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A review on brain-computer interface controlled movements using machine learning

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Abstract
Brain computer Interface (BCI) is device that allows the employment of the brain's neural activity to communicate with others or to regulate machines, robots, or artificial limbs without direct physical movements. Brain computer interface is an innovative and growing field of research which is used to generate control signals by analyzing the extracted brain signals. For such analysis of electroencephalography (EEG) signals the BCI can judge the mental state of any human being and generate respective control signals to react. 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

1. Introduction

A BCI (Brain Computer Interface) is an interface which co-ordinates the brain signals with mechanical device signals. For this EEG signals are extracted from brain. As it is known that brain is made up of billions of neurons which generates electrochemical signals or impulses. The brain machine interface (BMI) is used to convert these impulses into control signals for mechanical devices. As brain performs several activities at same time, so there is need of such intelligent interface which precisely distinguish among different activities from EEG signals. So, BCI can be used in several applications such as medical, defense, engineering and research fields [1, 2, 3].

The promising future foreseen for BCI has inspired analysis community to review the involvement of BCI within the lifetime of non-paralyzed humans through medical applications. However, the scope of analysis has been any widened to incorporate non-medical applications. newer studies have targeted traditional people by exploring the employment of BCIs as a completely unique data input device and investigating the generation of hands-free applications [4].

To control mechanical devices, neural activities are generally translated into real movement or activities by using BCI. These EEG signals are captured using electrodes placed on scalp of brain. All necessary signals are recorded which are required for making efficient brain computer interface. These interface acts as translator between human brain and mechanical devices. This process is conversion of electric impulse into control signals for devices. The control signal are often applied to regulate associate application like computer control and mechanical prosthetic device [5].

Study on the brain machine interface (BMI) using motor mental imagery still provides an open discussion forum among the researchers. Numerous feature extraction and classification strategies were applied by the early researchers to investigate the electroencephalogram signal [6, 7]. The objective of this paper is not only to study neurophysiological understanding of the human brain but also to investigate electroencephalography as a means of identifying mental activity. This paper reviews on EEG based BCI systems that are implemented and also compared the performance of different feature classification techniques and puts forth best classification methods for hand and leg movement.

2. Brain Computer Interface Structure

To advance an elementary conception concerning BCI, a insignificant data concerning brain functions and conditions is fascinating. In this chapter totally different brain observation methodologies are the area of concern with their basic dissimilarities and benefits.

The Electro-magnetic pulse generated by neurons makes observation of brains practically possible. Taking some properties of brain signal that is captured we can predict some of his activities i.e. whether or not the person is asleep etc. It's observed, that totally different sleep phases turn out different electromagnetic signals [1, 6]. In addition like emotions, activities or relaxing signals can also be determined to extent BCI is predicted on these dissimilarities, that makes computer control possible.

A Brain-Computer Interface (BCI) could be methods for correspondence that allows a subject to send commands to some gadget solely by the means of brain activity [7]. So, they state it can be the sole means of correspondence for people who are suffering from some specific motor disabilities. The aim of a BCI is to "peruse" the client's goal, that is generally done utilizing classifiers that take some delineation of readings of brain signals and translate them into a category from a collection of states or aim.

It is particularly essential for people affected by ALS, brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis. Though, taking into account EEG-based BCI, if a person is still able to use any muscle to correspond, that would allow faster communication [3]. Consequently, the only people with real benefits from such research are those suffering from these or similar diseases. BCIs are differentiated through their signal acquisition system, which may be invasive or noninvasive or their signal evocation scheme, which can be exogenous or endogenous (the way a subject is encouraged to make the preferred signals) [1]. Such evoked potentials are fluctuations in the voltage dimensions that happen either suddenly from inside the subject or after a certain event (exogenous) like a visual stimuli (Event-Related Potential-ERP). The universal structure of a BCI system can be seen in figure 1, taken from [3].

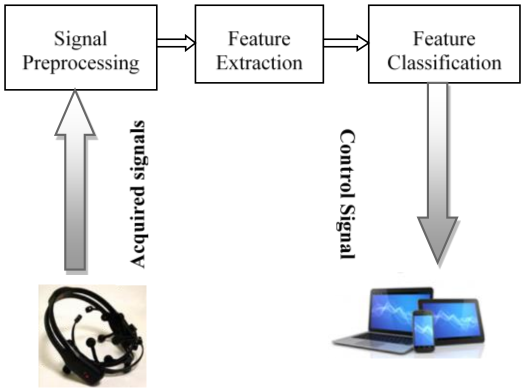

Fig 1: BCI structure

It may be divided into three parts

1. The Signal acquisition mechanism records signals from a subject and outputs their digital representation.
2. Signal processing, it transforms the data such that features may be retrieved. Then translates them into some demonstration appropriate to control or command a device. E.g. by means of a classifier, that takes the features as input and outputs some value hinting on a class, which may be interpreted as command or further processed.
3. The algorithm that finally outputs commands.

