IOSR Journal of VLSI and Signal Processing (IOSR-JVSP)
Volume 6, Issue 5, Ver. II (Sep. - Oct. 2016), PP 28-35
e-ISSN: 2319 – 4200, p-ISSN No. : 2319 – 4197
www.iosrjournals.org

A Feature Extraction Scheme to Classify Motor Imagery MovementsBased on Bi-spectrum Analysis of EEG

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Abstract:*In this paper, an effective but simple feature extraction procedure for motor imagery movement classification has been proposed. Higher-order statistical features are extracted using bi-spectrum analysisof the non-linear EEG signal. Firstly, EEG signals are filtered through a band-pass filter for decomposing EEG signal into several bands and then these signals are bi-spected. Higher-order statistical features i.e. skewness, kurtosis, V2 order, V3 orders, Variance etc. are investigated. From the one-way ANOVA analysis, these features are shown to be promising to distinguish motor imagery hand movement of EEG signals. The whole experiment accomplished by using the publically available benchmark BCI-competition 2003 Graz motor imagery dataset. Different types of classifiers have been tested to classify EEG signal, among them*K-Nearest Neighbors (KNN) *classifier provides a good accuracy of 84.29%. Finally, proposed method is compared with some of the existing methods and superior performance result is obtained.*

Keywords: *Electroencephalogram (EEG); Bi-spectrum; higher order statistics; motor imagery movement.*

I. Introduction

A neuromuscular disorder people can generate necessary brain signals for a specified task but could not able to perform that task due to the inactivity of the nervous system. In order to help those people, brain-computer interface (BCI) system is introduced. One of the major applications of BCI is to detect and classify different types of motor imagery (MI) movements, which can be implemented in real-time control and communication. Motor imagery can be defined as a dynamic state during which an individual mentally simulates a given action. This type of phenomenal experience infers that the subject feels herself/himself executing the action [1]. In this research, detection of left and right-hand movement from electroencephalogram (EEG) signals is developed.This is usually done by investigating the power in specific frequency bands in signals recorded from motor brain regions that have been validated to associate with the projected movement [2]. For analyzing motor imagery movements, the brain activity of a subject has to be documented either invasively or non-invasively. One of the popular tools for recording brain activity is Electro-Encephalogram (EEG). The term “Electroencephalography” (EEG) is the process of measuring the brain’s neural activity as electrical voltage fluctuations along the scalp that results from the current flows in brain’s neurons [3].

There are some efforts have been made to identify motor imagery action, such as authors in [4], reported a study on the use of bi-spectrum for classifying left and right hand MI based on surface EEG from electrode positions C3 and C4. Bispectrum analysis of EEG signal is proposed in [5], about recovery from coma. In a work [6], an advanced robust but simple feature extraction procedure for MI-based BCI system is shown. Authors in [7], made a study of the Motor Imagery left-hand and right-hand movement with different Classification Methods. Researchers worked on the chaotic property of EEG signal in [8]. Paper reported in [9], worked on the applications of brain-computer interface (BCI) systems using different machine learning techniques, Bayesian graphical network, Neural Network, Bayesian quadratic, Fisher linear and Hidden Markov Model classifiers. In order to detect motor imagery movements from EEG signal, in [10], a statistical feature extraction method is proposed in the Dual-Tree Complex Wavelet Transform (DTCWT) domain. In [11], a method is presented to differentiate fast and slow execution of left or right-hand movement using EEG signals. In [12] authors investigate the effectiveness of recently introduced multivariate extensions of empirical mode decomposition (MEMD) in motor imagery BCI to deal with data non-stationary, low signal-to-noise ratio and closely spaced frequency bands of interest. A bi-spectral analysis is performed in [13] of the EEG signal that is recorded from the posterior region of the head of the brain tumor patient in quantifying the quadratic phase couplings to indicate the presence of the tumor. A study on detection of motor imagery of swallow EEG signals is proposed in [14], in which novel features were extracted based on the coefficients of the dual-tree complex wavelet transform to build multiple training models for detecting MI-SW. A large clinical study on the ability of stroke patients was made in [15], which used an EEG-based motor imagery brain-computer interface. An efficient graphical tool Dynamic Bayesian Network is used in [16] for EEG motor imagery feature extraction. But, in the view of real-time application, a simple and less computational algorithm with ahigh detection accuracy of motor imagery movementis still in demand.

