Comparative Analysis Of Mother Wavelet Selection For EEG Signal Application To Motor Imagery Based Brain-Computer Interface

Sanjay Ganorkar, Vrushali Raut

Abstract: Brain-computer interface (BCI) system intends to control the environment for the individual using only his thoughts bypassing muscular pathway. Electroencephalography (EEG) is non-invasive signals corresponding to underlying brain wave acting as potential input to BCI. This paper used EEG corresponding to Motor Imagery (MI) of Right hand and Left-hand movement as input to the system designed. Spectral components with a temporal resolution of signal acted as strong features in BCI and achieved by using wavelet transform. Extracting relevant features is linked with wavelet basis selection. This work proposes a new method of energy compaction in the approximate band for wavelet basis selection. Daubechies and Bio-orthogonal family, the preferred wavelets for biomedical signals, are used for band energy comparison. Experimenting verifies biorthogonal wavelets bior2.8, bior3.1, bior5.5, bior6.8 and Daubechies wavelets db10, db13, db14, db15 carries more energy in the approximate band for signal under test. This paper further suggested the restriction on features extracting from µ band (8-12Hz) and β band (15-30Hz), reducing the burden on the classifier. The higher-order statistical features extracted in this work represent the dynamics of the signal. Bior6.8 and db10 emerge as the matching wavelets with a classification accuracy of 82.01% and 82.82% respectively using Support Vector Machine (SVM) for classification.

Index Terms: Band Energy Electro-Encephalography (EEG), Motor Imagery (MI), Brain-Computer Interface (BCI)

1 INTRODUCTION

A variable electrical potential on scalp corresponding to brain activities plays a vital role in the functioning of Brain-Machine Interface (BMI) or Brain-Computer interface (BCI). Thus BCI system consists of acquiring the brain activities, pre-processing it for artifact removal, feature extraction corresponding to underlying activity, classification of the extracted feature to distinguish between the activities. Corresponding brain activities which act significantly as input for BCI are Steady-State Evoked Potentials (SSVEP) and P300 these are evoked signals, whereas Motor Imagery (MI) is the spontaneous signal. An Evoked signal increases dependency on the evoking mechanism as well as proper training of the subject is required for its use. Spontaneous signals are self-modulating, user or subject has not to trained for it. Thus BCI using spontaneous signals like MI is the most widely used category. Imagining the motor movement or performing it, generate the MI signal, in both the cases mentioned above, identical modulation of EEG signal takes place[1]. This modulation corresponds to Event-Related Synchronization (ERS) in the β band(15-30Hz) over the ipsilateral side and Event-Related De-synchronization(ERD) in µ band(8-12Hz)over a contralateral side of primary motor cortex[2]. Hand movement, leg movement, and tongue movement or imagining them can act as conceivable input for modulation of brain activity pattern. Not only this even finer movement like finger movement can act as substantial input to motor imagery based BCI[3]. EEG electrodes corresponding to the motor area of the brain can collect MI signal with sufficient strength.

- *Sanjay Ganorkar currently working as professor at electronics and telecommincation department of Sinhgad College of Engineering, Pune, India. E-mail: srganorkar.scoe@sinhgad.edu*
- *Vrushali Raut research scolar at electronics and telecommincation department of Sinhgad College of Engineering, Pune, India. E-mail: vgraut.scoe@sinhgad.edu*