3. BCI Applications

Applications of Brain-computer interfaces can be applied in various applications such as in medical and research work, defense, neuroscience, engineering, gaming, security, smart technologies, etc. Some of the applications are discussed below:

1. Medical applications

In medical field BCI can be applied for various applications such as for analysis, diagnosis, assessment of brain signals and also in rehabilitation and recovery. By applying in such wide varieties in heath sector BCI research work need more and more innovations.

2. Prevention

Several levels of consciousness determination systems have been developed in parallel with their brain studies. The influences of smoking and alcohol on the brain waves are progressive in [19]. The importance of such studies to medical prevention is the probable loss of function and decreased vigilance resulting from smoking and alcohol consumption, while the authors [21] examined almost all parts of the brain that react to alcoholism.

3. Rehabilitation and Recovery

The natural disability is the condition in which patients have some mobility problems and rehabilitation provides a support to repair or recover from such disabilities [22]. People with serious injuries or acts such as stroke can also recover completely.

4. 4. Neuromarketing and advertisement

Marketing area has also been an interest for BCI researches. The survey [23] explained the compensation for the use of the EEG rating for commercial and political television advertising. Assessment procedures based on BCI have drawn attention to complementary observational activity [24]. On the other hand, researchers [25] have measured the collapse of another neuromarketing cognitive function.

5. Games and entertainment

5. The various games are available as in [26], where helicopters are ready to fly anywhere in a virtual world in 2D or 3D. Mixing the properties of existing games with brain computing skills has become a problem.

4. BCI Challenges

Challenges BCI has been an exciting forum for scientist, engineers and medical practitioners. BCI researchers and developers must engage themselves to tackle three critical problems for an exciting future: signal acquisition hardware, reliability and training process and it is not free from challenges

1. Signal acquisition hardware

The signal acquisition hardware up gradation necessary for developing usable nonmedical BCI applications is a core challenge. EEG sensors must be dry, agreeable, appropriate to use, and easy to modify since before BCI systems must be favorable for utilization beyond laboratories and hospitals. Deployed Sensors must impart good signal quality even in extremely noisy environments having mobile users. It has already been presented by researchers that BCIs can be used outside laboratories or with a mobile user however performance is comparatively poorer than in laboratory conditions. The work must satisfactorily focus on developing better active electrodes with active shielding.

2. Reliability

BCI systems have poor reliability for most of the applications. It is important that a BCI system must be appropriate for real time execution and well-founded for muscular actions in the human body. Without advancements, the actual usability of BCIs will continue to be the only most used communication functions for users with severe disorders. The main problem is dependent on identify and capture of 3 major issues: the intermediate role of a robust and interactive BCI system; the requirement in deploying a BCI system which emulate the diffuse the working of central nervous system; and a system which realizes the necessity of integrating extra brain signals providing a feedback mechanism.

3. Training Process

Training the user is a time-consuming activity. It finds its importance in either controlling the user through the procedure or the number of sessions that have been recorded. Either the preliminary phase or the classifier calibration phase can be used for the training process. The user may handle the system to control his/her brain feedback signals in the preliminary phase.

5. Signal Acquisition

One of the main functions of any BCI system is to measure the vibrations generated by the brain signal. This process is termed as signal acquisition. There are several methods for signal acquisition as studied in previous works. But signal acquisition method depends in the type of application for which it is intended to make. Generally it is categorized into two categories such as invasive and non-invasive. In invasive signal acquisition method some of the electrodes are implanted at the surface of the human brain [1-5], whereas in non-invasive signal acquisition some external electrodes captures the brain signals outside the surface of the brain.

A. Invasive BCI Techniques

In invasive BCI [9] techniques, devices which are used to capture brain signals are called invasive BCI devices. These devices are placed inside the brain scalp by operation in order to capture the brain signals from different areas of brain nerve cells. The detection of multiple areas inside the brain is called self-propelled units. From these implanted electrodes of invasive devices the Electrocorticogram (ECoG) signals obtained and further observed by the BCI devices.

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. According to [15], the invasive systems have mostly been tried in BCI systems' experiments that use monkeys. A few patients with tetraplegia have used implanted electrodes.

1. Intracortical

Intracortical acquisition technique represents the most invasive method shown in Fig. 2 [20]. 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. Monkeys and rats have been involved deeply in BCI.

