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Temporal based EEG Signals Classification for Talocrural and Knee Joint Movements using Emotive Head Set

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ABSTRACT

Recent developments in Brain Computer Interfacing (BCI) and neuroprosthetics have played a vital role for disable people to expect better life quality. In this contribution Electroencephalographic (EEG) signals acquired from six healthy test subjects, are used for the offline analysis of BCI through classification of four lower limb movements including talocrural (ankle) joint dorsi-planter flexion and knee joint extension-flexion. Fourteen channel Emotive EPOC head set is used to acquire EEG signals from sensorimotor cortex area of brain, using a particular data acquisition timeline protocol. Features are extracted in time domain from raw EEG data. Power spectral density, variance, mean value and kurtosis features are applied on raw EEG signals. Multiple classification algorithms are implemented for discrimination of four lower limb movements within data set. The paper uses Quadratic discriminant analysis, Naïve Bayes and Support vector machine classifiers to stratify the movement intent of lower limb. Maximum classification accuracies achieved through various classifiers are; 86.35% with average band power & QDA, 84.38% with mean value & QDA and 78.13% with power spectral density & Quadratic-SVM. The presented findings are optimistic in making the path easier towards the development of BCIs with rich EEG based control signals using noninvasive technology.

Keywords: kurtosis, Quadratic Discriminant Analysis, Naïve Bayes, Support Vector Machine.

1 Introduction

BCI technologies decode signals acquired from brain activities in order to translate the human intentions into useful readable commands to control external devices like prosthetics or computer applications. It provide an alternative opportunity to people suffering from severe diseases causing paralysis and motor disabilities. It is an emerging technique nowadays and provide a communication facility to control and actuate devices using brain signals [1]. Various techniques have been adopted to extract signals from brain which includes magneto electroencephalography (MEG), Functional magnetic resonance imaging

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(fMRI), near infrared spectroscopy (NIRS), electrocarticogram (ECoG) and electroencephalography (EEG) [1] & [2]. Among these aforementioned techniques signals acquisition using EEG is a rapid infusion in BCI since it reflects the electrical responses of human brain in actions and it is widely used because of its noninvasiveness, higher temporal resolution, Inexpensiveness, and no exposure to radiations.

In this contribution EEG data is collected from brain using EMOTIV Headset [13] with fourteen channel electrodes. The main benefit of using emotive headset is that it provides better portability along with providing a noninvasive medium for collection of EEG data. According to a survey majority of the cases of strokes or brain injuries causes disability of people and this type of disability can be addressed either by providing a prosthetic device or by restoring the motor function of such disable patients [6]. Nowadays with the advancements in the field of biomedical engineering, evoked potential recorded from brain combining with the robotic feedback is used to help people with disabilities. Some of the most recent and important research applications of BCI are human to human interface, control of a prosthetic robotic arm, exoskeleton control, mobile and guided robotics [4].

In this paper, classification of offline EEG data signals for lower limb joints movements is presented in which two knee movements (extension & flexion) and two talocrural (ankle) movements (dorsiflexion & plantarflexion) are included. According to literature review most of the work on EEG signals classification is carried out on distinguishing the movements of upper limbs which includes carpus, ante brachium, fingers and hand gestures whereas for lower limb movements higher number of electrodes are required to record the evoke potential from the scalp of the brain, as the signals are quite weak and noisy. Table 1 shows brief survey of bunch of the classification & features extraction techniques which have been implemented to classify different lower limb movements.