These signals are contaminated with noise as well interference not only from neighboring electrodes but also from Electro Cardiogram (ECG) and Electro Mayo gram(EMG) signals, eye blink, line interference, and movement artifacts, etc. These signals have a frequency range common to a signal of interest[4][5][6][7]. Due to high variability and artifact in the signal, feature extraction seems to be a crucial part of BCI from the signal processing point of view. Techniques suggested by literature are a Common spatial pattern(CSP) a technique known for statistical pattern recognition[8], Autoregressive(AR) and Autoregressive with exogenous input (ARX) are traditional techniques in BCI[9][10]. Bi-scale wavelet was used in asynchronous BCI[11][12]. Time-frequency spatial feature extraction was preferred[13], Frequency principal components analysis (fPCA) factors conform to the spectral structure of empirical data[14], Canonical correlation analysis spatial filter for identifying optimal weighted combinations of electrode signals[15]. Time domain, frequency domain as well as mixed domain features act as a possible input to the system. BCI needs feature selection as it has to deal with high dimensional input data. BCI Genetic Algorithm a heuristic search technique,[16] Principal Component Analysis a linear transformation[17][18] and DSLVQ are some of the feature selection or dimensionality reduction methods popularly used.
Linear classifiers come with advantages of robustness and are less prone to overfitting. Kernel-based classifiers are classification methods that apply a linear classification in some appropriate (kernel) feature space[19]. Support vector machines (SVMs) and kernel Fisher discriminant (KFD) are kernel-based classifiers preferred in BCI as well for seizure detection[20][21]. Nonlinear classifiers are preferred for a big amount of data with less knowledge. K-nearest neighbor classifier (K-NN) preferred for two-class BCI; it does not need training[22]. Genetic algorithm-based artificial neural network (GA-ANN) used for three mental tasks-based BCI classifications[23]. This paper dealt with spectral feature extraction in correlation with time, and the suited method is wavelet transform (WT). Other most important property of wavelet basis selection available with WT helps to choose the matching function with the input signal. Wavelet selection

technique proposed in this work is based on energy compaction in the approximate band. Energy compaction is more in the approximate band for more matching wavelet. The wavelets concentrating more energy in the approximate band after applying on the signal are selected for feature extraction. Paper also dealt with feature optimization, considering signal from selected channel C4 out of 28 available channels. Optimization continued by extracting the features from the approximate band and band covering μ and β range of frequency accommodating ERD and ERS. Along with statistical features, this work proposes higher-order statistical features representing dynamics of the signal as input to the classifier in this system. SVM with kernel trick variation ranging from Gaussian, polynomial, quadratic to multilayer perceptron used to get maximum classification accuracy.

2 Discrete Wavelet Transform for EEG Signal

Biomedical signals like EEG are non-stationary signals. A wavelet transform is an appropriate method for time-frequency representation of such signals. By literature survey, ERD and ERS can sever as distinguishing events for motor imagery signal. Extracting features from these events keeping correlation of time and frequency (T-F) domain can boost the classification accuracy. Wavelet basis function selection for WT further increases the correlation of the signal and basis, helping for efficient representation of the signal in the T-F domain[24]. Wavelet analysis consists of a signal representing the linear combination of a set of the function obtained by shifting and dilating mother wavelet. The decomposition of signal x(t) leads to a set of coefficients called approximate coefficients $a_{j,k}$ and detail coefficients $d_{j,k}$ as in equation (1).

$$x(t) = \sum_{j=-\infty}^{\infty} a_{j,k} \cdot \phi_{j.k}(t) + \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} d_{j,k} \cdot \psi_{j.k}(t) \qquad (1)$$

Where $\psi_{i,j}(t)$ is the wavelet function and $\phi_{j,k(t)}$ is the scaling function, j is scaling parameter and k is translation parameters.

2.1 Methods for Wavelet Selection

Selecting wavelet basis function plays a very crucial role in signal classification; it completely relies on the similarity between the signal under test and scaled version of the base wavelet. Wavelet band filter characterized by properties like regularity, vanishing moments, and shift variance degree used for wavelet basis selection[25]. Another basis selection criteria ratio of maximum energy to Shannon entropy used for mechanical signal[26]. Quantitative approaches also suggested for wavelet basis function selection works on minimum description length (MDL) principle[27]. As suggested by David Salomon, the energy of correlated data is concentrated in the first few transform coefficients[28]. This work uses the concept that, if the correlation between the wavelet basis function and the signal under test is more than the approximation band contains maximum energy. Thus paper suggests applying wavelet on the signals to check for the concentration of energy in the approximate band for selection of matching wavelet. This work further suggested that as μ and β band accommodates the modulations due to motor imagery, they will represent specific characteristics when applied by the wavelet matching with the basic signal. This will leads to efficient classification. An empirical analysis of various wavelet functions for band energy can help in supporting this idea. Daubechies and biorthogonal wavelets are preferred by literature to be applied on biomedical signals[29][30]. All variants of Daubechies, an orthogonal wavelet and biorthogonal wavelet with linear phase are selected for experimenting.