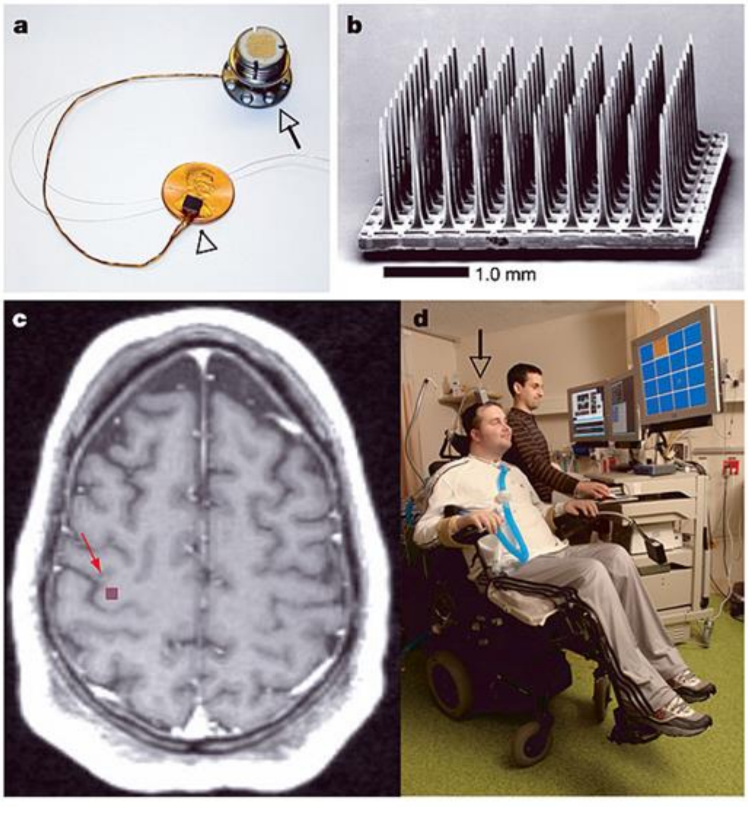

Fig 2: Intercortical Acquisition Technique

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 3 [21]. It records the electrical activity of neurons at the embracing area. has considered the number of electrodes as measurement for invasiveness degree.

Fig 3: Cortical Acquisition Technique

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 noninvasive 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

B. Partially Invasive BCI Techniques

Some devices are implanted on the human brain skull which receives signals from the human brain and such devices are called as partially invasive BCI devices [6]. As these devices are placed on skull so they have poor quality of signals as compared to the invasive type BCI devices as well as these devices have less ability to form scar tissue.

C. Non-Invasive BCI Techniques

Other than invasive technique there is another safe and cheap technique is Non-invasive BCI. In such type of techniques devices are not implanted inside the skull. The electrodes are placed over the skull. So, there is no need of operation in such type of technique. As the devices are not placed inside, so the signal received is of poor quality as compare to invasive devices. Most non-invasive techniques are record the ElectroEncephaloGraph (EEG) [10] signals from the scalp.

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 [15] as shown in Fig.4 [22]. 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.

Fig 4: Magnetoencephalography Technique

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. 5 [23]. 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 bloodoxygen-level-dependent (BOLD) contrast, which is sensitive to the hemodynamic response. 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.

Fig 5: Functional magnetic resonance imaging Technique

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 [18]. 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. 6 [24] and less expensive but provides less imaging capabilities. Its advantages present a viable alternative for clinical studies and possibly for practical use.

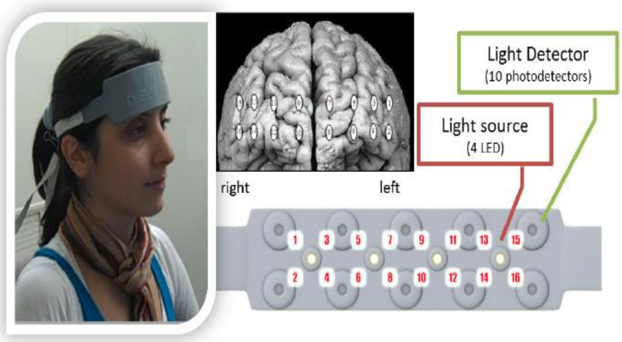

Fig 6: Functional near-infrared spectroscopy Technique

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. 7 [25]. 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.

Fig 7: EEG Electrodes Inset on the Human Scalp

As it is known that brain generates the electrochemical signals called as neural signals which can be used in many BCI applications [8]. These signals are divided into two classes: peaks and field potentials [9]. The peaks reproduce the possibilities of activity of the single neurons and are implanted by invasive micro-electrodes. The field potentials are the extension of the combined synaptic, neuronal and axonal activity of neuronal clusters and can be measured by EEG or implanted electrodes.