In order to detect left and right-hand motor imagery movement detection, an effective but simple feature extraction procedure is proposed. Firstly, EEG signals are filtered through a band-pass filter for decomposing EEG signal into several bands.After that bispectrum analysis is performed on that signals. Later on higher order statistical features i.e. skewness, kurtosis, V2 order, V3 orders, Variance etc. are calculated from bispected data. In order to find the effective feature that can distinguish motor imagery hand movement, the one-way ANOVA analysis is performed. The whole experiment accomplished by using the publically available benchmark BCI-competition 2003 Graz motor imagery dataset. Also, Different types of classifiers have been tested to classify EEG signal.

I. EEG DATABASE DESCRIPTION

In order to obtain EEG data, a well-known BCI database called BCI competition 2003 dataset (motor imagery III) is taken into consideration. This EEG signal was collected from a typical subject sitting in a chair with armrests during a response period. A feedback bar is controlled by the subject by creating imagery movements of left or right hands. Left and right cues for motor imagery were in random order.

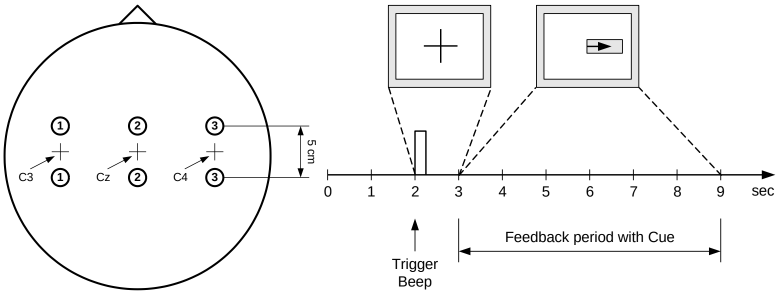


Fig. 1: Electrode Positions.**Fig. 2:**Timing Scheme of the Experiment.

The experiment involves of 7 runs with 40 trials each. For the period of each trial, at t= 2s an acoustic stimulus specifies the start of the trial and a cross '+' was shown for 1s. Next, an arrow (left or right) was displayed at t= 3s as the cue. Simultaneously the subject was requested to move a bar into the route of the cue which was controlled by adaptive autoregressive (AAR) parameters of channel C3 and C4. In order to achieve band limited signal, the acquired EEG signals are filtered within the range of 0.5 to 30 Hz. The sampling rate of EEG signals was 128 Hz. A complete description of the experimental setup can be found in [17].

II. Proposed Method

For the purpose of aquick overview of the proposed method a schematic diagram is presented in Fig 3. This diagram consists of three blocks: the first one is the signal extraction block used to alienate the MI signals from the entire EEG recording; the second block is for filtering or preprocessing which shows high-pass filtering of MI signal, the third block deals with bispectrum estimation of the MI signals followed by the feature

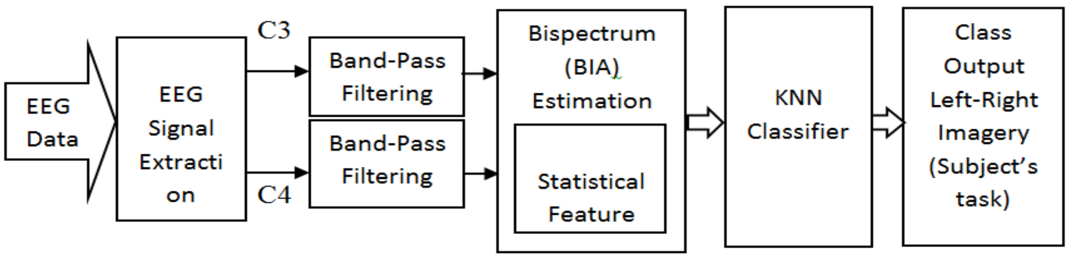


Fig 3: Schematic Diagram of Proposed Algorithm.

extraction process, the fourth block is the use of the classifier to perform the final MI movement classification and thefifth block gives the subject's mental task or output.

