Classification of Four Class Motor Imagery and Hand Movements for Brain Computer Interface

¹N.Gowri Priya, ²S.Anu Priya, ³V.Dhivya, ⁴M.D.Ranjitha, ⁵P.Sudev

¹Assistant Professor, ^{2,3,4,5}Students Biomedical Engineering, DR.N.G.P Institute of Technology, Coimbatore, India

Abstract— In this paper, four class motor imagery and hand movements classification has been done for brain computer interface. In this project, we proposed an automated computer platform for the purpose of classifying Electroencephalography (EEG) signals associated with left and right hand movements using a ENOBIO DEVICE.EEG signals were acquired on the Enobio device, with all 8 channels (F3, F4, FZ, P3, P4, CZ, C3 and C4) in alpha and beta rhythm in order to establish the active networks. Six volunteers were participated; the volunteers were instructed to perform motor imagery tasks and movements using both hands, and both legs. It is that EEG represents the brain activity by the electrical voltage fluctuations along the scalp using 8 Electrodes system. It uses advanced feature extraction techniques and machine learning algorithms. In this work, we aspired to find the best feature extraction method that enables the differentiation between left and right executed hand and leg movements through SVM classification algorithm. The EEG dataset used in this research was created and data was preprocessed using the MATLAB toolbox. An important part of a brain-computer interface is an algorithm for classifying different commands that the user may want to execute. The goal of this is to implement an algorithm that would be able to classify two different hand and leg movement tasks. The features such as Mean, Variance, Standard Deviation, Discrete wavelet transform have been extracted and finally classification is done using SVM classifier and the greatest accuracy is obtained.

Keywords- BCI, SVM, EEG, ENOBIO.

I. INTRODUCTION

Brain computer interface (BCI) is considered as one of neuroscience fields that connect the human brain with the outside world (computer). BCIs have offered valuable options for highly disabled patients with complete loss of their ability to move or speak, to live more independently. Recently, the developments of BCI-based schemes to control devices have promoted new opportunity for disabled patients. Thought-based control devices including EEG technology could allow patients, to not only communicate with the surroundings, but also provide navigation. As a result, the impact on reducing cost of health care could potentially be achieved. BCIs can be divided into two categories in term of recording methods: an invasive and a non-invasive BCI. The invasive approaches provide a much higher spatial resolution and signal-to-noise ratio (SNR) in comparison to the noninvasive ones. However, the non-invasive BCI is considered to be safer and more practical than invasive techniques. Hence, noninvasive techniques are used worldwide to monitor brain activities. A normal non-invasive BCI requires electrodes to be attached into the human scalp to monitor brain electrical activities. In this brain activity is monitored using ENOBIO device. Other noninvasive BCIs include magnetoencephalography (MEG) and Positron Emission Tomography (PET). In any case, the functionalities of EEG-based BCIs can be divided into four subsystems: signal acquisition, signal processing, translation of signal features into commands, and the application for a specific purpose .From a BCI point of view, several researchers have used sensorimotor rhythm (SMR) as an input signal. The signal can be modulated voluntarily by motor Imagery (MI). Brain oscillation at mu rhythm of 8–13 Hz and beta of 14–22 Hz displays a specific area corresponding to each motor imagery such as eventrelated synchronization (ERS) and event-related desynchronization (ERD). However, most BCI studies on motor imagery are based on ERS/ERD characteristics. Motor imagery investigation using single movement such as a foot or hand movement has been studied. However, fewer studies on analyzing EEG rhythm induced imagination of limb movements has been reported. From literature investigations, a four class motor imagery limb movements are still scarce. Therefore, in this study a four class motor imagery such as left hand, right hand and both feet movements were investigated. In this paper, an appropriate motor imagery task of a total locked-in user is provided. The information includes identification of predominant features that enhanced the classifications, EEG power spectra and evaluation of features. The evaluation is based on the selections of all (8 channels) and specified channels (C3,C4 and Cz) in alpha and beta rhythm using different classification algorithms. In addition, a four class motor imagery is employed to implement a multi-class BCI by considering brain oscillations in mu and beta rhythm in sensorimotor and motor imagination areas.