Table 1: Literature Review

Authors/References	No. of Electrodes	Classification Algorithm	Features Acquired	Accuracy
Josheph T. GWin, Daniel P Farris [4]	264 Channel	Naïve Bayes	Independent Components Analysis	80%
Kaiyang Li, Xiaodong Zhang, Yuhuan Du [14]	16 Channel	Support Vector Machine	Wavelet Transform	78.9%
Presacco A, Goodman R, Forrester L [9]	60 Channel	Linear Weiner Filter	Power Spectral Density	75%
Hosni S.M, Ain Shams Univ, Cairo [16]	16 Channel	Radial Basis Function Support Vector Machine	Auto Regressive, Band Power, PSD	70%
Fathy A, Elhelw M, Eldawlatly S [19]	14 Channel	Linear Discriminant Analysis	Principal Components Analysis	73%

This paper focuses on the Electroencephalographic signals (EEG) acquisition through noninvasive method in which Emotiv headset equipped with 14 active electrodes is used to collect EEG data from test subject. Data is recorded individually for four movements of lower limb for predefined period of time, according to data acquisition protocol. Once the EEG data is recorded, sixth order Butterworth filter is applied for removal of noise and undesirable artifacts from the data set. Further this paper uses multiple feature extraction techniques to figure out the prominent features and supervised learning classification algorithms to stratify lower limb movements including knee joint extension & flexion and talocrural joint dorsiflexion & plantarflexion.

2 Methodology and Data Acquisition

An experimental protocol for data acquisition is designed for offline analysis of the time series EEG data. Six volunteers (3 males & 3 females) age between 21 to 30 years participated in the data acquisition experimentation without any prior training of the experimental procedure. All test subjects are physically healthy and neurologically stable. Data acquisition is carried out in noiseless room with subjects sitting comfortably in a chair with arms rested on sides. The subjects performed the movements shown on a computer screen in the form of a video in which a person is performing lower limb movements (knee joint extension, knee joint flexion, talocrural joint dorsiflexion and talocrural joint plantarflexion). The test subjects are instructed to avoid any eye blinking, facial expressions in order to minimize unnecessary artifacts while performing the limb movements. Twenty five trials of each type of movement with 1000 data points in 9.50 seconds are acquired from each subject. Figure 1 shows the block diagram of whole process.

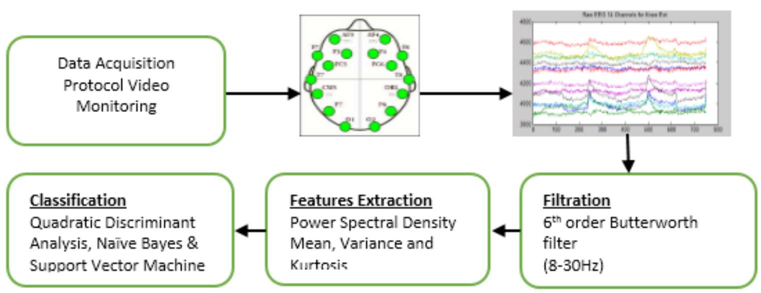

Figure 1: Block Diagram of Brain Computer Interface System

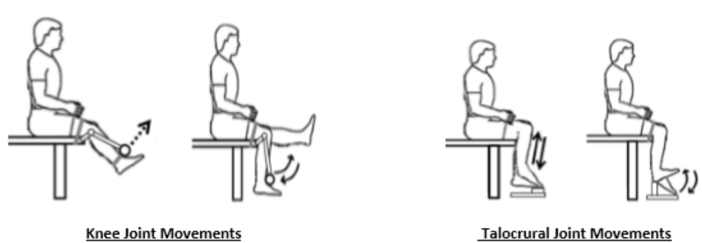

Figure 2: Lower Limb Movements

EEG signals recorded in this paper are based on the international 10-20 system [13] which are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 respectively. Signals were recorded at 128 Hz sampling rate and they are spontaneous signals as these signals have rhythmicity. It can be divided into different frequency bands out of which alpha (8-13Hz) and beta (14-30Hz) frequency bands [14] are more dominant during the state of consciousness and limbs movements therefore these two bands are filtered by applying Butterworth filter (8-30Hz) for the classification of lower limb movements, as Butterworth filter have smooth pas bands as compared to other types of filters.

Emotiv Headset equipped with 14 active electrodes is used to record visually evoked response from the sensorimotor cortex on the scalp of the brain. Specifications of the Emotiv headset are discussed in below mentioned table 2 [13].