*Data preprocessing:*Different types of activities are performed in different frequency bands of EEG signal. In this paper, EEG signal is decomposed in several bands as like as Y_1(0.5-4Hz), Y_2(4-8HZ), Y_3(8-14HZ), Y_4(14-14Hz). Motor imagery movements performed lower frequency bands of EEG signal and mu rhythms (7.5-12.5 Hz) [18]. Very low frequency as Y_1 band is not provided necessary information regarding MI task due to it is more relevant to deep sleep activity. Thus, in order to classify MI hand movements, it is important to extract potentialinformation from Y_2 bands. For the purpose of feature extraction, Y_2(4-8HZ) band limited EEG signal is considered and in order to obtain this a bandpass filter is used. The output of the bandpass filter is shown in the Fig. 4. In the figure, raw EEG signal is shown in the upper and Y_2 band signal is shown in the lower row. And left and right hand MI movement is represented in first and second column respectively.

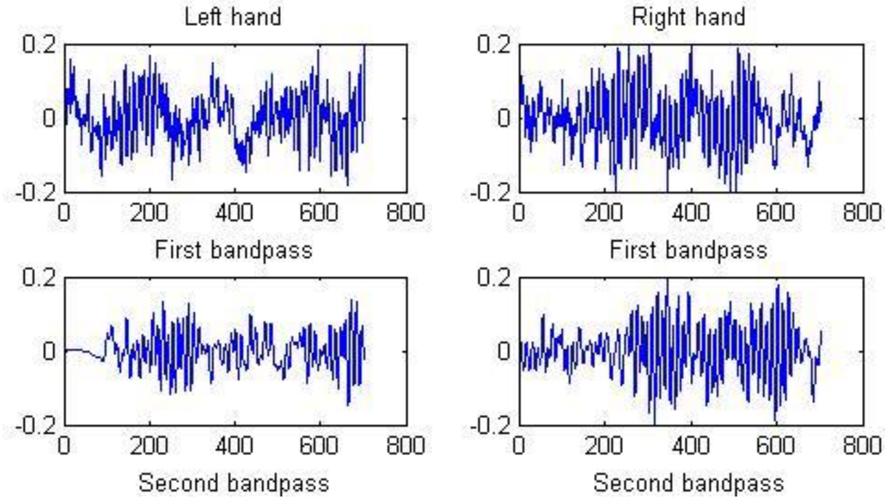


Fig 4: Left-hand and right-hand signals after first bandpass (8hz-14hz)

A. Bispectrum Analysis:

Bi-spectrum is a higher order statistical (HOS) analysis that determines quadratic nonlinearities (Phase Coupling) and variation from normality. It not only calculates the power distribution but also preserves the phase information of the signal. It is done by measuring the interaction among the components that composite a signal, for example, the EEG signals. Changes in the EEG that result in changing quadratic non-linearity will, therefore, yield quantitative changes in the bi-spectrum. It has been proven that bispectrum analysis has the capability to identify second-order nonlinear phase coupling statistics of the nonlinear system.Bi-spectrum analysis is defined as the expectation of three frequency components: two direct frequency components and the complex conjugate component of the sum of those two frequencies of a random signal [19]. Let a random signal $x(t)$, its Fourier transform is $x(f) = FFT[x(t)]$, and the complex conjugate term of x(f) denoted as (*), The bi-spectrum, $B_x(f_1, f_2)$, can be computed as

$$B_x(f_1, f_2) = E\{X(f_1)X(f_2)X^*(f_1 + f_2)\} \quad (1)$$

Where$E\{\bullet\}$ is the statistical expectation, $f_1, f_2$are the discrete frequency indices. Bispectraloutput $B_x(f_1, f_2)$, is a complex measurement hence amplitude and phase components are available. Therefore, the phase information of the analyzedsignal is preserved in the bispectrum analysis. Also, power spectrum information of given signal is obtained by bispectrum analysis. Besidesthat, a bi-spectrum has additive nature that means bispectrum of an independent multi-source signal is equal to the addition of that distinct bispectrum. Another advantage of it is that it offers zero value of a Gaussian or identically distributed signal. It is to be mentioned that generally, a system noise is predicted as Gaussian signal, thus, the bispectrum is not affected by system noise. In comparison with the power spectrum, instead of using single frequency variable, two frequency variables, $f_1$and f_2[6] is used in the bispectrum analysis.

