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Wavelet Decomposition using Matching Wavelet Function for Feature Extraction In EEG based BCI

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Abstract
Wavelet transform acts as the powerful tool for feature extraction as it map the wavelet with the signal and take out the required variations from the signals. This work empirically selected the matching wavelets db10 and bior6.8 for signal decomposition. The obtained wavelet coefficients are used for preparing statistical and higher order statistical (HoS) features. HoS features are preferred by this research as it represents dynamics of the signal. Support Vector Machine used for classification acts as the robust classifier for BCI application. The work analyzes various wavelets functions and different kernel functions using the performance parameters resulting in 92% classification accuracy.
Keywords – *Brain Computer Interface (BCI), electroencephalography (EEG), Higher order statistic (HoS)*

I. Introduction

Concept of Brain-Computer Interface (BCI) develops due to the need for establishing the communication channels which use the brain signals for controlling the environment bypassing muscular pathway. The BCI will work for the people suffering from physical disability like amyotrophic lateral scheloris (ALS) with undamaged cognitive system. It can also be used for other applications where it is required to remotely control the environment. Electroencephalography (EEG) collects the signals from the scalp of the subject, it is the non-invasive way of extracting the neural signals. The obtained version of the signal is very weak and has the contaminations from other neural signals as well as from the signals like electrocardiogram (ECG) and electromyogram(EMG). Thus there is signal processing requirement for the extracted signal for pre-processing, feature extraction and classifying the mental task under consideration. Figure 1 gives the signal processing requirements of EEG based non-invasive BCI in detail.

Various brain signals which can be used as input for BCI are steady state visually evoked potential(SSVEP), motor imagery(MI), slow cortical potential (SCP). MI signal acts the promising input for independent BCI as it does not need any external stimulus for generation. Imagery of different movement provide the signal with distinguishable difference and hence MI signal increase the class of BCI.

The variations in the brain signals are in form of event related synchronization(ERS) in β(18-25Hz) band and event related desynchronization (ERD) in μ(8-12Hz) band which can be captured from ipsilateral side and contralateral side of brain respectively. These ERD and ERS can if identified

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for various motor movements and can be used as efficient input to Feature extractor. Almost all literatures are using the concept of ERD and ERS but grossly they are extracting the feature on its basis.

The various signal processing methods used for BCI using MI as the input signal are reviewed as follows. EEG signal is captured with respect to reference electrode and hence carries the interference due signal at that reference electrode. Common average referencing is one of the most observed techniques preferred for EEG so as to remove the interference of reference signal from it[1][2]. Surface laplacian(SL) is further preferred over CAR as it claim to remove the reference contamination and gives the source specific representation of the signal[3]. The spherical spline implementation of SL is found to be more accurate way of representing the EEG signal[4][5]. Feature extraction methodologies used for EEG based BCI covers time frequency and time domain methods. Wavelet decomposition of the signal in wavelet coefficients and statistical representation of those coefficients is the trend covering time-frequency domain feature extraction[6][7]. Wavelet coefficients obtained from decomposed signals are also used to constructs the features like wave entropy and wave energy which are found to be useful for representing the motor movement related variations[8]. Features having time-frequency-space correlation are also popular for representing neural signals in BCI and are used in literature[9]. Spatial spread of the motor imagery(MI) signal on the neighboring electrodes acts the strong feature, it is used in research work without or with modifications[10][11].

II. METHODOLOGY

The implementation in the work covers wavelet decomposition of the signal using matching wavelet functions. Wavelet entropy and wavelet energy are used as the features prepared using the wavelet coefficients and they are passed to support vector machine for classification.

a. Wavelet Transform(WT)

Wavelet transform can be described as the time-frequency correlation estimation technique, which expresses the signal in form of wavelets coefficients as given in equation 1. The coefficients are estimated by matching the signal under test with the mother wavelet by shifting and dilating the mother wavelet. Inversely it can be stated that the original signal can be reconstructed by using the wavelet function and wavelet coefficients given by equation 2.

$$\Psi_{a,b}(\mathrm{t}) = \frac{1}{\sqrt{a}} \int x(t) \Psi^{*} \frac{(t-b)}{a}$$

(1)

$$W(a,b) = \int x(t) \Psi^{*}_{j,k}(t) dt$$

(2)

Discrete wavelet transform proposed by Mallat can be described as the algorithm which to decomposes a signal using a set of high-pass filter and low pass filters having properties specific to mother wavelets[12]. Figure 1 shows the three level wavelet decomposition of the signal.

