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EEG ANALYSIS FOR EMOTION RECOGNITION USING MULTI-WAVELET TRANSFORMS

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Abstract

Emotion recognition from EEG signals is a subject of interest for both psychologists as well as engineers. In BCI systems, EEG based analysis and classification of human emotions is a new and challenging field that has gained momentum in the past few years. In the present work, human emotion recognition has been carried out using Multi- Wavelet Transform (MWT) based features derived from the EEG signals. The random forest (ensemble technique) has been used for classification task.

The results of the study indicate that MWT Features along with Random Forest classifier yield the classification accuracy of 98.0% for classification between four classes of emotions i.e. happy, sad, exciting and hate states. The classification accuracy values of 99.7%, 97.3%, 97% and 95.8% are obtained for happy, sad, exciting and hate classes respectively.

Keywords: EEG, Human Computer Interface, Multi-Wavelet Transform, Statistical features.

1 Introduction

The use of electroencephalogram (EEG) or "brain waves" for human-computer interaction is a new and challenging field. EEG among all is the most used technique to capture brain signals due to its excellent temporal resolution, non-invasiveness, usability, and low set-up costs [1]. EEG signals play an important role in detecting the emotional states for developing the HCI (Human-Computer Interface) based analysis and classification of emotions. The applications of emotion recognition include medical areas of neurology and psychology.

HCI acts as a channel of communication between human brain and external world like computer system. It allows its users to control external devices which are independent of peripheral nerves and muscles with brain activities. It is very helpful to assist patients with impaired motor functions, such as completely paralyzed patients with amyotrophic lateral sclerosis [2, 3]. One key challenge in current HCI research is how to extract features of random time-varying EEG signals and classify the signals of human emotions as accurately as possible.

The success of this methodology depends on the selection of methods to process the brain signals in each phase.

2 Related Work

Several methods have been suggested in literature to diagnose the hidden dynamical features and abrupt changes that can take place. The interpretation of the signal implies three important aspects. The spectral analysis of the signal determines the dominant frequencies in the EEG.

The temporal analysis of the EEG keeps a record of normal and abnormal wave shapes in the signal and also presence and absence of these rhythms. The spatial analysis estimates the distribution of these rhythms over the different brain regions [1]. These interpretations have been on the basis of time and frequency domain analysis. Event-related potentials (ERPs) and SCP (slow cortical potential) components have reflected emotional states in the time-domain analysis [4-5]. In frequency-domain, the spectral power of different frequency bands corresponds to different emotional states.

At present, feature extraction techniques/methods for non-stationary EEG signals include: (i) FFT (Fast Fourier Transform), (ii) ARM (Auto Regression Method), (iii) DWT (Discrete Wavelet Transform), (iv) WPD (Wavelet Packet Decomposition), (v) MWT (Multi-Wavelet Transform). Bajaj et al. [6] applied MWT and extracted ratio of the norms, Shannon and normalized renyi entropy for classification of emotions. The accuracy was 84.79% using MC-LS-SVM (Multi Class Least Square Support Vector Machine) Morlet wavelet kernel function. Jenke et al. [7] used DWT technique for classification of 6 classes of emotions using Naïve Bayes with overall accuracy of 36.5%. WPD have been used by Vijayan et al. [8], the classification of accuracy resulted 94.097% using MC-SVM. Mehmood et al. [9] calculated Hjorth Parameters and classified emotions using SVM with 30% accuracy for 5 classes and 70% for 2 classes. AlZoubi et al. [10] calculated PSD for 10 different classes of emotions with 66.74% using KNN Classifier.

Nasehi et al. [11] calculated Gabor-based features using DWT and classified the emotions with 64.78% using PNN. Petrantonakis et al. [12], calculated HOC-Based Features using hybrid (adaptive filtering (EMD&GA). The results were 83.33% using SVM as classifier.

Murugappan et al. [13], calculated Energy, RMS, REE, LREE, ALREE, power using DWT (db4) and used KNN, LDA (Linear Discriminant Analysis) classifier for classification purpose. The results were 83.26% using KNN, 75.21% using LDA.

3 Methodology

The methodology which is adopted in carrying the present research work is discussed in Fig.1.

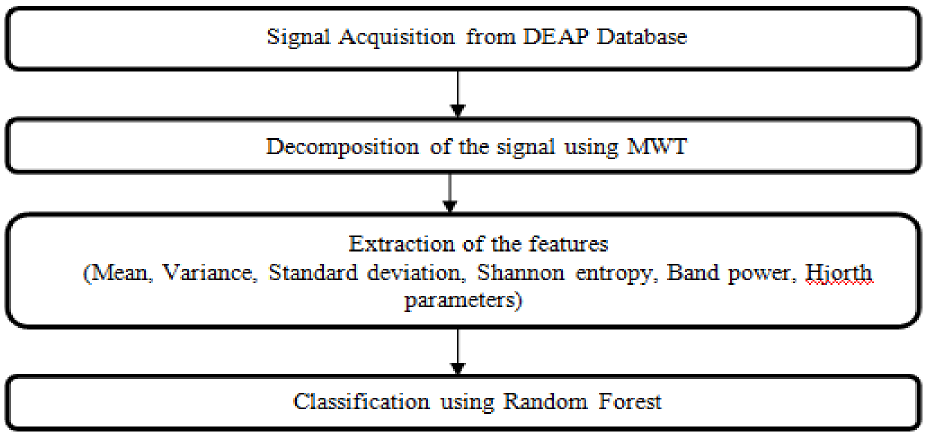

Fig 1: The proposed methodology for emotion classification from EEG signals.