EEG signal is extremely non-stationary and non-linear in nature. Traditional feature extraction method (i.e. time domain feature) cannot provide time invariant separable features and also lost phase information [6]. In order to overcome this non-linearity effect, in this paper, bispectrum analysis is performed. Bispectrumanalysis provides several advantages to detecting motor imaginary movement from EEG signals, such as 1) it provides both magnitude and phase information of EEG signals, 2) it reduces noise as in bispectrum analysis of a Gaussian and a linear non-Gaussian process become zero and constant, respectively, 3) it reduces non-linearity effect because bispectrum of a nonlinear process is varying and peaking due to the phase couplings arising from the nonlinearity. Bispectrum output of C3 channel of left-hand and right-hand MI movement signals are illustrated in Fig 5. From the figure, it is undoubtedly shown that bispectrum analysis provides greater values for right-hand movement.

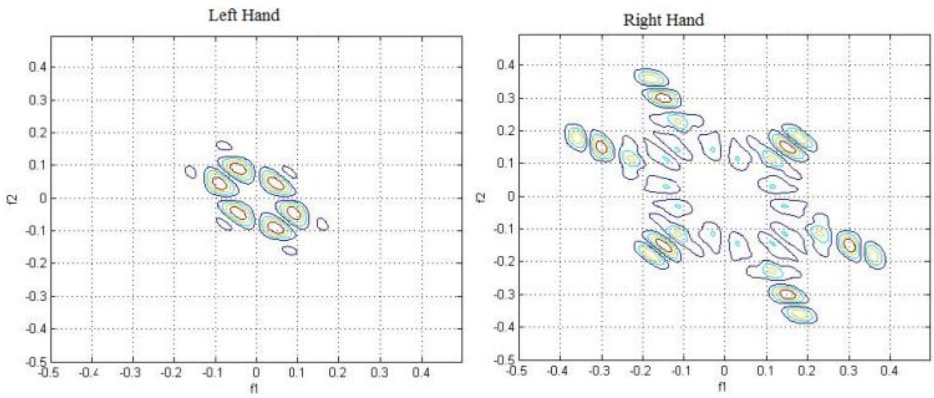


Fig 5: Bispectrum of left-hand and right-hand signals

B. *Feature Extraction:*

In this research, conventional higher and lower order statistical features like mean, variance, kurtosis, skewness, v3 order, LOG detector, sum of the logarithmic amplitudes of the diagonal elements etc. has been investigated. They are described as follows,

Mean of Absolute Value (MAV): The mean refers to the number you obtain when you sum up a given set of numbers and then divide this sum by the total number in the set. The mean is also referred to more correctly as thearithmetic mean. Mathematically it can be expressed as:

$$MAV = \frac{1}{n}\sum_{i=0}^{n} a_i \tag{2}$$

Sum of Absolute Value (SAV):This feature is an average value of the absolute values of given data.

$$Sum = \sum_{n=1}^{N} |x_n| \tag{3}$$

Simple Square Integral (SSI):SSI represents, similarly to Energy in thecontinuous-time signal, the area under the curve of the squared signal.

$$SSI = \sum_{n=1}^{N} |x_n^2| \tag{4}$$

Root Mean Square (RMS):RMSrepresents the root square mean power of the signal.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{5}$$

Variance (VAR):VARrepresents a statistical measure of how signal varies from its average value during the observation.