2.2 Feature Extraction and Feature Selection

A statistical representation of wavelet coefficients instead of wavelet coefficients corresponding to various bands characterized as strong input to the classifier. Second-order statistical features like variance standard deviation and mean when combined with higher-order statistical (HOS) feature can act as strong input to the classifier. HOS features are useful for extracting dynamics of signal and are proved for the characterization of sleep spindles in EEG signal[31]. Kurtosis is used in noise scaling more efficiently than other statistical quantities for noise estimation[32]. Higher-order statistics contain higher-order moments and non-linear combinations of higher-order moments, which are known as cumulants. In this work, Skewness and Kurtosis are two cumulants used as HOS features. Selecting the electrode of interest for motor movement and extracting features from a band of interest is an important step for feature selection as well optimisation.

3 Descriptions of Database

Dataset used for this work provided by Intelligent Data Analysis Group, Department of Neurology, Berlin. Dataset was recorded on a normal subject without feedback session. The subject was sitting in a chair with arms resting on the table and fingers in typing position on the computer keyboard. The task provided was to press the keys with the index and little fingers. The recorded experiment consists of 3 sessions of 6 minutes each. Average typing speed was 1 key per second.

3.1 Format of the data

Data consist of 316 epochs, each epoch is of 500ms length and is ending 130ms before a keypress to avoid signal due to mechanical movement. Labeling used is 0 for left-hand movements, and 1 for right-hand movements, the Sampling frequency is 1000Hz. A Neuro-scan amplifier with Ag/AgCl electrode used for recording. The number of electrodes is 28 and placed according to the international 10/20 system. Signals recorded at 1000 Hz with a band-pass filter between 0.05 and 200 Hz[33].

4 Proposed System

The system proposes wavelet decomposition of the signal and separates the band of interest. The work proceeds with the empirical analysis for wavelet basis selection by computing band energy for approximate coefficients. The wavelet accumulating more energy in approximate band is considered to be matching wavelet function. Wavelet coefficients extracted using matching wavelets are used for generating statistical and higher-order statistical features from a band of interest. The extracted features are passed to the classifier and classification accuracy is evaluated using different kernel function.

4.1 Wavelet Decomposition

Significant features can be extracted from the band corresponding to ERD and ERS. The precise level of wavelet decomposition can separate these band and statistics of these bands gives strong features. In particular, the band corresponding to hand movements are acting as significant features in this system. As these events occur after the imagination of movement, they are frequency and time-bound. Selecting the suitable variant of wavelet basis function matching these events can extract the important features. As the EEG signal under test is sampled at a frequency of 1000Hz and band to be separated are µ and β, Using equation (2), 6 levels for decomposition is obtained, the frequency range corresponding to each band is as specified in Table 1.

$$2^{-j-1}F_s < \Delta F_j < 2^{-j}F_s \tag{2}$$

TABLE 1
WAVELET DECOMPOSITION BAND AND CORRESPONDING FREQUENCY RANGE

Decomposed sub-band	Frequency Range(Hz)
D1	500-1000
D2	250-500
D3	125-250
D4	62.5-125
D5	31.25-62.5
D6	15.625-31.2
A6	0-15.625

