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EEG-Based Human Emotion Recognition Using Time Frequency Analysis Based Three Band Features

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Abstract: **Electroencephalogram (EEG)-based emotion recognition is a relatively new research field in the human computer interaction area to identify and recognize emotions from human brain activity measured by EEG signals. In this paper, EEG signals under audio visual induction environment are collected from 5 healthy subjects using only 3 EEG channels, namely Fp1, Fp2, and a bipolar channel of F3 and F4 positions according to international 10-10 system. The raw EEG signals are preprocessed using an IIR Butterworth Band pass filter to isolate only the frequencies within the alpha (8-16Hz), beta (16-32Hz) and gamma (32-64Hz) bands. The filtered signal is subjected to wavelet transform for feature extraction. The final feature vector is classified into six emotion classes i.e. Happy, sad, disgust, fear, surprise and neutral using two simple pattern classification methods, K-Nearest neighbor (K-NN) and Linear Discriminant Analysis (LDA). Finally, the classification performance of discrete emotions using these two classifiers justifies the efficiency of the EEG-Based emotion recognition approach.**

Index terms: **Electroencephalogram (EEG), Emotion recognition, Higher order crossings Analysis, Linear Discriminant Analysis (LDA), K-Nearest Neighbor (K-NN).**

I.INTRODUCTION

Emotion recognition is one of the key steps towards emotional intelligence in advanced human-machine interactions. Emotion is one of the most important features of humans. Measuring emotion from brain activity is a relatively new method.

The Electroencephalogram (EEG) is one of the useful biosignals to detect human emotions. The EEG is a recording of electrical activity originating from the brain. It helps in determining the changes in the electrical activity of the human brain related to distinct emotions. The electrical potentials measured by the electrodes on the scalps are rich in information on the brain activity and provide global information about mental activities and emotional states.

EEG signal always reflects the true emotional state of a person, while speech and facial expressions might be prone to deception. Additionally, in contrast to visual and auditory signals, bioelectrical signals are emitted continuously and are independent of lighting conditions. It has very high sensitivity to received information and to internal changes of brain state and offers a very high time resolution in the millisecond range. .

Emotion recognition from EEG signals outperform other modalities, such as speech, text or facial expressions, since brain activity has direct information about emotion, where other modalities are an indirect reflection of the emotion. Moreover, EEG signals can be measured at any moment, and are not dependent on someone speaking or generating a facial expression.

This paper provides the implementation of an EEG–based, user-independent emotion recognition system using a feature set drawn from higher order crossings analysis. The raw EEG signal is preprocessed with Butterworth bandpass filter for artifact filtering. Then the filtered EEG signal is subjected to wavelet based feature extraction in order to obtain the various features. With these features, the six basic emotions are classified using two different classifiers such as LDA and KNN classifiers.

II METHODOLOGY

A.EEG signal

The EEG signals from each subject are collected for each emotion at five timing instants. In order to reduce the number of EEG channels as much as possible and implement, an emotion recognition method that would result in a more user-friendly environment. The signals are obtained from four positions only, according to the 10-10 system. These positions are Fp1, Fp2, F3, and F4; Fp1 and Fp2 positions are obtained as monopole channels (channels1 and 2, respectively), whereas the F3 and F4 positions as dipole (channel 3), resulting in a three-EEG channel set.

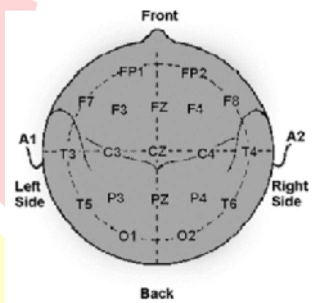

Fig1. Fp1, Fp2, F3, and F4 positions of 10-10 electrode system

According to psycho-physiological research, left frontal lobe and right frontal lobe appear to have certain activity during the experience of negative or positive emotions. Particularly, left frontal lobe exhibit a more intense activity while the subject experiences a positive effect whereas right frontal lobe shows the same activity during a negatively originated emotion. The role of prefrontal cortex in affective reactions and particularly in emotion regulation and conscious experience justify the selection of the Fp1, Fp2, F3 and F4 positions to collect the signals intended to be processed. Out of these three channels, EEG signals are taken from channel 3(F3/F4) for single channel case and all the three channels for combined channel case for processing.