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \tag{6}$$

V2-Order: V2 order of any values can be expressed as follow.

$$V2 = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^2\right)^{\frac{1}{2}} \tag{7}$$

V3-Order:V3-order can be expressed as below-

$$V3 = \left(\frac{1}{N}\sum_{i=1}^{N} |x|_i^3\right)^{\frac{1}{3}} \tag{8}$$

Log Detector (LOG):LOG detector of any absolute value can be written as-

$$LOG = e^{\frac{1}{N}\sum_{n=1}^{N} log\,|x_n|} \tag{9}$$

Skewness:Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. For univariate data $Y1, Y2 \ldots \ldots .., YN$, the formula for skewness is:

$$g1 = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3/N}{s^3} \tag{10}$$

Kurtosis: Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. That is, data sets with high kurtosis tend to have heavy tails or outliers. Data sets with low kurtosis tend to have light tails or lack of outliers. A uniform distribution would be the extreme case.

$$Kurtosis = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4/N}{s^4} \tag{11}$$

Standard Deviation (St.D):Standard deviation of a distribution is a measure of how widely values are dispersed from the average or mean value. It is denoted by Ϭ. It can be calculated as follows:

$$\sigma = \sqrt{\frac{\sum(x_i - \bar{x})^2}{N}} \tag{12}$$

Entropy: Entropy is a common concept in many fields, mainly in signal processing the entropy E must be an additive cost function such that where S is the signal and S_j are coefficients of S in an orthonormal basis.

$$E(0) = 0 \text{ and } E(s)=\sum_i E(s_i), \tag{13}$$

The sum of the logarithmic amplitudes of the bispectrum:

$$B1 = \sum log\left|B_{mrp}\,(\omega 1, \omega 2)\right| \tag{14}$$

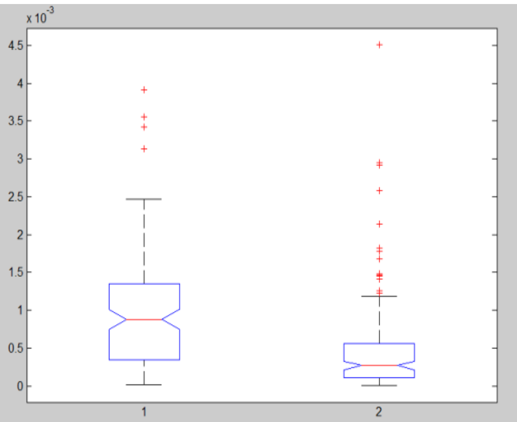
The sum of the logarithmic amplitudes of the diagonal elements of the bispectrum:

$$B2 = \sum_{\omega \epsilon F} log\left|B_{mrp}\,(\omega, \omega)\right| \tag{15}$$

The sum of the amplitudes of the diagonal elements of bispectrum:

$$B3 = \sum_{\omega \epsilon F} \left|B_{mrp}\,(\omega, \omega)\right| \tag{16}$$

Above the described features we have selected the efficient one which will be our proposed feature. Discrimination capability of the extracted feature is analyzed through various types of ANOVA analysis. The p-values of one-way ANOVA analysis for all the features are examined. The hypothesis about the p-values is that the value, $p<0.01$ indicates that at least one sample mean is significantly different than the other sample means statistically [20]. Box plot obtained from ANOVA analysis ofV3-order feature is presented in Fig 6.From the ANOVA analysis, it is shown that V3-order feature possesses distinguishable characteristic between left-hand and right-hand motor imagery movements with slight overlapped which can be overcome by the classifier.Also, it is observed that V3-Order provides smaller P-value which is a justification of being a worthy feature for classification. A feature vector is formed from V3-order both for C3 and C4 channel. This feature vector has been fed to the classifier.