3.1 Signal Acquisition

In this work, data was collected from dataset prepared by Queen Mary University of London. This dataset commonly known as the DEAP dataset consists of 32 participants while watching 40 different kinds of music videos. The data in this dataset was acquired with a 32 channel BioSemi acquisition system [5]. EEG signals of the participants were acquired using Biosemi Active Two system at a sampling rate of 512 Hz, which was down sampled to 128 Hz before processing. Out of 32 channels only 15 channels are considered to carry out the research. Those are FP1, FP2, F3, P3, F4, T7, T8, P4, O1, PZ, PO3, O2, P7, CP2, and C4. The selection of the channels is scrutinized on the basis of the significant signal acquisition as reported from the literature [7-8, 14].

3.2 Multi-Wavelet Transform (MWT)

Computation of features in transform domain is much more logical as human visual system characterizes any signal in a multiscale way.Accordingly Multi-wavelets, which are the wavelets having various scaling functions, are preferred over single wavelet/ scalar wavelet. In MWT, multiple scaling and wavelet functions are used rather than single functions. It yields the property of having more degree of freedom for generating multi-wavelets. Therefore, simultaneous gathering of properties like vanishing moments (higher order), symmetry, orthogonality and compact supporting is possible as opposed to case of scalar wavelets. There are two forms of Multi-wavelets: a) Orthogonal type like Geronimo-Hardin-Massopust (GHM), Symmetric Asymmetric (SA4) and Chui-Lian (CL); and b) Bi-Orthogonal type such as Bi-Orthogonal Hermite (Bih52S). MWT have some unique characteristics that cannot be obtained with scalar wavelets [15]. It motivates us to use multi-wavelet transform of EEG signals for classification of human emotions. In the present work 3-level MWT has been employed to carry the experiment. Multi-wavelets are also based upon multiresolution analyses (MRA), like wavelets. It gives sixteen sub bands after one level of decomposition as compared to four sub bands in Wavelet decomposition [16].

The features namely, Mean, Variance, Standard deviation, Shannon entropy measure, Hjorth parameter and Band-power have been measured from sub-signals obtained from the multi-wavelet decomposition of EEG signals. These features are briefly described as follows

3.3 Classification

In the present work, classification of the signals is carried through Random Forest, a very efficient algorithm in ensemble learning. Ensemble techniques are also suited for the classification of EEG signals for the following two reasons. (i) The dimensionality of the EEG is often high and one of the pre-requisites of HCI is to train the classifier as fast as possible, thus, the training set also must be small. (ii) EEG is a time-varying signal, and thus, it becomes hazardous to employ a single trained classifier to recognize the classes of the unknown (incoming) features. Random forest (RF) introduces both bagging and random variable selection for tree building, RF utilizes an ensemble of classification trees, which are built on the bootstrap sample technique of the data.

4 Results and Discussion

The data is acquired from DEAP dataset. The signals then are decomposed into 3-levels using MWT. Next, the features namely Mean, Standard deviation, Variance, Shannon entropy, Hjorth parameters and Band power are calculated.

For classifying the feature vector set, Random Forest algorithm is considered in the present work. Also, the proposed algorithm is compared with the performance of basic algorithm i.e. Logistic classifier, MLP classifier, KNN classifier with k=2 with Euclidian distance measure, and MC-SVM with Puk Kernel.The performance of all the classifiersareanalyzed in terms of Mean Absolute Error parameter and the classification accuracy (%). Next, the confusion matrix for the classifier giving the best accurate result i.e. having the highest accuracy is obtained. The values for Mean Absolute Error obtained for different classifiers for emotion recognition are tabulated in table 1.

Table I: Calculated values of Mean Absolute Error for the Classifiers.

CLASSIFIER	Mean Absolute Error
LOGISTIC	0.3477
MLP	0.3478
KNN	0.1624

MC-SVM Puk Kernel	0.3653
Random Forest (Proposed work)	0.1236

The result from the above table I clearly shows that the mean absolute error for the proposed work i.e. Random Forest is the least 0.1236, that means the classification of the instances or the classification rate is the highest among all. KNN classifier, mean absolute error is 0.1624 showing the next better accuracy result after Random Forest. All the remaining classifiers i.e. Logistic, MPL, MC-SVM with Puk kernel function varies slightly from each other having value 0.3477, 0.3478, 0.3653 respectively.