ENOBIO is an electrophysiology recording wireless system. The quality of the signal is proven to be as good as the signal that can be acquires with state of the art wired equipment. Different applications can be built on the ENOBIO system such as biometric application, a Human Machine Interface and a Sleepiness prediction system.

68

II .METHODOLOGY

BLOCK DIAGRAM



Figure 1: Block diagram

SIGNAL ACQUISTION AND PREPROCESSING

Signal acquisition is the measurement of brain signals using a particular sensor modality (e.g., scalp or intracranial electrodes for electrophysiological activity). EEG signals were acquired on the Enobio device, with all 8 channels (F3, F4, FZ, P3, P4, CZ, C3 and C4) in alpha and beta rhythm in order to establish the active networks is shown in figure 2.Volunteers were participated, and they were instructed to perform motor imagery tasks and movements as shown in figure 3. The signals are amplified to levels suitable for electronic processing (and they may also be subjected to filtering to remove electrical noise or other undesirable signal characteristics, such as 60-Hz power line interference). The signals are then digitized and transmitted to a computer. Pre-processing is important steps in EEG signal processing. Pre-processing techniques help to remove unwanted artifacts from the EEG signal and hence improve the signal to noise ratio. A pre-processing block aids in improving the performance of the system by separating the noise from the actual signal. The EEG signal is filtered using Butterworth band pass filter.



Figure 3 : Signal Acquisition

FEATURE EXTRACTION

Once the signals acquired in a form of digitized data are preprocessed, we need to determine features from the raw signal by the use of digital processing techniques. This process is named 'feature extraction'. Feature extraction is a special form of

dimensionality reduction. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. Since not all features that can be extracted from signals for a given classification problem need to be used, due to their redundancy, a further process is needed for redundancy reduction by retaining only an informative subset of them. This stage of processing is called 'feature selection'.

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called features extraction. Thus the extraction of discriminatory features in the signal enhances the reduction of the length of the data vector by eliminating redundancy in the signal and compressing the relevant information into a feature vector of significantly lower dimension. The oscillograms are a graphical representation in which it depicts some information regarding the variations in the pattern according to the type of the flaws. So these oscillograms can be described by pertinent features allowing the defect classification. After pertinent feature extraction, it is normally useful to elaborate a recognition procedure (identification) of the detected defect type.

A feature extraction block helps to retrieve the most relevant features from the signal. These features will aid the decision making mechanism in giving the desired output. The features such as Mean, Variance, Standard deviation, Discrete Wavelet Transform have been tested. Mean is nothing but an average value.

The variance is defined as the sum of square distances of each term in the distribution from the mean, divided by the number of terms in the distribution. Discrete wavelet transform is used to extract characteristics from a signal on various scales proceeding by successive high pass and low pass filtering. The wavelet coefficients are the successive continuation of the approximation and detail coefficients.

The basic feature extraction procedure consists of

1. Decomposing the signal using DWT into *N* levels using filtering and decimation to obtain the approximation and detailed coefficients

2. Extracting the features from the DWT coefficients

The features extracted from the discrete wavelet transform (DWT) coefficients of ultrasonic test signals are considered useful features for input into classifiers due to their effective time-frequency representation of no stationary signal.

CLASSIFICATION

The very aim of BCI is to translate brain activity into a command for a computer. The classification stage involves the identification of the feature patterns to facilitate the categorization of the user's intents. The output of the classification stage is the controlling input of the device.

The various classification algorithms used to design BCI systems are: linear classifiers (Linear Discriminant Analysis- LDA, Support Vector Machine- SVM), neural networks and non-linear Bayesian classifiers. The main drawback of LDA is its linearity that can provide poor results on complex non-linear EEG data, so support vector machine algorithm is used.