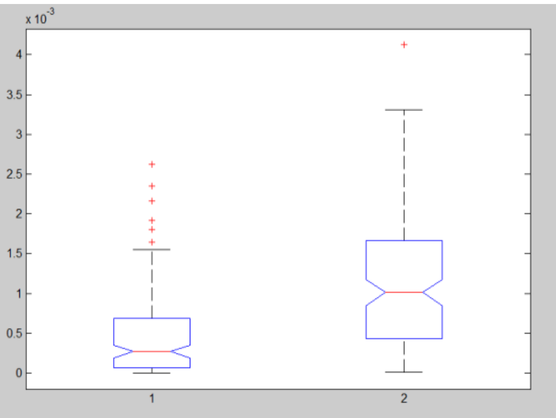


Fig.6: ANOVA Analysis of V3-Order for C3 channel**Fig. 7:** ANOVA Analysis of V3-Order for C4 channel

C. *Classifier:*

A good classifier selection is very important for any classification task. The different classifier is tested in our experiment and the best performance result is obtained by K-Nearest Neighbors (KNN) classifier which is reported in the result section. K-Nearest Neighbors (KNN) is a non-parametric learning algorithm method used for classification. Among the various methods of supervised statistical pattern recognition, the Nearest Neighbor rule achieves consistently high performance, without prior assumptions about the distributions from which the training examples are drawn. A new sample is classified by calculating the distance to the nearest training case; the sign of that point then determines the classification of the sample. The KNN classifier extends his idea by taking the k nearest points and assigning the sign of the majority [21].The number “K” decides how many neighbors influence the classification. If K = 1, then the algorithm is simply called the nearest neighbor algorithm.

III. Results And Discussion

Extensive simulation is carried out to obtain the performance result of the proposed method. 140 samples of each motor imagery movements are tested using leave one out method. All of the analytical results are taken for the absolute value of bispectrum analysis. Result section is segmented into several parts. At first analysis of variance is performed to acquire the best feature among the higher and lower order statistical features. Secondly, with the potential feature, performance result is evaluated using different classifier and hence declared the best classifier that suit for MI movement detection. Finally, proposed method is compared with some of the existing methods.

Analysis of Variance: Analysis of Variance (ANOVA) is a statistical method commonly used to compare the means of two or more group data. It actually indicates how overlapped the data set. Here we can use ANOVA for finding the best features that can classify MI hand movements. In Table I, C3 and C4 indicate two channels. Here, absolute value has been taken. Table I shows the p-values of one-way ANOVA analysis for thedifferent band and different features. If P<0.01 then there is at least one sample mean is different from other sample mean. Thus, small P-value provides good feature. From Table I, it is clearly shown that for both C3 and C4 channel very small P-value is achieved in the case of MAV, RMS, V3-Order, St.D, entropy, sum, kurtosis, and V2-Order feature. Those features are the potential feature for motor imagery hand movement detection and further classification results are obtained using those potential features.

Table I: P-value Obtainedfrom Different Statistical Features

Feature Name	Using Absolute Value	
	Channel C3	Channel C4
VAR	0.0025	$2.6688e^{-9}$
MAV	$1.723e^{-6}$	$3.4636e^{-11}$
RMS	$4.832e^{-7}$	$2.23e^{-17}$
V3-Order	$3.7624e^{-7}$	$3.8409e^{-15}$
LOG	0.0030	$2.4671e^{-5}$
Skewness	$3.4207e^{-5}$	$9.3595e^{-13}$
St.D	$3.7575e^{-7}$	$8.5091e^{-15}$
Diagonal Sum, B_3	$9.5919e^{-4}$	$1.6807e^{-7}$
Logarithomic sum, B_1	$5.1315e^{-4}$	$3.3640e^{-8}$
Entropy	$7.1711e^{-8}$	$1.4014e^{-15}$
Diagonal Log Sum, B_2	$9.2702e^{-4}$	$1.7191e^{-7}$
SSI	0.0025	$2.7552e^{-9}$
Sum	$1.723e^{-6}$	$3.4636e^{-11}$
Kurtosis	$3.4207e^{-5}$	$9.3595e^{-13}$
V2-Order	$4.832e^{-7}$	$2.23e^{-17}$

Table 2: Performance Evaluation Using Different Classifiers

Feature Name	LDA Classifier (%)	NB Classifier(%)	KNN Classifier(%)	SVM Classifier(%)
MAV	78.21	74.29	80.71	79.29
RMS	78.93	75.71	83.21	80.71
V3-Order	80	75.71	82.86	81.07
St.D	78.93	75.71	82.86	80.71
Entropy	80	76.79	81.07	80
Sum	78.21	74.29	80.71	79.29
Kurtosis	73.57	68.57	77.14	73.93
V2-Order	78.93	75.71	83.21	80.71

