Feature Extraction of Motor Imagery EEG Data Using Time Domain Statistical Parameters

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Abstract: A brain–computer interface (BCI) provides a communication pathway between the brain and the outside world. It is a boon for people disabled by neuromuscular disorders. BCI works by measuring brain signals, analyzing, interpreting them and translating them into actions. Electroencephalography(EEG) is the measurement of electrical activity produced by the brain. Motor Imagery is the mental simulation of a kinesthetic movement without any physical movement. Each brain signal is quantified by a few relevant values known as features. Once the features are extracted the users intentions can be identified. Feature extraction module is responsible for choosing the features which are very important for classification. In this paper we propose time domain statistical feature extraction techniques such as mean correlation, Kurtosis, Skewness which are classified with KNN classifier. The results are compared with features extracted by Common Spatial Pattern (CSP) and classified using Linear Discriminant Analysis classifier.

Keywords: BCI, EEG, Motor Imagery, Feature extraction

1. Introduction

Brain Computer Interface (BCI) provides a pathway for communication between the brain and external devices Mak Joseph N et al,, (2009),Kanimozhi M et al., (2018), Y. Wang et al., (2008) [1-3]. Human brain is a complex structure filled with neuron cells Mane et al., (2014), K, Manjula et al., (2018), Teplan et al., (2002) [4-5].Whenever we think, intend to move, move, remember or feel the neuron cells produce electrical signals. These signals can be measured by Electroencephalography (EEG) through the electrodes placed on the scalp. Electroencephalography is a medical imaging technique that reads scalp electrical activity generated by the brain Abdulkader et al., (2015) [6]. EEG based BCI are characterised by using non-invasive techniques to measure the brain signals.It is easy to use, portable and inexpensive Diwaker et al.,(2016) [7]. The main task of establishing a communication link between a computer and human brain is to predict what the human intends to do. For this we need classification of EEG signals into the movements about which the person is thinking Barros et al., (2018)[8].

Motor Imagery

Motor Imagery (MI) is defined as the cognitive process of imagining the movement of our own body part without actually moving it. Whenever we move a muscle, oscillations occur on the sensorimotor and motor areas of the brain Pfurtscheller et al., (2001) [9]. In fact even imagining the movements produce oscillations very similar to the actual movements in the primary sensorimotor area Pfurtscheller et al., (1997) [10]. Motor Imagery works by making the people imagine the movement of the left hand, right hand or feet and measuring the brain signals over the respective cortical areas R. Walpow et al., (2002) [11]. The EEG signal processing of MI BCI involves feature extraction and classification.

Feature Extraction

In BCI systems the signals are recorded from multiple channels to preserve high spatial accuracy Diwaker et al.,(2016) [7]. Each and every brain signal is quantified by a few relevant values known as features. BCI are designed to extract and quantify temporal, morphological features from the recorded brain signals. Feature extraction is construction of the most discriminative signal characteristics and representing them in a compact form. Feature extraction mode is responsible for choosing the features which are most important for classification. Various feature extraction techniques can be used to extract important features from the raw EEG data.Pfurtscheller et al., (2002) [12] Feature extraction technique can be based on either calculating statistical descriptions or producing syntactic descriptions. It can either be time domain or frequency domain Rahman M.A. et al., (2019) [13]. The important time domain features are maximum value, mean value, standard deviation, skewness, kurtosis, etc…which can be extracted from raw EEG data Vacius Jusas et al., (2019) 14].

In this paper we propose time domain feature analysis such as mean correlation, kurtosis and skewness to extract the features and classify it with knn classifier. The results are compared with accuracy obtained by CSP feature extraction and Linear Discriminant Analysis classifier. The rest of the paper is organised as follows. Section II is about literature review, Section III describes the data set used. Section IV is about the time domain feature extraction followed and Section V is about results and discussion. Section VI is the conclusion.

2. Literature Review

Various feature extraction techniques and classification are adopted by different authors. Ali Ahmadi et al., (2011) [15] presented a computationally lightweight classification method based on several time and frequency domain features. After preprocessing and filtering, wavelet transform and Short Time Fourier Transform (STFT) are used for feature extraction.