Table 2: EMOTIV Headset Specifications

Number of channels	14 (plus CMS/DRL references)
Channel names (Int. 10-20 locations)	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2
Sampling method	Sequential sampling, Single ADC
Sampling rate	~128Hz (2048Hz internal)
Resolution	16 bits (14 bits effective) 1 LSB = 1.95μV
Bandwidth	0.2 - 45Hz, digital notch filters at 40Hz and 60Hz
Dynamic range (input referred)	256mVpp
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Battery type	Li-poly
Battery life (typical)	12 hrs
Impedence measurement	Contact quality using patented system

3 Filtration of Acquired EEG Data

Once the data is recorded, band pass filter is applied (8-30Hz) in both forward and reverse direction with sampling frequency of 500Hz. In Brain computer interfacing, the purpose of filtration is to minimize the undesirable artifacts recorded during data acquisition [9]. Most common source of artifacts are physiological artifacts like eye movement and muscles movements [7], where eye movements have frequency of 2-5 Hz which are removed by bandpass filter[10] & [17]. Frequency response of the sixth order Butterworth filter, raw and filtered EEG data is shown in figure 3.

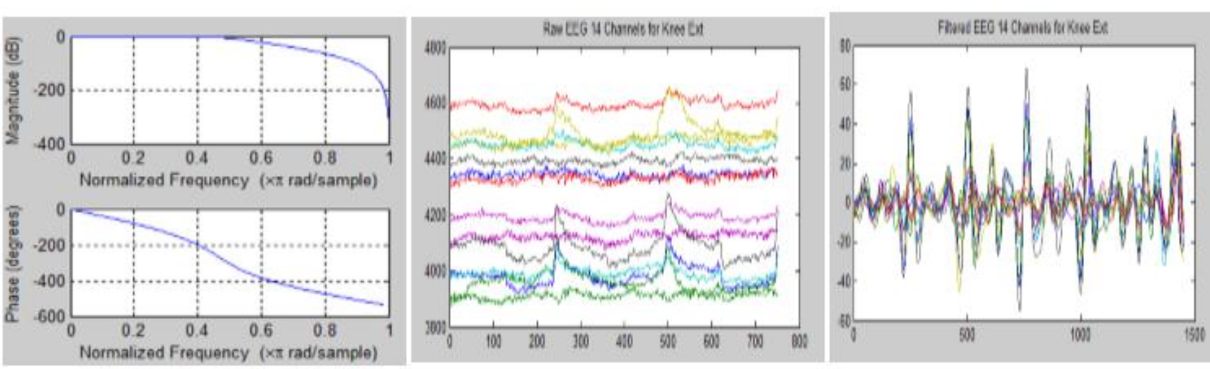

Figure 3: Frequency Response of Band Pass Filter, Raw EEG Acquired Data of 14 Channel, Filtered Data

4 Feature Extraction

Multiple feature extraction techniques are implemented to extract the features from filtered EEG data in time domain [16]. Average band power (PSD) [12] provides us information about the distribution of time series data over different frequencies. It shows the variation of data with respect to different frequencies.

$$Average\ Power_{PSD} = \frac{1}{2\pi}\int_{w1}^{w2} S_{X_w}.\ dw$$

Where S_{X_w} is the power spectral density of the filtered EEG signal ($x_i(t)$) and X_w is Fourier transform of filtered signal $x_i(t)$.