B. Signal preprocessing

EEG signals recorded over various positions on the scalp are usually contaminated with noises and artifacts (Ocular (EOG), Muscular (EMG) and Vascular (ECG) artifacts). The complete removal of artifacts will also remove some of the useful information of EEG signals. Hence by selecting specific features, artifacts in other areas are automatically avoided. The influence of EOG artifacts (eye movement/blinking) is most dominant below 4Hz, ECG (heart) artifacts around 1.2Hz and EMG (muscle) artifacts above 30Hz. Nonphysiological artifacts caused by power lines are in the high 50Hz range. Therefore by extracting only the alpha and beta frequencies, the influence of much noise has already been reduced much.

Bandpass Butterworth filtering is the method by which specific frequency bands can be extracted. The Butterworth filter is a type of signal processing filter designed to have a flat frequency response as possible in the passband so that it is termed a maximally flat magnitude filter.

C. Wavelet Based Feature Extraction

In this paper, four features such as REE (Recoursing Energy Efficiency), ALREE (Absolute Logarithmic REE), Entropy and HOC are extracted using Wavelet Transform.

1. REE is an energy based feature given by

$$REE_{gamma-3b} = E_{gamma} / E_{total-3b}$$

2. ALREE is a modified energy based feature given by

$$ALREE_{gamma-3b} = abs(\log_{10}[E_{gamma} / E_{total-3b}])$$

where $E_{total-3b} = E_{alpha} + E_{beta} + E_{gamma}$

3. Entropy measures the useful information about the EEG signal for emotion under intrusive noise.

4. HOC

The filtered and averaged EEG signal is subjected to HOC analysis. In HOC analysis, the feature vector is obtained by determining the number of zero crossings. The numbers of observed zero-crossings are determined in a finite time series oscillations after removing the mean value. This counting procedure is repeated after application of a differential filter. The filtered EEG signal is filtered again and the numbers of resulting zero-crossings are determined. The resulting series of filter order (number of filtering) and zero-crossing counts at each filter stage are referred as higher order crossings. The number of zero-crossings observed in a finitely long real-valued time series can be used as a measure of the oscillation exhibited in the time series. In general, if more oscillations are present then the expected numbers of zero-crossings is higher. Conversely, fewer zero-crossings are expected when the time series is rather "smooth" and slowly varying.

Consider a time series { Z_t }, t=1, 2, 3,…..,N.

Define $Z_t = S_t - m$.

where S_t is the discrete time signal and m is the mean value of S_t

$$m = (1 / N) \sum_{t=1}^{N} s_t$$

Let ∇ be the backward difference operator defined by

$$\nabla Z_t = Z_t - Z_{t-1}$$

The difference operator ∇ is a high-pass filter. Hence the following sequence of high-pass filters

$$\Im_k = \nabla^{k-1}, \text{ k=1, 2, 3,.....}$$

with $\Im_1 = \nabla^0$ being the identity filter. The corresponding HOC can be estimated, namely simple HOC, by

$$D_K = NZC\{\Im_k(Z_t)\}$$

$$k = 1,2,3\ldots \quad t = 1,2,..N$$

where NZC {.} denotes the estimation of the number of zero-crossings and

$$\nabla^{k-1} Z_t = \sum_{j=1}^{k} \binom{k-1}{j-1} (-1)^{j-1} Z_{t-j+1}$$

with $\binom{k-1}{j-1} = (k-1)!/(j-1)!(k-j)!$

For the estimation of the number of zero-crossings, a binary time series is initially constructed given by

$$X_t(k) = 1, if\, \Im_k(Z_t) \geq 0$$

$$= 0, if\, \Im_k(Z_t) < 0$$

and the desired simple HOC are then estimated by counting symbol changes in $X_1(k), \ldots X_N(k)$

$$D_k = \sum_{t=2}^{N} [X_t(k) - X_{t-1}(k)]^2$$

HOC are used to construct the feature vector (FV_{HOC}).

$$FV_{HOC} = [D_1, D_{2,\ldots} D_L]$$

where L denotes the HOC order up to they were used to form the FV_{HOC}. These feature vectors are then subjected to HOC-EC for classification of emotions.

D. Emotion classification

In this paper, two simple classifiers such as Linear Discriminant Analysis (LDA) and K Nearest Neighbor (KNN) for classifying the discrete emotions. Among these two classifiers, LDA provides extremely fast evaluations of unknown inputs performed by distance calculations between a new sample and mean of training data samples in each class weighed by their covariance matrices. A linear discriminant analysis tries to find an optimal hyper plane to separate six classes of emotions (happy, sad, disgust, fear, surprise and neutral). Besides the training and testing samples, the LDA does not require any external parameter for classifying the discrete emotions.