In Table 2, performance is evaluated using different classifiers such as linear discriminant analysis (LDA), naïve Bayes (NB), KNN and support vector machine (SVM) classifiers. From the table, it is observed that the best performance result is obtained using KNN classifier.After that, the performance evaluation of different kernelof KNN classifier is reported in Table 3. In order to obtain the accuracy of MI hand movement activity, in this paper, linear, correlation, cosine and cityblock kernels are used. The best performance result is achieved utilizing the linear kernels of V3-order feature. It is reported as 84.29%. Thus, in the paper,V3-order feature with either linearkernel of KNN classifier is proposed.

Table 3: Performance Evaluation Varying Kernel of KNN Classifier

Classifier	Kernel	MAV(%)	RMS(%)	V3Order(%)	St.D(%)	SSI(%)	Skewness(%)
KNN	Linear	81.79	82.86	84.29	83.57	83.57	74.29
	Correlation	50	85	70	83.57	61.43	60.71
	Cosine	80.71	83.21	82.86	82.86	82.86	77.14
	Cityblock	81.43	83.21	83.93	83.93	82.50	76.64

Table 4: Performance Evaluation of different feature combination

Classifier	Feature	Accuracy (%)
KNN	**V3-order**	**84.29**
	VAR+RMS+MAV+V3+St.D+Entropy+SSI	81.79
	VAR+RMS+MAV+V3+St.D+Entropy	81.69
	VAR+RMS+MAV+V3+St.D	81.14
	VAR+RMS+MAV+V3	80.79
	VAR+RMS+MAV	81.49
	VAR+RMS+SSI	81.57
	VAR+ SSI	83.57
	VAR+ St.D	82.86
	VAR+ RMS	82.14

Table 5: Comparison of mean accuracy of different methods

Method	**Proposed by**	**Classifier**	**Mean Accuracy (%)**
PSD	Solhjoo et al. [8]	Mahalanobis distance	63.01
		Gaussian Classifier	65.40
		LDA	65.60
Raw EEG	Solhjoo [22]	HMM	77.50
AAR	Tavakolian et al. [9]	Bayes quadratic	82.36
		BGN	83.57
Proposed Method(Bispectrum)		**KNN**	**84.29**

MI movement classification is performed using adifferent combination of higher and lower order statistical features and the performance result is reported in Table 4. Feature vector resulting out of acombination of the two or more types of features has shown inferior results than when these features have been used alone.From the table, it is observed that only v3-order feature provides the best accuracy which is 84.29%. Among all of the extracted features V3-Order has shown the highest accuracy from bispected data which has been achieved 83.93% whereby the combination it obtained maximum 83.57%. We have used one frequency band only for the absolute value both for C3 and C4 channels. So feature vector length is two for the classifier input. Feature vector can be expressed as

$$FT = [V3(C3)\ V3(C4)]$$

In order to compare our proposed feature performance with some of the existing methods Solhjoo et al.[8], Solhjoo [21] and Tavakolian et al. [9] are considered. In [8], power spectrum density (PSD) is used to classify motor imagery task. And in [22] raw EEG signal are used along with hidden Markova model (HMM). Adaptive AR parameters (AAR) are proposed in [9]. Performance comparison result is presented in Table 5 and from the table it is observed that superior performance is achieved from the proposed method with comparison to some of the existing methods.

IV. Conclusion

This research is mainly focused on bispectrum analysis and finds a better way to classify left and right-hand motor imagery movements which play an important role in BCI system. This was done by transforming into their higher order spectra. Different statistical features of bispected signal have been derived. Among them, themost significant feature has been found out by using one-way ANOVA analysis. The ‘P’ value of ANOVA analysis gives the most significant feature. From the research, it is proposed that V3 order is the most significant feature to classify MI movement task. Finally, we have compared our result with several other methods available in EEG literature and superior performance result is obtained. In the view of real-time application, the proposed method is fast, less complex and easy to implement with high accuracy.

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