Huang D et al., (2012) [16] presented a feature extraction algorithm for EEG-based emotion detection problem. The algorithm, Asymmetric Spatial Pattern (ASP), extracts pairs of spatial filters, with each filter corresponding to only one of the two sources. They have shown the effectiveness of the proposed algorithm by application to real data for two types of EEG-based emotion detection problems: arousal detection (strong vs calm), and valence detection (positive vs negative).

von Bunau P et al., (2010) [17] showed that Stationary Subspace Analysis (SSA), a time series analysis method, can be used to identify the underlying stationary and non-stationary brain sources from high-dimensional EEG measurements. Using CSP they were able to identify imagined left and right hand movement with 70% accuracy.

Sannelli C et al., (2012) [18] proposed the Common Spatial Patterns Patches (CSPP) technique which improves the co-adaptive calibration. CSPP is an ensemble of localized spatial filters, each of them optimized on subject-specific data by CSP analysis.

Fan X et al., (2012) [19] proposed a method to detect pedestrian sudden occurrence, as an example of emergency situations, by monitoring drivers' state from EEG. The (LDA) classifier with power spectrum of EEG potentials as input features of the detection model was used to recognize the emergency situation, and (ROC) was used to determine the threshold of the classifier. The experimental results of three healthy subjects indicated that the detection model can recognize the emergency situation within one second (shorter than the response time of drivers) with an accuracy of about 70%, showing that it is feasible to detect emergency situations by monitoring driver's states from EEG.

Swati Aggarwal et al.,[20] presented the comprehensive comparison of prominent feature extraction techniques used for EEG based BCI for motor imagery tasks.

S. M. R. Islamet al., [21] paper presents the EEG datasets that are built with different cognitive task such as left, right, back and front imaginary movement with eye open. They have used different feature extraction methods to classify these EEG signal using Support Vector Machine (SVM), k-Nearest Neighbor (k-NN) and Artificial Neural Network (ANN).

Manjula K et al., [5] showed that EEG signals are non-stationary that is, its spectrum changes with time so we have to adopt different feature extraction methods.

M. Rajya Lakshmi et al.,[22] described the feature extraction techniques, such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Auto Regressive Model (AR), Wavelet Transform (WT) and Wavelet Packet Decomposition (WPD) and has explored the signal processing methods used in each stage of brain computer interface.

Vacius Jusas et al., [23] research paper explored the methods of band power, time domain parameters, Fast Fourier Transform and channel variance for feature extraction.

Bajaj, Varun, et al.,(2020) [24] explored the non-stationary characteristic of the EEG signal by tunable Q-factor wavelet transform (TQWT). Statistical features of the Hjorth mobility such as minimum value, maximum value, mean and standard deviation (SD) are used for characterization of the alertness and drowsiness states.

Shoeibi, Afshin, et al. 2021 [25] proposed an approach to extract features from EEG signals based on spectrograms. First, STFT is applied to EEG to obtain time-frequency representations.

3. Description of Data

In this study, we used data set provided by the Dr. Cichocki's Lab (Lab. for Advanced Brain Signal Processing), BSI, RIKEN collaboration with Shanghai Jiao Tong University. These data sets of EEG data were recorded from several healthy subjects. The cue-based BCI paradigm consisted of two/three motor imagery tasks, namely the imagination of movement of the left hand (LH), right hand (RH) and both feet (F). Several sessions on different days were recorded for some subjects, the data of each session was stored in one data file respectively. In this data sets, the two devices of g.tec (g.USBamp) and Neuroscan (SynAmps RT) were used for recording the EEG signals. The EEG signals were band-pass filtered between 2Hz and 30Hz with sample rate of 256Hz and a notch filter at 50Hz was enabled for g.tec whereas the band-pass filter between 0.1Hz and 100Hz with sample rate of 250Hz was applied for Neuroscan device. The signals are measured in µV and V for Neuroscan and g.tec respectively. All data sets are stored in the Matlab format (*.mat). The file name consists of subject ID, channel number, imagery tasks and session number. For example, 'SubC_6chan_3LRF_s1': Subject C, 6 channels, 3-class imagery tasks of left hand, right hand and feet and session 1. Table 1 provides information for each data set file including subject ID, motor imagery class, channel number, duration of each imagination task, trial number, sample rate, device name and the 10x10 folder cross validation performance (accuracy ± standard deviation) on this data set. The performance is roughly obtained by basic preprocess, CSP feature extraction and LDA classifier.