4.2 Wavelet selection

Daubechies and biorthogonal, popular mother wavelets for biomedical signals are selected. Wavelets available in the library of MATLAB for Daubechies and used for testing are db1, db2, db3, db4, db5, db6, db7, db8, db9, db10, db11, db12, db13, db14, db15, and db16. Biorthogonal wavelets used are bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8. Approximate band energy is extracted by applying each wavelet on all 316 signals under test. Average approximate band energy is calculated for every wavelet as specified in table 2 for Daubechies wavelet and table 3 for biorthogonal wavelet. Based on these average values, lower limit has been set to 80% of maximum band energy and the numbers of signals having band energy above this threshold are calculated. It has been found that 90% of signals lay above the threshold. Concluding that approximate band of wavelet concentrates energy depending on its matching with the underlying signal. From table 2 it can be acknowledged that db10, db13, db14, and db15 carries maximum energy in approximate band whereas Table 3 acknowledged bior2.8, bior3.1, bior5.5 and bior6.8 carrying maximum energy in the approximate band. These variants of wavelet basis functions are selected for the process of feature extraction.

TABLE 2
AVERAGE APPROXIMATE BAND ENERGY OF DAUBECHIES WAVELETS APPLIED ON 316 TEST SIGNALS

Daubechies wavelets	Average Band Energy
db1	51.20994
db2	65.18798
db3	69.74599
db4	71.78429
db5	73.28987
db6	74.33134
db7	74.6944
db8	74.58228
db9	74.9237
db10	75.25192
db11	74.96743
db12	75.0679
db13	75.32244
db14	75.55061
db15	75.38548

TABLE 3
AVERAGE APPROXIMATE BAND ENERGY OF BIORTHOGONAL WAVELETS APPLIED ON 316 TEST SIGNALS

Biorthogonal wavelets	Approximate Band Energy
bior1.1	51.20994
bior1.3	66.01561
bior1.5	71.41573
bior2.2	72.00769
bior2.4	75.81602
bior2.6	77.83013
bior2.8	78.59862
bior3.1	78.49326
bior3.3	70.9335
bior3.5	72.86749
bior3.7	74.2057
bior3.9	74.53814
bior4.4	77.86559
bior5.5	81.09622
bior6.8	81.57216

4.3 Optimized Feature extraction

After selecting the variant of wavelet basis next step is to extract the features. Motor movements are prominently observable on electrode C3 and C4, which are situated on motor-related part of the brain. Electrodes on the contralateral side are responsible for capturing ERD whereas that on ipsilateral for ERS. Thus C3 and C4 electrode can collect ERD and ERS of the signal and hence the motor-related variability. In this work signals only from channel C4 are considered. Applying wavelet transform on signals from the selected electrode with a specific wavelet and extracting statistical(mean, variance and standard deviation) as well higher-order statistical features(skewness and kurtosis) from the approximate band and the band of interest is the process coming under optimized feature extraction. Wave energy is one more feature extracted from wavelet bands of interest. Limiting the electrodes as well as limiting the features is usefull in boosting classification accuracy.

4.4 CLASSIFIER AND EVALUATION MEASURES

SVM though a linear classifier can be used for nonlinear boundaries by “kernel trick”. It adds a little to the classifier’s complexity but is useful for mapping the data too much higher dimensionality. Out of 316 signals available, 158 alternate signals are used for training of SVM and remaining 158 used for testing. This work dealt with kernels like Gaussian (RBF), Quadratic kernel, polynomial kernel, and MLP kernel.

5 EXPERIMENTAL RESULTS FOR CLASSIFICATION

Based on quantitative analysis of approximate band energy, eight wavelets are selected. Selected wavelets are tested for linear, Gaussian kernel, polynomial kernel, Quadratic kernel, and Multilayer Perceptron as kernel functions to obtain classification accuracy as given in table 4. The results indicates that maximum classification accuracy obtained is 83% for db10 using MLP kernel function. Db10 also claims the maximum classification accuracy for almost all kernel functions. The variation introduced in feature of the signal by ERD and ERS is key factor for classifying the right-hand movement (RHM) and left-hand movement (LHM). This reason leads to proclaiming separate classification accuracy for left-hand movement and right-hand movement (RHM), if signal collected from a specific electrode. The signal from channel C4 used in this work lays on the ipsilateral side of the brain for RHM thus collect ERD for LHM and ERS for RHM.

