EEG Signal Classification by Combining Discrete Wavelet Transform and Empirical Mode Decomposition

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***Abstract*:**The most complicated body part is the human brain which can regulate and perform many activities and can perceive. A brain that is working in good condition is capable of producing responses to the received signal and then forward the information to the entire body. A few syndromes of the brain adversely affect the interactions between the brain and the remaining part of the body and thereby limiting the transmission of signals. The device that is capable of helping diseased people with neural abnormalities is termed Brain-Computer Interfaces (BCIs) which assist in evaluating the activities of the brain, interpreting and categorizing different actions of the brain, and later forwarding the signals to the external system and possibly back to the body. One of the significant aspects of optimizing the efficiency of the brain-computer interface is the rate of recognition for the categorization of neural activity. Therefore, the technique of extracting feature is presented in this work which is based on the entropy approach, discrete wavelet transform (DWT), and empirical mode decomposition (EMD). By employing various characteristics like standard deviation, mean, RMS, entropy, and average, the feasibility of the designed framework can be analyzed. Initially, a series of low-frequency signals along with DWT is obtained from the decomposition of electroencephalogram (EEG) signal, further with the help of EMD the sub-band signal is processed to obtain the number of which stationary time series known as intrinsic mode functions (IMFs). Meanwhile, for the reconstruction of the signal, suitable IMFs are chosen.decomposed into a series of narrowband signals with DWT, then the sub-band signal is decomposed with EMD to get a set of stationary time series, which are called intrinsic mode functions (IMFs). Meanwhile, for the reconstruction of the signal, the

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suitable IMFs arechosen.Therefore, the associated feature vector is extracted with the help of the computed entropy of the received signal. At last, classification is carried out through k-nearest neighbors (KNN) and support vector machine (SVM). Thus, the coverage of large frequency issues during EMD is overcome by the proposed framework and thereby enhancing the classification efficiency of EEG signal motion imaging. The experimental results show that the KNN classifier is more efficient and achieves 93.84% accuracy when compared to the SVM classifier which achieves 87.64% accuracy.

Key words: KNN, EMD, DWT, CSD

I. INTRODUCTION

A straight forward interaction path between the human brain and a peripheral device is achieved through Brain-Computer interface (BCI) and are introduced to assist the individuals with disabilities, evaluating the activities of the brain by interaction with computer [6]. The conversion of an individual neural activity into signals or instructions are done through BCI for an experimental platform. Electroencephalography (EEG) is a commonly utilized technique to obtain the control signals of BCI and is typically employed to evaluate the electrical activities of the brain which are extracted from BCI [9]. The neurophysiological activities produced from theelectrical activity of cortical which is estimated via scalp and skull are illustrated in the archives of EEG. Due to the technological advancement in BCI, persons with physical disabilities can utilize devices like computers, artificial limbs, systems that can recover the functioning of the lost nervous system and thereby accomplishing various activities like monitoring the environment, exchange of information, and signal rehabilitation [7]. Depending on the recording method of signal, the technology of BCI is further subdivided into two main groups they are non-invasive and invasive techniques. In the case of invasive technique, the neurologists insert the microelectrodes array directly into the brain but in the case of a non-invasive approach, the functioning of neurons present in the brain are noted down by inserting the electrodes on the scalp or by employing functional Magnetic resonance Imaging (FMRI) method. Approximately ten billion neurons are present in the brain of a human. A highly parallel data processing system is constituted by the set of neurons present in the brain. The flexible nerve cells are present in the nervous system and are having the ability to communicateand exchange data by switching the transmission of electron flow throughout the nerve cells resulting in the production of the magnetic field and electric field which are noted down through the scalp surface (Brazier, 1949). By inserting trivial electrodes on the scalp, the electric fields can be determined. With the help of an electroencephalogram (EEG), the electrical activity of the brain is noted and the voltage difference between two electrodes can be intensified and measured. By employing Magnetoencephalogram (MEG) that originated in 1970, relatively small magnetic fields that are produced by the nerve cells are evaluated.

The remaining part of the research work is systemized as follows: Section II explains the related work, the methodology proposed is demonstrated in Section III, Section IV illustrates the analysis of result and at last, the conclusion is presented in Section V.

II. RELATED WORK

Comprehensive research work has been carried out to analyze the issue in this proposed work. Table 1 illustrates the publications referred to accomplish the proposed work.