Dataset	**Subject**	**Class**	**Channel**	**Duration (sec)**	**Trial number**	**10x10 CV (Acc.±std.)**	**Sample rate**	**Device**
SubA_5chan_3LRF	A	LH/RH/F	5	4s	270	0.92±0.004 0.91±0.03(2c)	256Hz	g.tec
SubB_5chan_3LRF	B	LH/RH/F	5	4s	174	0.86±0.01 0.92±0.01(2c)	250Hz	Neuroscan
SubB_6chan_3LRF			6		150	0.80±0.03 0.94±0.01(2c)		
SubC_5chan_3LRF	C	LH/RH/F	5	4s	180	0.86±0.01 0.90±0.04(2c)	256Hz	g.tec
SubC_6chan_3LRF_s1			6	3s	300	0.89±0.01 0.92±0.004(2c)		
SubC_6chan_3LRF_s2					300	0.84±0.01 0.87±0.01(2c)		
SubC_6chan_3LRF_s3					204	0.89±0.01 0.92±0.01(2c)		
SubC_5chan_3LRF _Day1	C	LH/RH/F	5	4s	210	0.72±0.02 0.78±0.02(2c)	256Hz	g.tec
SubC_5chan_3LRF _Day2					210	0.81±0.01 0.88±0.01(2c)		
SubC_5chan_3LRF _Day3					180	0.81±0.01 0.86±0.02(2c)		
SubC_5chan_3LRF _Day4					180	0.83±0.02 0.90±0.01(2c)		
SubC_5chan_3LRF _Day5					234	0.87±0.01 0.96±0.002(2c)		
SubC_5chan_3LRF _Day6					150	0.88±0.01 0.92±0.01(2c)		
SubC_5chan_3LRF _Day7					180	0.88±0.01 0.94±0.01(2c)		
SubC_14chan_3LRR	C	LH/RH/R	14	4s	350	0.78±0.01 0.88±0.004(2c)	250Hz	Neuroscan

Table 1 : Data set

4. Methodology

Time domain feature extraction techniques such as mean correlation, kurtosis and skewness are used to extract the important features from the three class data sets. Figure 1 describes the methodology used.

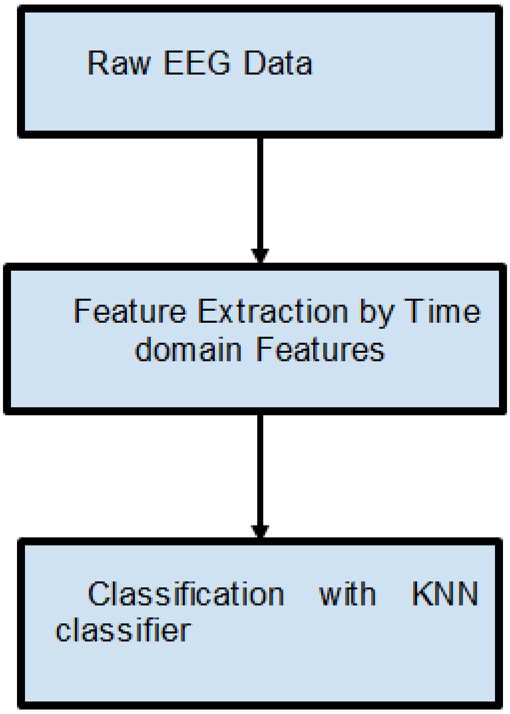

Figure 1 : Methodology

Mean Correlation

The following equations used for extracting the features. The correlation coefficient that indicates the strength of the relationship between two variables can be found using the following formula:

$$r_{xy} = \frac{\sum(xi - \underline{x})(yi - \underline{y})}{\sqrt{\sum(xi - \underline{x})^2(yi - \underline{y})^2}} \qquad (1)$$

Where:

r_{xy} – the correlation coefficient of the linear relationship between the variables x and y

x_i – the values of the x-variable in a sample

$\bar{x}$ – the mean of the values of the x-variable

y_i – the values of the y-variable in a sample

$\bar{y}$ – the mean of the values of the y-variable

Kurtosis

The kurtosis of a distribution is defined as

$$k = \frac{E(x-\mu)^4}{\sigma^4} \qquad (2)$$

where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t. kurtosis computes a sample version of this population value.