The measurement of spread between the numbers in the observed data set is termed as variance and kurtosis depicts the statistical distribution of observed EEG data around the mean, as EEG data is a nonstationary data and its distribution is purely non Gaussian.

$$Variance = \frac{1}{N-1}\sum_{i=1}^{N}|X_i - \mu|^2$$

Where X_i is a 14 column vector representing the EEG data recorded from 14 electrodes and μ is the mean of individual columns and N is the number of data points.

$$\text{Kurtosis} = \frac{\sum_{i=1}^{N}\frac{(X_i-\bar{X})^4}{N}}{S^4}$$

Where X_i is the observed data, N represents number of points, $\bar{X}$ indicates mean of observed data and S^4 represents the standard deviation. There are multiple techniques available to translate the features from observed data in combine frequency-time domain like Hilbert Transform, Wavelet Transform and Auto Regressive [8] & [17] but these methods increase the complexity of parameters and enhancing the difficulties like overfitting of data during classification. Topographical distribution of feature vectors (average band power) of lower limb movement's data is shown in figure 4. The red area shows convergence of the data over the left hemisphere of frontal lobe of motor cortex.

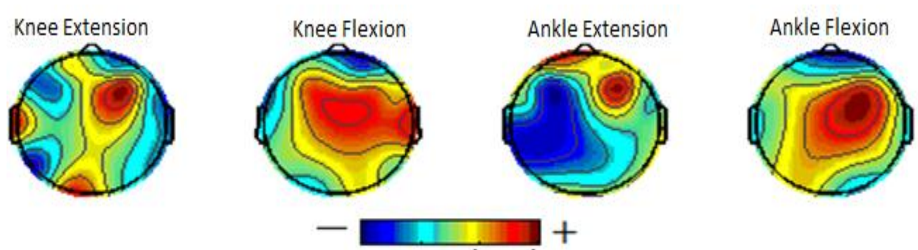

Figure 4: Topoplots of feature vector (Average band power) for knee extension movement, knee flexion movement, Talocrural Dorsiflexion movement and Talocrural Plantarflexion movement

5 Classification Techniques

Once the feature vectors are extracted from filtered EEG data, these feature vectors are classified into four classes representing four types of lower limb movements. This paper used Quadratic Discriminant Analysis (QDA), Naïve Bayes and one to one support vector machine (SVM) [12] & [14] with quadratic kernel. Mathematically QDA can be formulated as;

$$g_{j(x)} = \sum_{i=1}^{4} w_i x_i + w_o + \sum_{i=1}^{4}\sum_{j=1}^{4} w_{ij} x_i x_j$$

where w_i is the weight vector $w.x \propto \in^{-1} (x-\mu)^t (x-\mu)$, w_{io} is the bias threshold/ weight threshold and μ is the average mean. Discriminant analysis assigns objects to one of the several classes depending upon the 14 column feature vector. The classifier is said to assign feature vector x to a class w_i if.

$$g_i(x) > g_j(x) \qquad \text{for all } j \neq i$$

Architectural diagram of the QDA is shown in figure 4.

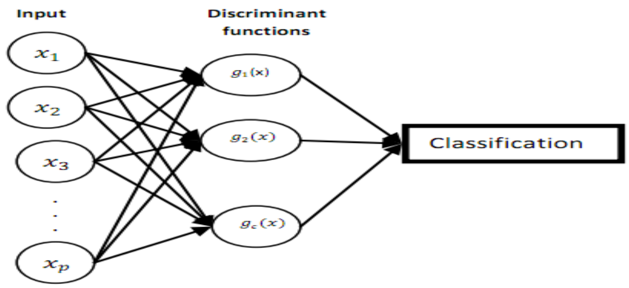

Figure 5: Quadratic Discriminant Analysis Architecture

Naïve Bayes [15] is based on Bayesian Theorem according to which it splits the posterior in terms of prior distribution and likelihood. Bayes classifier assumes that the values of a particular feature of EEG signal is unrelated to the presence or absence of any other feature translation given the class. Mathematical formulation is presented as;

$$P(W|X_1, X_2 \dots\dots\dots X_n) = \frac{P(X_1, X_2 \dots\dots\dots X_n|W)\, x\, P(W)}{P(X_1, X_2 \dots\dots\dots X_n)}$$

where $P(W|X_1, X_2 \dots\dots\dots X_n)$ represents the posterior probability of the class given feature vectors (X1,X2……X14), $P(X_1, X_2 \dots\dots\dots X_n|W)$ represents likelihood of the feature vectors given Class(W1,W2,W3 & W4). $P(W)$Indicates prior probability about the class (0.25 for each class) and $P(F_1, F_2 \dots\dots\dots F_n)$ represents evidence or normalizing factor.