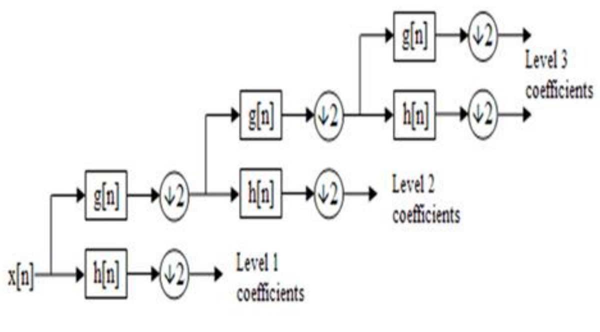

Figure 1: Three Level Wavelet Decomposition

b. Wave Energy and Wave Entropy

Wave energy is one more important parameter considered for feature extraction. Wavelet coefficients corresponding to specific bands are used for computing the wavelet energy, thus approximate band energy and all detail band energy will be

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separately computed giving the vector denoting wave energy.

Wave Entropy measures the information content in the signal or the events. It is measure of amount of uncertainty about the event depending on the probability distribution. The entropy for wavelet band will give the measure of randomness related to that particular band which can properly represent the variations of the signals and can be used as the feature.

c. Support Vector Machine(SVM) for classification

SVM can be described as the robust linear classifier used for the non-linear separations of the classes using non-linear kernel functions. The generally used kernel function are radial basis function(RBF), polynomial functions, Gaussian kernel etc. for the application related to BCI.

III. IMPLEMENTATION

Flow of the implementation is as given in figure 2. Th implementation follows wavelet decomposition of signal using matching wavelet function. Wavelet entropy and wavelet energy are the feature extracted from the wavelet decomposed band. Along with it statistical features are also extracted from the wavelet coefficients. These features from the selected electrode act the training vectors for the SVM. 70% signals are used for training and remaining 30% are used for the testing purpose.

a. Dataset used

Dataset used for this work is provided by Intelligent Data Analysis Group from Department of Neurology, Berlin. The data is extracted from the subject seating on a normal chair, with his arms resting on the table, and his fingers positioned on the keyboard of computer. The subject has to press the key of keyboard with the index and little fingers in self-chosen manner. 3 sessions were recorded and every session last for 6 minutes.

Data format: Total 416 trials of 500msec length of each trial are provided. 316 trials are provided with labelling of left-hand movement and right-hand movement, 100 trials are for testing purpose. Data is sampled at 1000Hz and down-sampled version at 100Hz is also available.

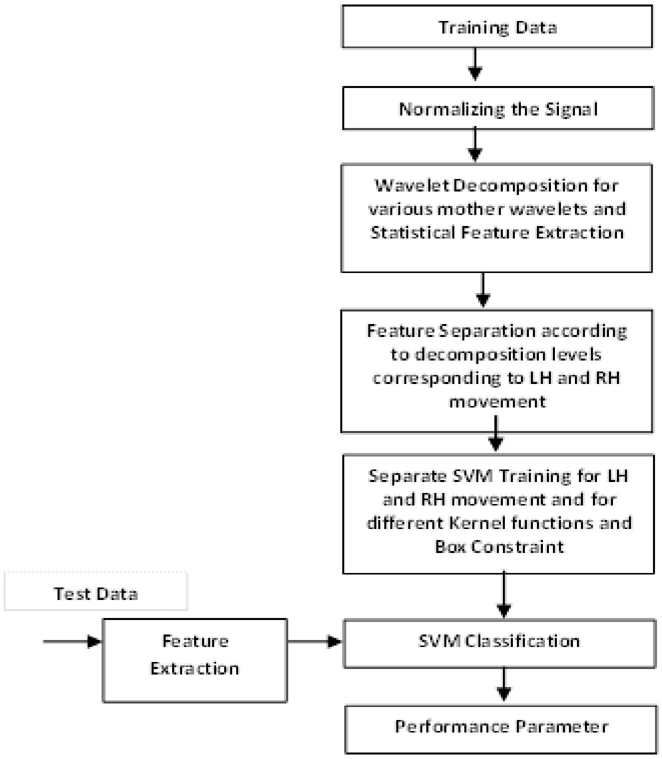
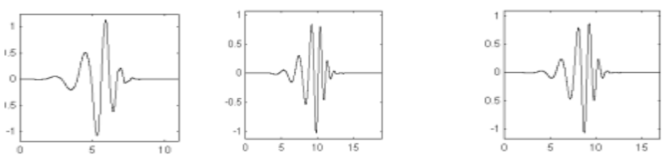