Table **1: Related literature review**

Ref.no	Methods	Accuracy
[1]	EEG signal	80%-
[2]	EEG signal	85%-
[3]	K-complex	87%-
[4]	SPIHT	78.6%-
[5]	SVM	87.5%
[6]	Signal acquisition pre-processing enhancement	89%
[8]	W-CSP	83.71%
[9]	CSP-ELM	87.54%
[10]	Data acquisition Data pre-processing	81%
[11]	SVM, KNN, ANN	95.21%
[12]	MEMD.SIFT, IMFS, KNN	90.71%

[13]	KNN, Dual tree complex wavelet transform	90.00%
[14]	KNN	92.84%
[15]	ERSP, PSE, CSP.SVM	84%
[16]	FHNN, ANN, HNN	85.6%
[17]	DFC	93.3%
[18]	MEMD-CCD	90%-
[19]	EEG signal	87%-
[20]	SFFS	78.6%-

III. Proposed Methodology:

An algorithm based on EMD that is associated with approximate entropy and discrete wavelettransform (DWT) is introduced in this proposed work. In this work, we do not employ any multivariate signals approaches like main or self-reliant data preprocessing to extract the input signals of EEG because they result in deterioration of few EEG modules, and artificial discrimination of pseudo-components consumes more time and are inefficient. Rather than computing the approximate entropy of a solitary EEG signal, we compute the approximate entropy of every individual band of frequency in the existing EEG signal. Imperfections in the EMD extracted is illustrated by EMD through the dissolution of EEG signals. Consider an instance, in the region of lower frequency, the produce IMF's are found to be non-ideal, and further, the frequency spectrum extracted initially is significantly large. Therefore, to overcome the above drawbacks, the EEGG signal is disintegrated through WT to extract a large number of narrow-band signals and further EMD decomposition is employed for the appropriate band of frequency signals to extract highly focused signals. An appropriate method called approximate entropy was determined to differentiate the imagination of motion to optimize the classification and recognition. Figure 3.1 illustrates the algorithm's flow chart. The key phase of the technique are: (1) Disintegrating the signals of EEG into a narrowband signal through WT, (2) decomposing proper sub-band signals to IMF’s is done by employing EMD, (3) the band of IMF is extracted through FFT, the signal matrix is formed by choosing IMF’s wavelength and

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movements; (4) the approximate entropy of the signal matrix is computed as the feature vector; (5) the features are classified throughKNN and SVM classifier.

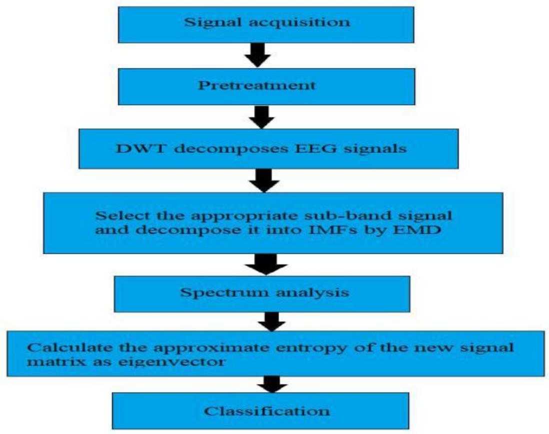

Figure 1: Flow chart of the proposed method

Some of the Parameters:

1. Sensitivity:

Sensitivity is also referred to as the ability to remember, true positive rate, or the possibility of recognition in certain areasto evaluate the number of real positives which are predicted clearly.

Sensitivity= TP / (TP + FN)

Where TP = True Positive

FN = False Negative

2. Specificity:

The true negative rate methods for assessing the number of real negatives that are predicted are termed as Specificity.

Specificity= TN / (FP + TN)

Where TN = True Negative

FP = False positive

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3. Accuracy:

Accuracy signifies that how the computed value is similar to the real target value. Possessing extremely small debt predictions in business domains means that clients' estimates are approximately equal to the target value.

Accuracy = (TN + TP)/(TN+TP+FN+FP)

Where TN = True Negative

FP = False positive

4. Positive Predictive Value (PPV):

PPV is employed to determine the positive patterns which are accurately identifiedfrom the overall forecasting pattern either in the positive or non-positive group.

PPV=TP/(TP+FP)

Where TP= True positive

FP=False positive

5. Negative Predictive Value (NPV):

NPV of the typical structures that are classified/identifieddo notsignifythe irregularities.

NPV=TN/(TN+FN)

Where TN= True negative

FN= False negative

6. False Positive Rate (FPR):

The addition of true negative and false positive is termed as a false positive rate (FP+TN ensuing as the overall negatives). There is a chance of obtaining a false positive, only when a true value is non-positive and thereby the result obtained is non-negative.