Support vector machine constructs a hyperplane in feature space to classify different classes of data. Nature of hyperplane depends upon the type of kernel function used as in this paper quadratic kernel is implemented to classify EEG data among four classes by drawing a nonlinear hyperplane. Mathematically SVM is represented by following equation [14];

$$y = \sum_i a_i \beta(s_i, x) + b$$

Where S_i is support vector, a_i is weight and b is the bias which is used to classify feature vector x into four classes. Here β represents the kernel function. As stated above quadratic kernel is implemented in this paper and mathematically it can be represented as.

$$\beta(s_i.x) = (s_i.x + r)^2$$

where r is the quadratic function parameter and for the sake of better classification it is selected carefully.

6 Results and Discussion

Classification rates achieved using multiple feature extraction techniques with different classifying algorithms are presented in table 3. Based on the analysis, results obtained and the literature survey, it can be concluded that Quadratic Discriminant Analysis with average band power as feature vector give the best classification accuracy of 86.25% whereas SVM with average band power feature set give 78.13% and Naïve Bayes give 74.38% respectively. Mean, variance and kurtosis as feature set also showed classification accuracy in acceptable range.

Table 3: Percentage Accuracies of Different Classifiers verses Multiple Feature Sets

Classification Algorithm	Average Band power	Mean Value	Variance	Kurtosis
QDA	86.25%	84.38%	83.10%	60.63%
Quadratic SVM	78.30%	65.53%	71.88%	51.26%
Naïve Bayes	74.56%	71.29%	73.75%	53.45%

The research work carried out in this paper has of great importance as one can understand that how specific neural activity differs from the other motor cortex area, as primary motor cortex of brain is organized such that the left side of the primary cortex is responsible for the movements of right side of the body and right side of brain cortex is responsible for movements of left side of the body. Stratified and cross validated results along with the weighted average results of Naïve Bayes and average band power, Kurtosis & Variance as feature set, are presented in table 4.

Table 4: Naïve Bayes Classified Cross Validation, Weighted Average by Class and Relative Error

Naïve Bayes Classifier	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error	Coverage of Cases (0.95 level)	Mean Rel. Region Size	True Positive Weighted Avg.	False Positive Weighted Avg.
Average Band Power	0.1259	0.3378	33.57%	78.01%	78.75%	28.59%	0.750	0.083
Kurtosis	0.2238	0.4326	59.67%	99.90%	71.25%	35.15%	0.550	0.150
Variance	0.1363	0.3552	36.24%	82.02%	\78.125%	28.12%	0.725	0.092

The deviation in results occur due to variation in the size of classes as it increases the misclassification rate and the weighted average of false positives. As shown in table 4, weighted average of false positives in case of average band power is 0.083, in case of kurtosis 0.150 and in case of variance 0.092 whereas weighted average for true positives is 0.750, 0.550 and 0.725 respectively. In this research, a novel combination of feature vectors and classification algorithms has been implemented to decode lower limb movements (knee and talocrural joint extension/flexion) with maximum classification accuracy of 86.25%.

7 Conclusion

This research work is focused on the optimization of classification techniques with multiple set of feature vectors. In this study, the performance of Quadratic discriminant analysis, Naïve Bayes and Support vector machine using average band power, mean value, variance and kurtosis feature vectors for the classification of four lower limb movements has been analyzed. The performance metric for this study was to achieve better classification accuracy by using lesser number of EEG electrodes. At the culmination of this research work, it was shown that maximum classification accuracy of 86.25% is achieved using 14 channel Emotive headset. Future work is aimed at the online EEG data acquisition and processing along with interfacing of robotic lower limb with FPGA controller and Emotiv Headset.

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