The classification accuracy (%) obtained from different classifiers for emotion recognition from EEG signals is tabulated in Table II.

Table II: Classification accuracy (%) with different classifiers for emotion recognition.

CLASSIFIER	HAPPY	SAD	EXCITING	HATE	AVERAGE (%)
LOGISTIC	98.1	1.6	1.8	2.9	42.8
MLP	92.5	13.1	3.30	3.1	43.6
KNN	100.0	61.4	36.3	21.1	67.4
MC-SVM Puk Kernel	97.6	6.8	6.1	8.1	45.4
Random Forest	**99.7**	**97.3**	**97.0**	**95.8**	**98.0**

It can be observed from table II, for happy state the highest accuracy obtained is 100% using KNN (k=2), shows all the instances of happy state were correctly classified with zero error. Whereas, it is 99.7%, very near to the previous classified value with Random Forest. For the second class i.e. sad state Random Forest outperform all the classifier with accuracy of 97.3%. Next, is KNN with 61.4% accuracy. Discussing about the exciting state, again the highest accuracy is obtained from Random Forest with 97.0%. Remaining classifier accuracies are not to the mark. For hate state, Random Forest classification accuracy is the highest i.e. 95.8%. No other classifier is able to even classify the half of the accuracy obtained from Random Forest. The overall average accuracy of 98.0% is obtained using proposed classifier i.e. Random Forest. The confusion matrix of Random Forest for performance analysis is obtained and is shown in table III. The diagonal values of the matrix shows the correctly classified instance for the particular class and the other values in the respective row shows the incorrectly classified instance. Describing it for happy state the first value (99.7) indicates the value for class happy classified as happy. The next value in the row i.e. 0.25

indicates the value for class happy classified as sad. The third value in the row indicates that .05 percent of the happy state was incorrectly classified as exciting state. For the happy class no instance is there that classified happy as hate state.

Table III. The confusion matrix for Random Forest for the classification of emotions from EEG signal.

	HAPPY	**SAD**	**EXCITING**	**HATE**
HAPPY	99.7	0.25	0.05	0
SAD	2.3	97.3	0.25	0.15
EXCITING	2.04	0.72	97	0.24
HATE	2.63	0.97	0.60	95.8
Accuracy (%)	99.7	97.3	97.0	95.8

Table IV presents a comparison of the emotion classification accuracy with the proposed method and other existing methods in the literature. Number of class is same i.e. 4 classes in the work. Vijayan et al. [8] classified for emotion state happy, exciting, sad, hate using WPD as feature extraction technique and MC-SVM as the classifier for classification of the emotion and obtained 94.097% accuracy. Bajaj et al. [6] classified happy, neutral, sad, fear emotions using MC-LS-SVM Morlet wavelet kernel function with 84.79% accuracy using MWT as feature extraction technique. The proposed work also explore the capability of MWT as feature extraction technique and Random forest as classifier to classify happy, sad, exciting and hate state.

Random Forest selected as classifier in the present work outperforms all the other classifiers as reported in the literature giving overall accuracy of 98% for recognition of emotions.

Table IV. A comparison of classification accuracy of deferent classifiers for emotion recognition.

AUTHORS	CLASSES	FEATURE EXTRACTION METHOD	CLASSIFIER	ACCURACY (%)
Vijayan et al. [8]	4	WPD	MC-SVM	94.097
Bajaj et al. [6]	4	MWT	(MC-LS-SVM) Morlet wavelet kernel function	84.79
Proposed Work	4	MWT	Random Forest	98.0

5 Conclusion

EEG signals play an important role in detecting the emotional states for developing the HCI based analysis and classification of emotions. Different emotional states can be detected by individual, age, gender, mental state, background and ethnicity. The EEG signals are very subjective, non-Gaussian, non-correlated, random in nature and are considered as a chaotic signal. Due to natural limitations like time dependency, large dimensions of feature vector set, doubtfulness, it is a challenge for the engineers to make fast and correct decisions for recognition of emotions from EEG signal. In the present work, we explore the capability of proposed features (Mean, Standard deviation, Variance, Shannon entropy, Hjorth parameters and Band power) derived from MWT, an approach for classification of human emotions from EEG signals. The feature vector set obtained are then used as input for MLP, KNN, MC-SVM with Puk kernel function and Random Forest (ensemble) classifier for the classification. The present work have been compared with the existing research on the basis of having same number of class size i.e. 4 classes (happy, sad, exciting, hate) .The experimental results indicate that Random Forest has provided classification accuracy of 98.0% for classification of emotions from EEG signals. The classification accuracy for different emotion state happy 99.7%, sad 97.3%, exciting 97%, hate 95.8% are obtained by the proposed method. The mean absolute error is also the least among all i.e. 0.1236 for the proposed work.

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