Skewness

The skewness of a distribution is defined as

$$s = \frac{E(x-\mu)^3}{\sigma^3} \qquad (3)$$

where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t. skewness computes a sample version of this population value.

After feature extraction, knn classifier is used to classify the extracted features.

5. Results and Discussion

The classification accuracy of the three class data sets with the extracted features are listed in the table 2.

	Dataset	Trial number	Attributes	Classification accuracy		
				Mean Correlation	Kurtosis	Skewness
1	SubA_5chan_3LRF	270	1024	78.6	76.7	77.9
2	SubB_5chan_3LRF	174	1000	84.9	87.4	86.5
3	SubB_6chan_3LRF	150	1000	87.6	83.8	85.7
4	SubC_5chan_3LRF	180	1024	85.8	84.0	84.8
5	SubC_6chan_3LRF_s1	300	768	88.3	82.5	85.3
6	SubC_6chan_3LRF_s2	300	768	82.2	77.8	80.4
7	SubC_6chan_3LRF_s3	204	768	84.5	83.2	86.5
8	SubC_5chan_3LRF _Day1	210	1024	89.2	90.1	89.7
9	SubC_5chan_3LRF _Day2	210	1024	85.9	84.8	81.2
10	SubC_5chan_3LRF _Day3	180	1024	82.5	79.3	80.9
11	SubC_5chan_3LRF _Day4	180	1024	89.0	88.4	88.0
12	SubC_5chan_3LRF _Day5	234	1024	91.0	89.6	90.7
13	SubC_5chan_3LRF _Day6	150	1024	86.7	85.2	87.8
14	SubC_5chan_3LRF _Day7	180	1024	89.5	90.6	89.1
15	SubC_14chan_3LRR	350	1000	85.9	80.6	85.7

Table 2: Classifiction Accuracy

The comparative analysis of classification results with mean correlation, kurtosis and skewness are shown in figure 2.

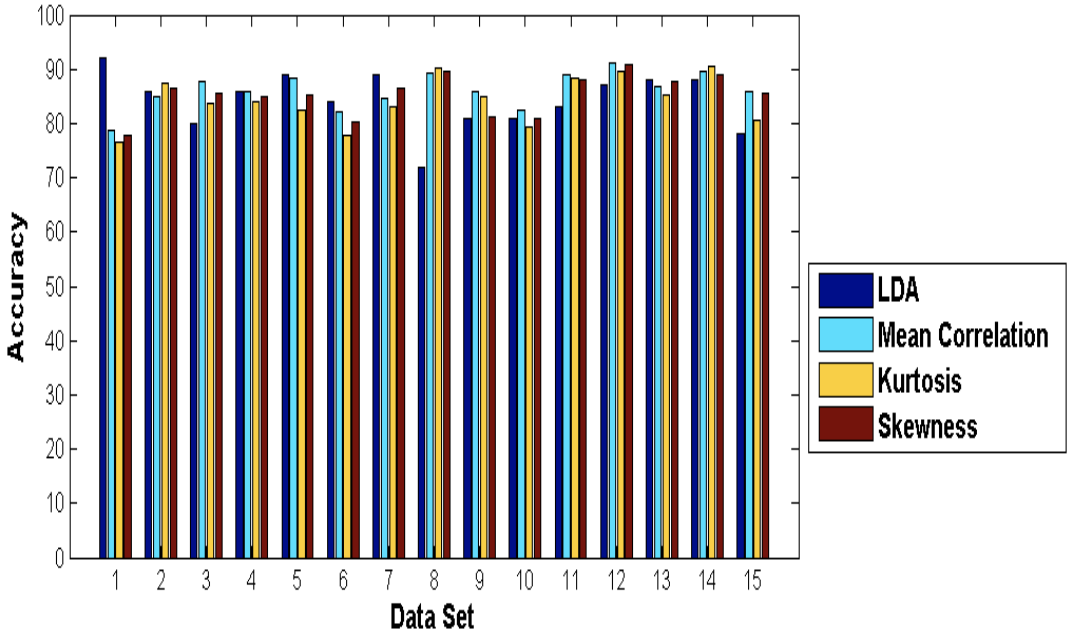

Figure 2 : Classification results

The comparison of accuracy obtained by the features of mean correlation, kurtosis and skewness which are classified using knn classifier with CSP feature extraction classified with LDA classifier are shown in figure 3, figure 4 and figure 5 respectively.