TABLE 4
CLASSIFICATION ACCURACY FOR DIFFERENT KERNEL FUNCTION

	Percent Classification Accuracy				
Wavelet Function	Linea r kerne l	MLP Kernel	Quad. Kernel	Gaus. Kernel	Poly. Kerne l
bior2.8	81.71	80.88	77.56	77.56	78.67
bior3.1	77.56	80.27	74.51	77.56	77.00
bior5.5	78.39	81.16	78.67	80.05	79.50
bior6.8	80.55	82	80.62	81.16	80.37
db13	80.45	80.60	78.39	79.77	79.50
db10	81.60	83	80.60	82.32	81.80
db14	78.67	79.50	80.33	80.33	79.77
db15	77.56	75.90	74.51	77.83	76.73

5.1 Results for Daubechies wavelets

Table 5 displays the difference in classification accuracy for RHM and LHM for db10. Wavelet classified RHM accurately with 83.83% for MLP kernel, whereas it gives an average accuracy of 83%. Table 6 gives a result for db13, the classification accuracy of 83.83% obtained for RHM with a linear and polynomial kernel, whereas 81% average accuracy. Db14 gives 88.3% classification accuracy with the gaussian(RBF) kernel for RHM, but average accuracy goes down to 81.16% displayed in Table 7. Db15 displays classification accuracy of 84% with gaussian (RBF) kernel for RHM but average accuracy is not comparable as is less than 80% in Table 8. From these results, it can be concluded that accuracy for RHM is more as wavelet found more matching with ERS of the C4 channel. Finally, db10 emerges to be matching wavelet from the Daubechies family, which gives maximum average accuracy. Comparison of classification accuracy of db10 for various kernel functions is given in Fig. 1.

TABLE 5
CLASSIFICATION ACCURACY FOR DB10

Kernel Function	*%Accuracy for LHM*	*%Accuracy for RHM*	*%Average Accuracy*
Linear	*80.9141*	*82.2929*	*81.6035*
Quadratic	*81.5951*	*79.798*	*80.6094*
MLP [1 -6]	*81.5951*	*83.8384*	*82.8255*
Gaussian(rbf)	*79.7546*	*81.1634*	*82.3232*
Polynomial 1	*80.7791*	*82.8283*	*81.8037*
Polynomial 2	*80.9141*	*82.2929*	*81.6035*
Polynomial 3	*81.5951*	*79.798*	*80.6094*

TABLE 6
CLASSIFICATION ACCURACY FOR DB13

Kernel Function	*%Accuracy for LHM*	*%Accuracy for RHM*	*%Average Accuracy*
Linear	*79.1411*	*83.8384*	*80.3324*
Quadratic	*76.6871*	*79.798*	*78.3934*
MLP [3 -2]	*79.7546*	*81.3131*	*80.6094*
rbf [2]	*83.3333*	*75.4601*	*79.7784*
Polynomial 1	*79.1411*	*83.8384*	*81.7175*
Polynomial 2	*76.6871*	*79.798*	*78.3934*
Polynomial 3	*77.7778*	*81.5951*	*79.5014*

TABLE 7
CLASSIFICATION ACCURACY FOR DB14

Kernel Function	*%Accuracy for LHM*	*%Accuracy for RHM*	*%Average Accuracy*
Linear	*76.6871*	*80.303*	*78.6704*
Quadratic	*77.3006*	*83.3006*	*80.6094*
MLP [1 -6]	*74.2331*	*83.8384*	*79.5014*
Rbf [2]	*70.5521*	*88.3838*	*80.3324*
Polynomial 1	*76.6871*	*80.303*	*78.6704*
Polynomial 2	*77.3006*	*83.3006*	*80.6094*
Polynomial 3	*78.2828*	*84.6626*	*81.1634*

