

# A Comprehensive Review on Brain-Computer Interface Controlled Movements

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**Abstract-** A brain-computer interface (BCI), also referred to as a mind-machine interface (MMI) or a brain-machine interface (BMI), provides a non-muscular channel of communication between the human brain and a computer system. With the advancements in low-cost electronics and computer interface equipment, as well as the need to serve people suffering from disabilities of neuromuscular disorders, a new field of research has emerged by understanding different functions of the brain. The electroencephalogram (EEG) is an electrical activity generated by brain structures and recorded from the scalp surface through electrodes. Researchers primarily rely on EEG to characterize the brain activity, because it can be recorded noninvasively by using portable equipment. The EEG or the brain activity can be used in real time to control external devices via a complete BCI system. For these applications there is need of such machine learning application which can be efficiently applied on these EEG signals. The aim of this research is review different research work in the field of brain computer interface related to body parts movements.

**Keywords-**electroencephalogram (EEG), Brain-Computer Interface (BCI), Arm Movements, Machine Learning

## I. INTRODUCTION

The term BCI was coined in 70's and since then, this field of research has grown tremendously. From early experiments on the monkey to use of BCI in daily life, the evolution of BCI, all these years has resulted in a very large number of methods, paradigms, concepts, and applications. This survey thus aims at providing an introduction and brief overview of the concepts and rich facets of BCIs. The primary motive for the development of BCI was to provide means of communication for people with disabilities. And therefore there is a misunderstanding that the scope of BCI is limited to the medical field only. Today applicability of BCI has reached far beyond communication, like rehabilitation, hand free gaming, etc. Even after all these advances, there are still many practical challenges for BCI systems, which are yet to be solved.

A BCI system is made of four components, signal acquisition, signal processing, application interface, and a feedback mechanism. Brain activity is recorded by the signal acquisition module using either of two techniques i.e. invasive or noninvasive electrodes. Signal processing module helps to extract necessary information from recorded signals. It is composed of data preprocessing, feature extraction and classification algorithms.

The translated signals are communicated using an application interface. Finally, a feedback mechanism produces results in real time which helps the user to understand the actions taken by the system. Brainwaves are the result of synchronized electrical pulses from numerous neurons communicating with each other during some cognitive activity [1].

These are categorized into four groups: alpha, beta, theta, and delta. Whenever brain is busy. in some mental activity beta waves are generated. These are the fastest waves with lower amplitude, and frequency in the range of 15 to 40 Hz. Alpha waves are observed when a brain is in the non-arousal state. An individual who has finished an assignment and takes a seat to rest is regularly in alpha state.

These have higher amplitude, with frequency around 9 to 14 Hz. Theta waves are of even greater amplitude and slower frequency, ranging from 5-8 Hz. An individual daydreaming is often in a theta state. Delta waves are the slowest of all and have the greatest amplitude. Their frequency range from 1.5 to 4 Hz. Delta waves cannot reach zero as it symbolizes a dead brain.

## II. BCI APPLICATIONS

BCI is not limited to the medical field. Various other areas are making use of the advancements in this technology in inventive ways. The application domains are only growing with time. Some of them are as follows [2]:

1. Medical : Using BCI, we can measure the mental state of a person and detect and even predict health issues like tumor, sleep disorder, etc. Prosthetic limbs using BCI can be used by disabled people to regain mobility to some extent, thus empowering them to do some of their chores.
2. Home automation : BCI can be used in home automation. We can control various appliances in our home using the signals generated by our brain. This completely changes the way in which we interact with our environment.
3. Marketing, Advertisement and entertainment: Some researchers have studied the extent of memorization of different advertisements using EEG, thus providing a way of evaluating advertisements. Various games can be designed which interact with the users using their brains.
4. Education : Neurofeedback, utilizes the brain's electrical signals to determine the degree of clearness of studied information. Using the feedback, which may be unique to a learner, personalized interaction is established.
5. Security : Security systems like Cognitive Biometrics or electrophysiology can be developed which uses the user's brain signals for authentication which are more secure rather than password, biometrics or other methods. Cognitive Biometrics or electrophysiology are more secure because they use brain signals which cannot be picked up or acquired by external observer.
3. Data transfer rate : Current data transfer rates for BCI systems is very low. Due to this low data transfer rate, BCI applications suffer from fast response as well as accurate control.
4. Training process : Training process in BCI applications is very lengthy. It involves training the users and guiding them through the system and control their brain feedback signal. Sometimes users find it difficult to use such systems.
5. Non-linearity : The brain is a convoluted system which is not linear in which disorderly behavior of neural ensembles can be found. Training and building effective classifiers based on non-linear data requires research level work.
6. Small training sets : The training sets available are comparatively small and tested on limited number of subjects. Furthermore, the time required to train users for specific tasks can be high. Hence, the problem of establishing a balance between the problem of interpreting the user's neural activity and the training period needed to do build classification models arises.