FPR=FP/FP+TN

Where FP=False positive

TN=True negative

7. False Negative Rate (FNR):

The fraction of false-negative to the addition of false-negative and true positive is termed as a false negative rate.

FNR=FN/(TP+FN)

Where FN=False negative

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TP=True positive

8. False Discovery Rate (FDR):

The proportion of false non-negative outcomes to the true non-negative outcomes is termed as false discovery rate

FDR= FP/TP

Where TP=True positive

FP=False positive

IV. Result and Analysis

EEG-Motor Imagery: (2 classes of the left hand, right-hand movement)Particularly EEGs are biomedical signals which are sensitive to sound/noise. Highly developed techniques for signal processing in the application areas like surveillance, equipment utilized for diagnosis, BCI are introduced. The quality of EEG signals along with the external sources and few biomedical signals are adversely affected by various ambient noises. For example, the EEG signals interfere with biomedical signals which are similar to EEG electrodes namely Electromyograms (EMG). The movements of eyes and flickering are termed as an electrooculogram (EOG) which is considered as one of the significant causes for noise in EEGs. During the process of validating the respondent's signal, the issue of eye movements must be correctly handled. Few instances of external noise sources that are employed to increase the computational complexity of EEG are the material and characteristic of electrodes, liquid which is employed as an electrolyte on the skin, and 50 or 60 Hz electromagnetic interference caused by overhead cables. The three important steps involved in Biomedical signal processing are:

- Pre-Processing
- Feature extraction
- Classification.

Figure 4.1. illustrate the typical block diagram of the processing unit of a Biomedical Signal. Pre-processing is considered one of the significant phases in the processing of biomedical signals toimprove the SNR before the phases of classification and extraction of the feature. Since EEG signals are highly complicatedsignals, various signal processing techniques have been employed for a certain application to spatially or temporally obtain probably efficient features. A few significant techniques utilized in this work are Wavelet Transforms and autoregressive

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coefficients. Also, selecting a classifier model that is appropriate for the feature vectors can enhance the output with regards to efficiency and precision. Some of the commonly employed classification techniques are K-Nearest Neighbor (KNN) and Support Vector Machines (SVM).

Training Data:

Data gathering is the initial phase of the brain-computer interface. Several steps are carried out before extracting the parameter. With the help of electrode positioning the signals are extracted or else the signals of EEG are obtained through brain-computer interface Competition IV in http://www.bbci.de/competition/iv website (A01T.MAT and A01E.MAT). The filtered signal is obtained by the methodology of pre-processing where the unnecessary features are eliminated from the EEG signals and thereby enhancing the system efficiency by removing noise from the target signal. Here the training data sets (raw EEG information) are considered which are of low frequency and the necessary information is obscured from the noise present. The necessary data is obtained by applying bandpass filtering which is of 4^{th} order. Also, low-frequency signals such as gamma, alpha, and beta are required to examine the EEG signals.8 to 30 Hz is the frequency range of bandpass and A01T.mat is the set of data provided for training the samples and 250 Hz is the rate of sampling. Once the data set is loaded, the filtered signals are extracted. With the help of DWT and EMD methods, features of a signal areobtained. Feature extraction is achieved by disintegrating thesignals with the help of DWT and further EMD is employed to the processed signal. Here the implementation of 7 level wavelet decomposition is executed. Accurate coefficient and approximate coefficient are obtained with the application of wavelet decomposition. D1, D2, D3, D4, D5, D6, D7 are the detailed coefficients. In this case, D1, D2, D3 are considered as the higher frequency components and the low-frequency components are D4, D5, D6, D7. The low-frequency detailed coefficients such as D4, D5, D6, D7 are received by the EEG sample and further applied with db6 (Daubechies) wavelet.

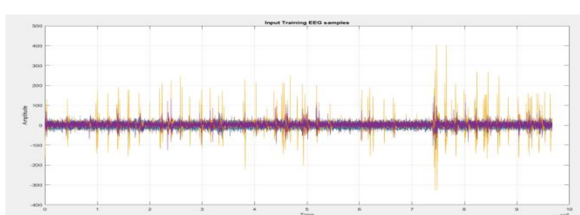

Figure 2: Input training EEG samples

Approximation and Detailed Coefficients:

To extract the sub-band approximation that is of low frequency and sub-band detailed coefficient of high frequency, 7th order wavelet decomposition is acquired by employing the db6 wavelet. The filtered signals such as detailed coefficient signals D1, D2, D3, D4, D5, D6, D7 as well as approximation coefficient signal A7 are extracted with the application of discrete wavelet transform. In this work 7 level, wavelet decomposition is executed. The detailed coefficient (D1-D7) and the eight approximate coefficients (A7) signals are extracted and are illustrated in Figure 3. Here D1 is the signal of high frequency and when it moves towards D7 the frequency of thesignal reduces. For the restoration of signals in the EEG band of signal D4, D5, D6, D7 are chosen.