5.2 Results for biorthogonal wavelets

From the results for biorthogonal variants, it can be stated that bior3.1 gives classification accuracy of 82 % for RHM and average accuracy of 80% for MLP kernel as in Table 9. Gaussian kernel gives classification accuracy of 89% for RHM when decomposed using bior3.8. Whereas linear kernel function offers the average accuracy of 81.71% to bior3.8 as in table 10. MLP kernel offers maximum accuracy of 82% when the wavelet decomposition uses bior5.5 as given in table 11. Bior6.8 gives an accuracy of 85% with polynomial kernel for RHM also it gives average accuracy of 83.6% as in Table 12 which is highest average accuracy, Fig. 2 gives a comparison of classification accuracy of Bior6.8 for various kernel functions. From the above results, it can be claimed that accuracy is more for classification of right-hand movement as wavelet found more matching with ERS of the signal on channel C4.

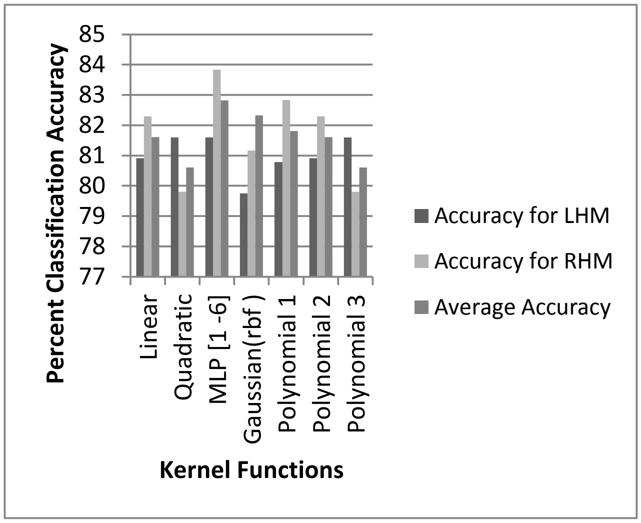

FIGURE 1 COMPARISON OF CLASSIFICATION ACCURACY FOR WAVELET DB10 USING DIFFERENT KERNEL FUNCTIONS

TABLE 8
CLASSIFICATION ACCURACY FOR DB15

Kernel Function	%Accuracy for LHM	%Accuracy for RHM	%Average Accuracy
Linear	*75.4601*	*79.2929*	*77.5623*
Quadratic	*71.7791*	*76.7677*	*74.5152*
MLP [1 -6]	*77.3006*	*74.7475*	*75.9003*
rbf [2]	*69.3252*	*84.8485*	*77.8393*
Polynomial 1	*75.4601*	*79.2929*	*77.5623*
Polynomial 2	*71.7791*	*76.7677*	*74.5152*
Polynomial 3	*77.3006*	*76.2626*	*76.7313*

Comparative analysis of db10 and bior6.8 suggest both suitable for signal under test. Comparing with the classification accuracy obtained for other BCI database as well Berlin database used for this work, It can be stated that results are competitive and can be further improved by modifying the classifier[34][35][36].

TABLE 9
CLASSIFICATION ACCURACY FOR BIOR3.1

Kernel Function	%Accuracy for LHM	%Accuracy for RHM	%Average Accuracy
Linear	73.6196	80.8081	77.5623
Quadratic	73.2323	76.0736	74.5152
MLP [1 -2]	78.2345	82.3232	80.27885
rbf [2]	74.2331	80.303	77.5623
Polynomial 1	73.6196	80.8081	77.5623
Polynomial 2	73.2323	76.0736	74.5152
Polynomial 3	74.2331	79.2929	77.0083

TABLE 10
CLASSIFICATION ACCURACY FOR BIOR3.8

Kernel Function	%Accuracy for LHM	%Accuracy for RHM	%Average Accuracy
Linear	74.2331	85.3535	81.7175
Quadratic	75.4601	79.2929	77.5623
MLP [3 -25]	74.8466	85.8686	80.8864
rbf [24]	63.1902	89.3939	77.5623
Polynomial 1	74.2331	85.3535	81.7175
Polynomial 2	75.4601	79.2929	77.5623
Polynomial 3	76.0736	80.8081	78.6704

