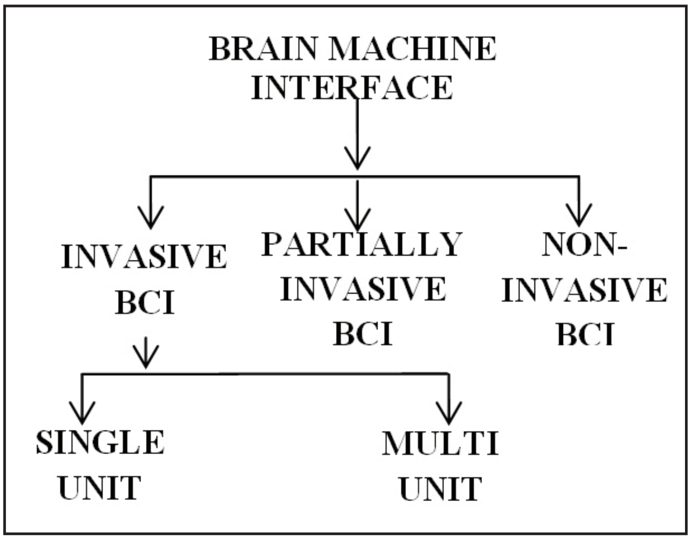

Fig. 1:

A. Invasive BCI Techniques

In invasive BCI techniques [9], distinct devices have to be used to obtain and record the brain signals. Such devices are called Invasive BCI devices which are based on identifying from single area of brain cells is called single unit while the recognition from multiple areas is called multi-units. Invasive BCI devices are implanted directly into the human brain by a critical surgery. The electro-corticogram (ECoG) is the obtained signals from these implanted electrodes. These devices have the highest quality of human brain signals but have the risk of developing scar tissue.

B. Partially Invasive BCI Techniques

Other devices that can obtain the signal from the brain are the partially invasive BCI devices [6-8]. Devices are implanted in the skull on the top of human brain. These devices have little weaker quality of human brain signals than invasive BCIs and have less possibility of forming scar tissue.

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C. Non Invasive BCI Techniques

Non Invasive BCI devices are deliberatedas the safest type and costs lowest than Invasive techniques. However, these devices have weaker human brain signals than other BCI devices due to the skull. The recognition of signals is done by some electrodes placed on the scalp (as shown in Fig.1). At the same time, retaining such electrodes is easy as well as convenient to handle. Most noninvasive techniques are fabricated by recording Electro Encephalo Graphs (EEG) signals [10-8] from the scalp.
While others, Non Invasive BCI devices, use functional Magneto-Resonance Imaging (fMRI) [8-9], Positron Electron Tomography (PET), Magneto Encephalo Graphy (MEG) and Single Photon Emission Computed Tomography (SPECT).

Fig. 1: EEG Headset

III. Types of BCI Signals

The brain produces a measure of neural movement. There are a plenty of signals, which can be utilized for BCI [8]. These signals are categorized into two classes: spikes and field potentials [9]. Spikes reproduce the activity possibilities of individual neurons and procured through microelectrodes embeddedby invasive techniques. Field potentials are extent of combined synaptic, neuronal, and axonal activity of clusters of neurons and can be measured by EEG or implanted electrodes. The following are the taxonomy of EEG signals based on their frequencies/bands.

A. Delta Signal

It is caught inside the recurrence scope of 0.5–3.5 Hz. It has a tendency to be the most astounding in adequacy and the slowest waves.It is seen normally in adults in slow wave sleep as well as in babies.

B. Theta Signal

The frequency range of these signals is from 3.5 to 7.5 Hz. Theta is interrelated to inefficiency and daydreaming. Indeed, the very lowest waves of theta signifythe fine line between being awake or in a sleep. However,high levels of theta are deliberated abnormal in adults.

C. Alpha

This signal frequency range varies from 7.5 to 12 Hz.It is brought out by closing the eyes and by relaxation.

D. Beta

Beta is a different brain signal in which its frequency ranges from 12 Hz to about 30 Hz.

E. Gamma

It is a signal with frequency range of 31 Hz and up. It reflects the mechanism of awareness.

IV. BCI System Components

BCI system be made up of four basic modules [10-13], as shown in Fig. 2, that includes signal acquisition, signal preprocessing,feature extraction, and classification.