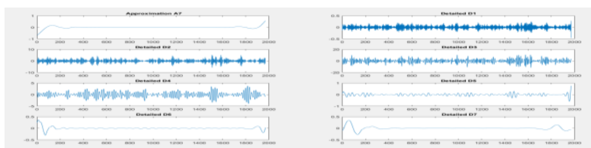

Figure 3: Wavelet decomposition sub-band signal

IMF Signal Generation:

Figure 4 illustrates the 12 IMFs signals which are extracted by the addition of accurate coefficients D4, D5, D6, D7signals which are of low frequency to obtain a solitary signal for which EMD is utilized. The range of frequency that is less than 24 Hz and more than 6Hz is taken into account to acquire the signals of IMFs by performing feature extraction. Standard deviation, RMS value, mean, entropy, and average are some of the factors measured during feature extraction. By restructuring (RHH and LHH) we distinguish the two classifications and further feature extraction is handled independently.

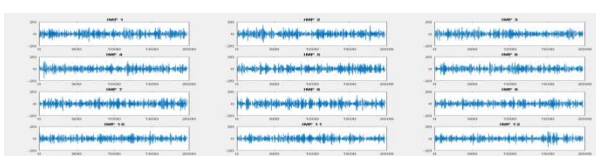

Figure 4: IMFs and the corresponding spectrum of orders of 1-12 by EMD method

Testing data:

The relatively similar operation that is used for the training data set is carried out.

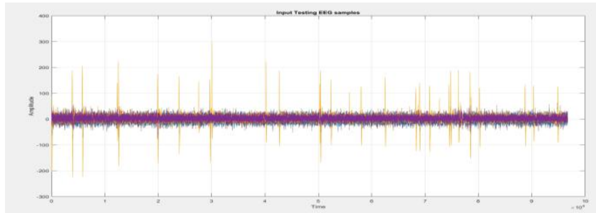

Figure 5: Input testing EEG samples

The training signals such as RHH and LHH are integrated once the samples of training are extractedas well as the trained model is achieved by integrating the respective labels. Some of the values present during the feature testing are given as input to the trained model one after the other. Class 1 and Class 2 are the two groups involved in a trained feature that possess distinct values of the label. The calculated parameters for the SVM and KNN classifier are presented the table 2.

Table 2: Comparison Results between SVM and KNN Parameters

Parameters	SVM classifier	KNN classifier
Sensitivity	98.05%	97.11%
Specificity	80.94%	90.98%
Accuracy	87.64%	93.84%
Positive Predictive Value	76.81	90.36
Negative Predictive Value	98.47	97.31
False Positive Rate	19.05	9.01

False Negative Rate	1.94	2.88
False Discovery Rate	23.18	9.63

The overallcompletion results are compared with the other publications with other state of work presented in the table 3. From the table is clear that results obtained in the proposed are better than the other publications.

Table 3: Comparison of brain-computer interface (BCI) competition results and the results of the proposed method:

References	Method	Channel	Classifier	Result
[10]	C-SVC	5	SVM	81%
[19]	Autoregressive Model and Wavelet Packet Decomposition	5	SVM	98%
[9]	FDDL-ELM	3	CSP	87.54%
[11]	-	3	SVM	98.95%
			KNN	90.88%
[14]	Wavelet Packet Domain	Not given	KNN	92.84%
Proposed Method	DWT + EMD	14	SVM	87.64%
			KNN	93.84%

V. Conclusion

A technique for extracting the features of EEG that are based on EMDassociated with approximate entropy and DWT is introduced in this work to overcome the drawback of handling large frequency bands for EMD and thereby enhancing the classification precision of the EEG signal motion imaging. The experimental outcomes illustrate that the proposed technique is

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significantly efficient and accurate. By employing KNN and SVM classifiers various factors namely sensitivity, False Positive Rate (FPR), False Discovery Rate (FDR), precision, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), False Negative Rate (FNR), is determined for the proposed system. The experimental results show that the KNN classifier is more efficient and achieves 93.84% accuracy when compared to the SVM classifier which achieves 87.64% accuracy

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