Delta Signal

It lies in range of 0.5–3.5 Hz. There is a tendency to be more surprising about relevance and slower waves. It is usually seen in slow-wave adults and babies in adults.

Theta Signal

Such signals are generated in brain while a human being is in state of sleeping or meditation or beyond the normal conscious awareness. The frequency range of these signals is between 3.5 and 7.5 Hz. Theta waves are considered to be as gateway between intuition and memory. However, high levels of theta are considered abnormal in adults.

Alpha Signal

Such signals are generated in human brain when anyone is in relaxed state or may be in meditation state. This signal frequency range varies from 7.5 to 12 Hz. Overall mental coordination and relaxation is performed in alpha frequency range.

Beta Signal

Beta is another brain signal which is generated while anyone is in alert state and the frequency range varies from 12 Hz to about 30 Hz. Further beta signals are divided into beta-1, beta-2 and beta-3 signals which shows the anxiety and excitement state.

Gamma Signal

Gamma signals are considered as high frequency range also considered as the fastest brain signals. Its frequency range is above 30 Hz. Such brainwaves pass information rapidly [1].

Research Work

Gitey *et al*. [8] proposed EEG signal classification using DWT feature extracted and reduction using genetic algorithm.

Marquez L. *et al*. [9] 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*. [10] used DWT as feature for EEG signal and used SVM as classifier.

Ting *et al*. [11] 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 [12], 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*. [12], introduced neuro-fuzzy algorithm to recognize arm movement. In this work ANFIS is used to classify arm movement into multiple classes [14]. This algorithm was designed to control real time movement of the robotic arm and achieved about 65-70% accuracy.

Prasant KumarPattnaik *et al*. [15] 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.* [16] 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 1: Comparative Analysis in the Field of BCI

Author	Description	Results
Faisal Farooq, 2013.	Dataset: BCI competition dataset II for healthy subjects Feature Extraction: Feature vector for the classifier is the time-averaging of 1 sec Classifier : Random Forest (RF)	Accuracy = 97%
Howida A, 2013	Dataset: Real dataset of 26 year old man with 19 electrodes and 3008 samples. Real dataset extracted of 26-year male for opening and closing hand. Feature Extraction: Wavelet Transform Classifier: Multi-layer Perceptron Neural Network trained by back propagation.	Accuracy = 91%
Mohd Shuhanaz Zanar Azalan, 2014	Dataset: Real dataset of 22-34-year-old subjects for arm movements. Feature Extraction: Chebyshev bandpass filter is used and further Fast Fourier transform is used for feature extraction. Classifier: Feed-Forward Neural Network.	Accuracy = 97%
Syed Khairul Bashar, 2015	Dataset: arm movements, right hand forward and backward; left hand forward and backward Feature Extraction: Wavelet packet transform (WPT) and found kurtosis feature. Classifier: KNN classifier is deployed for separating arm movements.	Accuracy = 92.84%
Gerrit Lange, 2016	Dataset: Real dataset is extracted for Hand Grasp and Release Movements. Classifier: The EMG sensors for marker generation	Accuracy = 98.5%
Muhammed Al-Suify, 2017	Dataset: Graz 2003 datasets has been used Feature Extraction: Used non-linear features extracted from density matrix. Classifier: Classified using linear discriminant analysis (LDA), support vector machine (SVM), Bayes and KNN classifiers.	Accuracy = 89%
Prasant Kumar Pattnaik, 2018.	Dataset: Data sets obtained by NUST has been used for left and right-hand movement classification Feature Extraction: Discrete Wavelet Transform Classifier: Support Vector Machine	RMSE = approx. 50
Jiankui Feng, 2018	Dataset: BCI Computation IV dataset Feature Extraction: correlation-based time window selection (CTWS) algorithm is to extract the discriminative MI features in the time domain. Classifier: Support Vector Machine	Accuracy = 85%
Hauke Dose, 2018	Dataset: Physionet database for left and right foot movement Feature Extraction: Convolutional Neural Network (CNN) layers for learning generalized features and dimension reduction Classifier: Conventional Fully Connected (FC) layer is used for classification	Accuracy= 86%

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 research presented the current evaluation and trends in BCI. Non-invasive methods such as EMG, NIRS and fMRI are more popular and easier to use because no surgical implant is required. Non-invasive BCI techniques records more artifacts such as eye blinking, muscular activity etc along with brain signals. Such artifacts must be removes by some techniques such as by using filters. In this research work a study is performed on BCI application for body parts movements that are needed to be classified. Features are extracted from these datasets for classification of type of movements. So in future work, in all above areas it is needed to be used more effectively in real-life environments.

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