Figure 2: Implementation flow

b. Wavelet Function Selection

It is very important to select the wavelet function matching with the signal under test, as the matching function will extract the required information from the signal. Biomedical signals are generally decomposed using various variant of Daubhechies and Biorthogonal. In this work the empirical analysis selected the wavelets db6, db9, db10, bior3.7 and symlet7.

Daubechies Wavelet



db6 db10 db9

Biorthogonal Symlet

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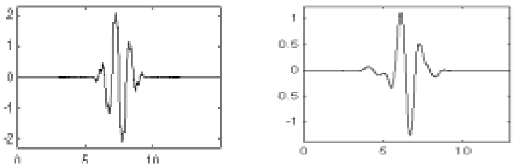

bior3.7 Sym7

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c. Level of Decomposition

The sampling frequency for the signal is 1000Hz and the band of interest are μ band(5 to 15Hz) and β band (12 to 35Hz). Thus level of decomposition required is calculated using formula given in equation 3. Table 1 gives the frequencies covered by each level of decomposition.

$$2^{-j-1}Fs \leq \Delta Fj \leq 2^{-j}$$

(3)

Table 1 Decomposed Signal Level and Corresponding frequencies

Decomposed signal	Frequency Range(Hz)
D1	250-500
D2	125-250
D3	62.5-125
D4	31.25-62.5
D5	31.25-15.625
D6	15.625-7.812
A5	0-7.812

IV. Results

Results are evaluated for 5 different wavelets which are selected on basis of its physical resemblance with the signal. As well variations is applied in terms of SVM parameters like RBF values and boxconstraint. For representing the results performance parameters used are Classification Accuracy is evaluated in table 2, Table 3 gave Statistical Precision.

Table2 Classification Accuracy for different Wavelets

Wavelet	RBF 0.8	RBF 1.4	RBF1.4 bc1.4	RBF0.8 bc0.8	RBF0.4 bc0.8	RBF0.2 bc 0.6
bior3.7	71.20	71.84	70.57	77.22	83.54	60.44
db6	72.47	68.04	66.46	68.99	71.84	61.39
db9	72.78	76.27	72.47	68.67	81.65	62.66
db10	72.15	70.57	69.94	71.52	65.82	92.72
bior 4.4	72.15	64.56	66.77	71.84	70.57	57.91

Table 3 Statistical Precision for different Wavelets

Wavelet	RBF 0.8	RBF 1.4	RBF1.4 bc1.4	RBF0.8 bc0.8	RBF0.4 bc0.8	RBF0.2 bc 0.6
bior3.7	70.00	71.88	70.37	85.95	84.52	55.99
db6	72.47	67.26	66.67	78.50	92.68	56.58
db9	72.78	78.00	75.71	81.91	80.24	57.45
db10	72.15	68.75	70.51	91.57	96.36	90.48
bior 4.4	72.15	65.36	68.49	68.82	66.50	54.45

V. Conclusion

DWT is selected as the suitable way of feature extraction as EEG is non-stationary signal. Motor imagery signal and database obtained from BCI competition is used for processing. Motor imagery is selected as input signal as there is good scope of adding motor movement for controlling the environment. Depending on range of frequency of interest wavelet decomposition to sixth level is done and the detail coefficients of 5th and sixth level along with approximate coefficients are used as extracted feature. Statistical features such as variance, standard deviation and wave entropy,

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wave energy are selected statistical features calculated from the feature extracted and passed to SVM. Support Vector Machine(SVM) with Gaussian kernel is used as classifier. Bior3.7 with RBF 0.4 and Boxconstraint 0.8 gives classification accuracy of 83.54%. Wavelet function db9 with RBF 0.4 and Boxconstraint 0.8 gives classification accuracy of 81%. db10 with RBF 0.2 and Boxconstraint 0.6 gives classification accuracy of 92.72%. Other performance parameters like sensitivity, specificity and precision are ranging from 96% to 98% for db10. db10 can be selected as matching wavelet for motor imagery signal of BCI.

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