In addition, KNN is also a simple and intuitive method of classifier used by many researchers typically for classifying the signals and images. This classifier makes a decision on comparing a new labeled sample (testing data) with the baseline data (training data). In general, for a given unlabeled time series X, the KNN rule finds the K "closest" (neighborhood) labeled series in the training data set and assigns X to the class that appears most frequently in the neighborhood of k time series.

III IMPLEMENTATION

A. Signal Preprocessing

After the acquisition part, the signals are filtered in order to isolate the recordings during the projection period only. A bandpass Butterworth filter of tenth order is used in order to retain frequencies within the alpha (8-12Hz) and beta (13-30Hz) bands in order to exploit the mutual relation regarding the prefrontal cortical activation or inactivation. In particular, an increased alpha band activity joined with a decrease one in the beta band activity indicates a cortical inactivation whereas the opposite indicates an active prefrontal cortex.

Finally, after the filtering, the EEG signals are averaged for noise elimination. The filtered and averaged EEG signals are subjected to zero mean process by subtracting their mean value in order to apply any feature vector extraction method.

B. Wavelet Based Feature Extraction

The EEG data from each channel is subjected to wavelet transform. The features such as REE, ALREE, Entropy and HOC are extracted. For HOC analysis, the feature vector is extracted from the signal within the range of order k=1, 2,..50(=J) in order to provide the optimum k (=L) that would result in the maximum classification rate of the six basic emotions (L=13).

C. Emotion Classification

The feature vector based on the selection of L value is used throughout the channel, ensuring the highest classification efficiency and the minimum size of the feature vector. Nevertheless, the increase in feature vector size should be handled with care, as it severely affects the computational burden of the classification process, especially when the issue of real-time implementation is of primary priority.

The EC presents the lowest misclassification distribution, as it exhibits very low or zero mean misclassification rate. EC has the ability to better discriminate the EEG potentials stemming from emotion stimulus. EC is a user independent approach; hence, it has high degree of generalization facilitating its transfer to many HMI environments without requiring an arduous adaptation or pre-analysis phase.

IV RESULTS AND DISCUSSION

The EEG signals are acquired from 5 healthy subjects using 10-10 system from channel 3. The acquired EEG signals for all the six basic emotions for five subjects are processed.

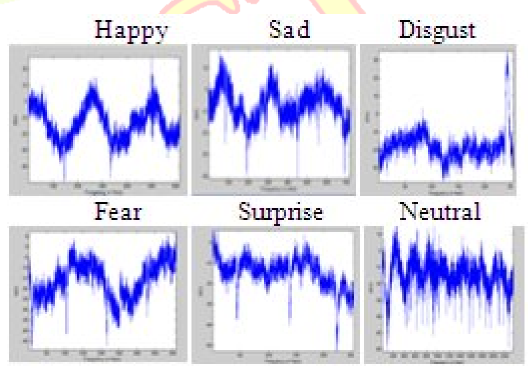

Fig 2.EEG signals of six basic emotions

The database involves the EEG signals for six classes of emotion from 5 subjects. The classification is carried out by employing training signals for each class of emotion. Then testing is carried out.

The four wavelet based features decomposed using "db4" are classified using LDA and KNN classifiers. The classification rates for single and combined channel cases are given in table 1.

Table 1: Classification rates

	REE	ALREE	Entropy	HOC
	Single Channel case			
LDA	62.63	72.73	63.64	63.64
KNN	63.64	72.74	54.55	72.74
	Combined Channel case			
LDA	54.55	63.63	54.54	63.64
KNN	54.55	63.64	54.55	72.74

From the classification rates, the two features ALREE and HOC classifies better when compared to other features.

V .CONCLUSION

In this paper, a feature vector extraction method based on wavelet transform is used to extract the features from EEG signal for distinguishing human emotions. The extracted features from the wavelet analysis are classified using EC (LDA and KNN). EEG data under an audio-visual induction environment is used. Hence for the single-channel case and combined channel case, the results are obtained by the LDA and K-NN, for differentiating among the six basic emotions. Therefore this wavelet based method effectively discriminates the six basic human emotions from EEG signals. Further enhancement can be done with different set of statistical features for improving the classification rate.

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