### III. BCI CHALLENGES

Development of BCI depends on the selection of signals, data acquisition methods, feature extraction methods, translation algorithms, output devices, depended/independent modes, synchronous/asynchronous mode, development of training strategies, protocols, choice of application and user group. During movement proprioceptive and another sensory feedback occurs as part of cortical and subcortical neuron activity. Without actual movement, it is still not clear that up to what extent users can produce this activity and other sensory mobility. With long-term stability whether the neuronal activity can function without movement is yet to be established. The performance of BCIs depends on its signal to noise ratio, and also on a variety of options for improving the signal to noise ratio. Some of the major challenges faced are discussed below:

1. Low BCI signal strength : It is not easy to extract signal from brain as the signal itself is very weak. Thus, it is a challenge to record a BCI signal of good strength. Amplifiers can be used to overcome this issue but concomitant noise also gets amplified.
2. High error rate : BCI signals captured using non-invasive techniques have noise and artefacts accompanying the desired data. Noise and artefacts make the captured signal highly erroneous.

### IV. RELATED WORK

Marquez L. et al. [7] designed an algorithm for classification of right and left arm movement. Discrete wavelet transform is used for feature extraction. Multilayer perceptron neural network (MPNN) is used as classifier to predict arm movement. The accuracy obtained was 88.72%.

Zhiwei et al. [8] used DWT as feature for EEG signal and used SVM as classifier.

Ting et al. [9] used discrete wavelet transform and k-nearest neighbour for classification. As it is known that DWT decomposes the signal into different frequency range. For analysis and study of these frequency is decomposed into different levels. Further k-NN classifier is applied for performance evaluation and compared with ANN classifier.

Syed Khairul Bashar and Mohammed Imamul Hassan Bhuiyan [10], discussed an algorithm for EEG signal classification into different arm movement using DWT feature extraction technique as well as k-NN classifier for evaluation of performance parameters. This algorithm is designed for forward and backward movement of arm and achieved an accuracy of about 93%.

Saugat Bhattacharyya et al. [11], introduced neuro-fuzzy algorithm to recognize arm movement. In this work ANFIS is used to classify arm movement into multiple classes [12]. This algorithm was designed to control real time movement of the robotic arm and achieved about 65-70% accuracy.

Prasant KumarPattnaik et al. [13] discussed the importance of brain machine interfaces for disabled or mentally challenged

persons. In this paper author performed their algorithm by acquisition of EEG signals. The EEG signal is used for arm and finger movements. First of all artifacts or noise are removed from EEG signals by applying DWT. Further alpha and beta frequency are extracted and used for classification of arm movement. After simulation of proposed algorithm, RMSE of about 50 is achieved which is quite high.

Muhammed Al-Suify et al. [14] proposed an algorithm for left and right-hand movement detection from EEG signals. The proposed algorithm enhances the classification rate by

using linear and non-linear characteristics of EEG signals. For classification different classifiers are used such as support vector machine (SVM), Naïve Bayes (NB), linear discriminant analysis (LDA) and k-NN and achieved about 89.3% accuracy.

It is observed through literature is that extracting important features and use of various classifiers with more statistical features and use of classifier for better result can be obtained. Comparative analysis of some noteworthy contributions in field of BCI are mentioned in table I.

**Table I: Comparative Analysis in the Field of BCI**

Author	Aim of Experiment	Description	Results
S. Chatterjee et al [2]	Motor imagery classification (left/right limb)	Wavelet transforms was used.	Using only wavelet coefficient feature vector, gave poor accuracy. Using full feature vector of all extracted features gave higher accuracy.
Tang, Chao Li et al. [3]	Classify MI tasks (left / right hand )	Band pass filter + FFT	CNN effectively classify MI with accuracy of 86.41%
Barachant A et al. [4]	Classify motor imagery	Log Covariance of spatially filtered signals	Accuracy of 70%.
Bonnet S. et al. [5]	Riemannian geometry for mental task classification	Band-pass filter, 5th-order Butterworth filter	Spatial filter can be by-passed, this makes calibration easier & robust to overfitting. Accuracy was 80%.
L. Bougrain et al. [6]	New Multilabel Classification Method	Band Pass Filter	No of classifiers required are reduced to $\log(2k)$ , where k is the no of classes. Accuracy was 51.67%

## V. CONCLUSION

BCI is gift for people with disabilities, especially for those who cannot use the normal way out and muscle movements of the brain. BCI techniques vary depending on the application and require different methods to recognize the characteristics of pre-processed EEG signals and monitoring gadget. This survey focused on BCI components, in general, method of signal acquisition, feature identification and acquisition by the various algorithm, challenges in BCI, methodologies used in BCI research and application. The work presented evaluation and current trends in BCI.

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