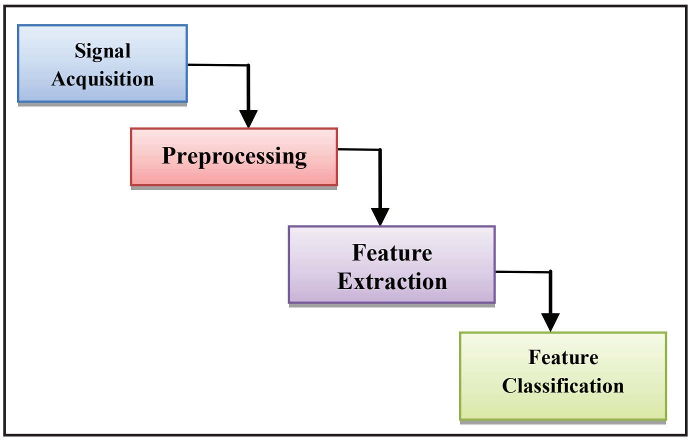

Fig. 2: BCI System

A. Signal Acquisition

The acquisition of brain signals is skilled by the means ofseveral non-invasive methods like Electro Encephalography (EEG), functional Magnetic Resonance Imaging (fMRI) [8], Near Infra-Red Spectroscopy (NIRS) and, Magneto Encephalography (MEG).

B. Signal Pre-Processing

After signal acquisition phase, signals are to be pre-processed. Signal pre-processing is also called as Signal Enhancement. In general, the obtained brain signals are adulterated by noise and artifacts such as eye blinks, eye movements (EOG), heart beat (ECG) [9]. In addition to these, muscular movements and power line interferences are also intermingled with brain signals. Artifact removal can be done using methods such as Common Average Referencing (CAR), Surface Laplacian (SL), Independent Component Analysis (ICA), Common Spatial Patterns (CSP), Principal Component Analysis (PCA), Single Value Decomposition (SVD), Common Spatio-Spatial Patterns (CSSP), Frequency Normalization (Freq-Norm), Local Averaging Technique (LAT), Robust Kalman Filtering, Common Spatial Subspace Decomposition (CSSD) etc. The most commonly used methods are ICA, CAR, SL, PCA, CSP and Adaptive Filtering.

C. Feature Extraction

Subsequent to acquiring the noise-free signals from the signal enhancement phase, fundamental features from the brain signals were dig out[6]. For feature extraction from EEG signals[5-3] use methods such as Adaptive Auto Regressive parameters (AAR), bilinear AAR, multivariate AAR, Fast Fourier Transformations (FFT)[3], PCA, ICA, Genetic Algorithms (GA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD). Among these ICA, PCA, WT, AR, WPD, FFT are mostly used.

D. Classification

After feature extraction the signals are classified into various classes using various classifiers. Different types of classifiers include linear classifiers, Artificial Neural Networks (ANN) based classifiers, Support Vector Machine (SVM) [3] based classifier, nonlinear Bayesian classifiers and, nearest neighbor classifiers [1-2]. Of these classifiers linear classifiers and non-linear Bayesian classifiers are mostly used in BCI design and their comparative analysis is given in Table 1.

Table 1: Comparative Analysis of Different Types of Classifiers

Method	Advantages	Disadvantages
SVM	It provides good generalization. Performance is more than other linear classifier.	High computational complexity.
ANN	Ease of use and implementation. Robust in nature. Simple computations are involved. Small training set requirements are required.	Difficult to build. Performance depends on the number of neurons in hidden layer.
NBC	Requires only small amount of training data to estimate parameters. Only variance of class variables is to be computed and no need to compute the entire covariance matrix.	Fails to produce a good estimate for the correct class probabilities.
k-NN	Very simple to understand. Easy to implement and debug.	Poor runtime performance if training set is large. Sensitive to irrelevant and redundant features. On difficult classification tasks out performed by other classification methods.

V. Conclusion

Brain signals reflect the controlled activities and regulatorybehavior of the brain or the effect of the acknowledged informationfrom other body parts either sensing or internal organs.

Brain Computer Interfacing be responsible for a channeling skillbetween brain and external equipment.BCI applications have concerned the research community.Several studies have been offered in this paper concerningthe growing interest in BCI application fields such as medical,

games and entertainment, security and authentication areas. It also make evident the variousdevices used for capturing brain signals.These recording devices are divided into two main categories:invasive and non-invasive. Invasive category, which necessitates implanting surgery which is usually needed for critical paralyzedcircumstances because of their higher accuracy rates, attained either spatially or temporally. On the other hand, the non-invasive category, as stated formerly, has been widely spread in other application fields due to its advantagesover the invasive one. Other challenges and issues posed as aresult of utilizing brain signals have also been discussed alongwith some solutions offered by different algorithms at various BCI processing components.

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