TABLE 11
CLASSIFICATION ACCURACY FOR BIOR5.5

Kernel Function	*%Accuracy for LHM*	*%Accuracy for RHM*	*%Overall Accuracy*
Linear	*75.4601*	*80.8081*	*78.3934*
Quadratic	*77.3006*	*79.798*	*78.6704*
MLP [4 -2]	*80.8466*	*82.8283*	*81.83745*
rbf [8]	*78.5276*	*81.3131*	*80.0554*
Polynomial 1	*75.4601*	*80.8081*	*78.3934*
Polynomial 2	*77.3006*	*79.798*	*78.6704*
Polynomial 3	*77.2727*	*82.2086*	*79.5014*

TABLE 12
CLASSIFICATION ACCURACY FOR BIOR6.8

Kernel Function	*%Accuracy for LHM*	*%Accuracy for RHM*	*%Average Accuracy*
Linear	*81.8182*	*79.3006*	*80.5594*
Quadratic	*76.0061*	*85.2525*	*80.6293*
MLP [1 -6]	*77.9141*	*83.8384*	*82*
rbf [2]	*86.5031*	*77.2727*	*81.1634*
Polynomial 1	*75.4601*	*85.2828*	*80.37145*
Polynomial 2	*81.8182*	*79.3006*	*80.5594*
Polynomial 3	*76.0061*	*85.2525*	*80.6293*

7 CONCLUSIONS

This work proposes effective signal processing techniques for Independent BCI. Motor imagery is used as the potential signal to the BCI with the scope of adding more motor movements. Proposed band energy-based wavelet selection method help in selecting optimally matched wavelets. Four wavelets from Daubechies family; db10, db13, db14, and db15 and four from biorthogonal family; bior2.8, bior3.1, bior5.5 and bior6.8 are selected on basis of high band energy.

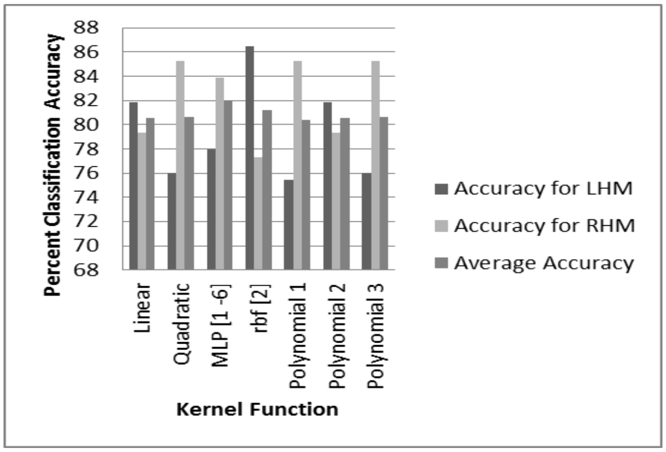

***FIGURE 2** COMPARISON OF CLASSIFICATION ACCURACY FOR WAVELET BIOR6.8 USING DIFFERENT KERNEL FUNCTIONS*

Out of 28 Channels available, the signal from channel C4 corresponding to ERD of LHM and ERS of RHM is used for applying wavelet. Wavelet Coefficients are extracted for the signals by applying selected wavelets. Higher-Order Statistical features skewness and kurtosis are proposed with second-order statistical features for representing dynamics of the signal. Extracted features are passed to the classifier and tested for linear, Gaussian, quadratic, polynomial, and multi-layer perceptron kernel. Classification accuracy calculated with selected wavelets verifies bior6.8 and Db10 as the optimally matched wavelet. Bior6.8 and db10 give an average classification accuracy of 82.01% and 83% respectively. Classification accuracy can further be improved by upgrading machine learning used in the classifier. The proposed system will be helpful for building MI based independent BCI.

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