We chose support vector machines (SVMs) as a learning algorithm because they have performed well as a classifier in past BCI competitions and because they generally perform well on a variety of classification problems. Additionally, SVMs allow for rapid classification from trained models and are capable of handling very high-dimensional input vectors. The classification problem can be restricted to consideration of the two-class problem without loss of generality. In this problem the goal is to separate the two classes by a function which is induced from available examples. The goal is to produce a classifier that will work well on unseen examples, i.e. it generalizes well. There are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin (maximizes the distance between it and the nearest data point of each class). This linear classifier is termed the optimal separating hyper plane. Intuitively, we would expect this boundary to generalize well as opposed to the other possible boundaries.

NIC SOFTWARE

NIC stands for Neuroelectrics Instrument Controller. NIC is the software required to pair with the Neuroelectrics devices, like ENOBIO and Starstim. It has a user-friendly interface packed full of features. NIC is a platform full of capabilities: Control Neuroelectrics devices via Bluetooth, Manage and record EEG sessions, Stream data over the network, Receive network triggers, Visualize EEG features online: raw or filtered data and spectral power scalp maps, Set up and launch multielectrode stimulation protocols, Visualize the electric field on the cerebral cortex that results from the stimulation currents.

III. RESULTS AND ANALYSIS

This work reported the data of BCI Competition Datasets have been applied for analysis. During signal acquisition, EEG analysis such as spectrogram and band power configuration was done as shown in figures 4 and 5. Six subjects have been chosen for the feature extraction and classification experiment. And the classification is done using the SVM technique for classifying the hand and leg movements and it is plotted using scatter plot as shown in the figure 6. And the average accuracy is 86%.

71



Figure 4 Spectrogram configuration





1V. CONCLUSION

We have applied Butterworth band pass filtering to extract the meaningful EEG data in order to correctly classify the left hand, right hand, up and down motor imagery and movement task before feature extraction step. The filtering method helps us to reduce the effect of artifacts and to enhance the performance of a motor imagery based brain computer interface (BCI). A combination of features whose frequencies fall in the frequency range of μ and β rhythms has provided improvement in the accuracy of classifying left and right hand MI EEG signals as compared to μ and β feature individually. In future, it would be of interest to develop and implement new features along with the band-pass filtering method for classifying MI EEG signals. Although enhanced feature seperability offered by the band-pass filtering method has helped to increase the classification accuracy by reducing the effect of artifacts.

REFERENCES

- [1] Parthana Sarma., et.al., (2016) "Pre-processing and feature extraction techniques for EEG –BCI applications" Volume 5-AJET (ABDU- Journal of Engineering and Technology).
- [2] K.Sercan Bagram., et.al., (2013) "Classification of EEG signals by using support vector machines" IEEE (Institute of Electrical and Electronics Engineering).

[3] Mohammad H.Alomari., et.al.,(2013) "Automated Classification of L/R hand movement EEG signals using advanced Feature Extraction and Machine Learning" Volume 4-IJACSA (International Journal of Advanced Computer Science and Applications).
[4] A.Sivakami, S.Shenbaga Devi., et.al.,(2015) "Analysis Of EEG For Motor Imagery Based Classification Of Hand Activities", Volume 2-IJBES (International Journal of Biomedical Engineering and Science).

[5] Cynthia A Chestek., et.al.,(2013) "Hand Posture Classification using Electrocorticographic signals in the Gamma band over Human sensorimotor brain areas", JNE (Journal of Neural Engineering)

[6] Ehsan Heidari., et.al.,(2012) "Brain EmotionalLearning based Brain Computer Interface", IJCSI (International Journal of Computer Science Issues).

[7] Mandeep Singh., et al., (2013) "Feature Extraction from EEG for Emotion Classification", Volume 7-IJITKM (International Journal of Information Technology and Knowledge Management).

[8] Rashima Mahajan., et al., (2014) "A Real Time Set Up for Retrieval of Emotional States from Human Neural Responses", Volume 8-International Journal Of Medical, Health, Biomedical, Bioengineering And Pharmaceutical Engineering.