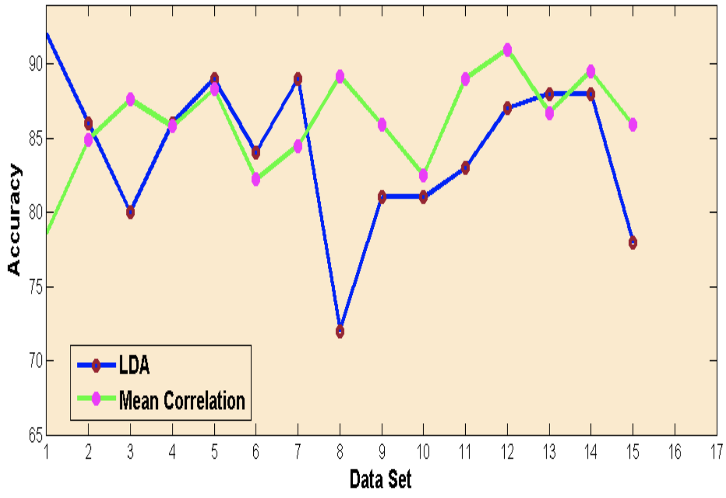

Figure 3 : Comparison of LDA with Mean Correlation

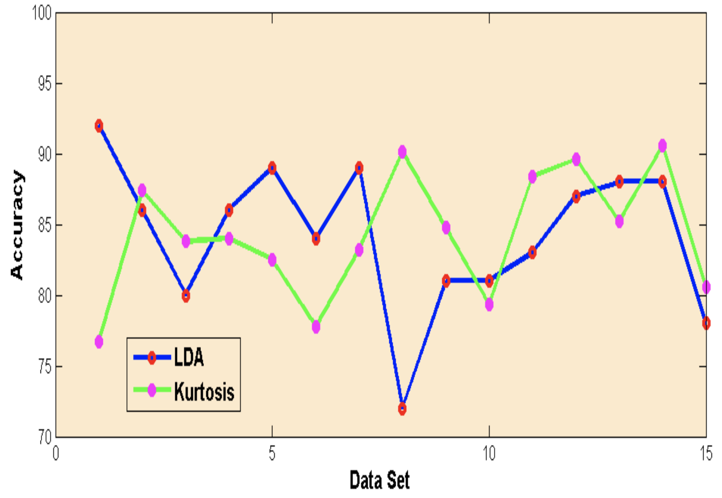

Figure 4 : Comparison of LDA with Kurtosis

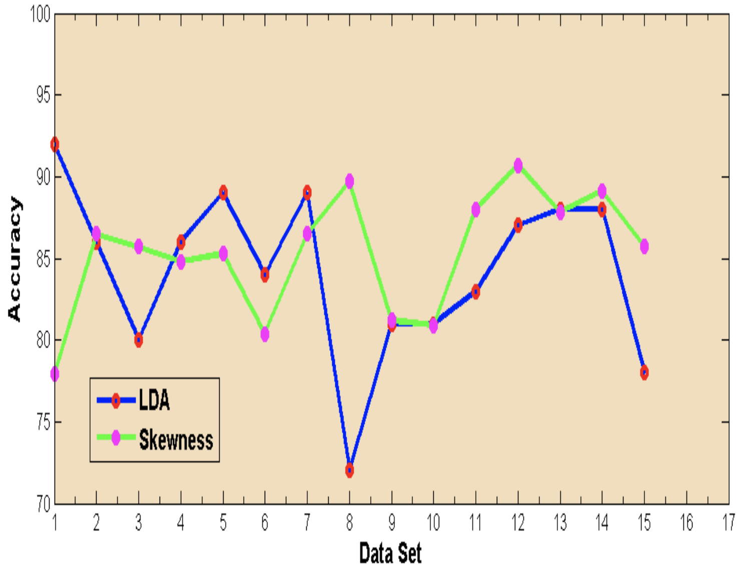

Figure 5 : Comparison of LDA with Skewness

6. Conclusion:

In this study we have used time domain statistical feature extraction techniques to extract important features, which are classified with KNN classifier.The results of the classification are compared with LDA classifier. Mean correlation, kurtosis and skewness gives an accuracy of 91%, 90.6%, 90.7% accuracy respectively. The accuracy can be improved further by adopting proper preprocessing techniques.

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