Time-Frequency Analysis of EEG Signals for Human Emotion Detection

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Abstract — **This paper proposes an emotion recognition system from EEG (Electroencephalogram) signals. The main objective of this work is to compare the efficacy of classifying human emotions using two discrete wavelet transform (DWT) based feature extraction with three statistical features. An audio-visual induction based protocol has been designed to acquire the EEG signals using 63 biosensors. Totally, 6 healthy subjects with an age group of 21-27 years old have been used in this emotion recognition experiment. In this work, we have used three statistical features (energy, Recoursing Energy Efficiency (REE) and Root Mean Square (RMS)) from the EEG signals for classifying four emotions (happy, disgust, surprise and fear). An unsupervised clustering called Fuzzy C-Means (FCM) clustering is used for distinguishing emotions. Results confirm the possibility of using "db4" wavelet transform based feature extraction with proposed statistical feature for assessing the human emotions from EEG signal.**

Keywords — **EEG, Human Emotions, Wavelet Transform, Fuzzy C-Means clustering (FCM).**

I. INTRODUCTION

The responsibility of creating intelligent buildings which offer the potential for enhancing home based care service for physically disabled persons has grown in recent years. The operations of agents controlling such environments might be improved by including emotion sensing in their input space and utilizing emotional information in decision making. Recent studies in neurology and psychology have shown the importance of emotional interface with logic and rational thinking, affective states play a role of paramount importance in the way human make decisions [1,2]. In neuropsychological work [3] the signals measured from the central nervous system will give a relationship between psychological changes and emotions. The electrical potentials measured by the electrodes on the scalps are rich in information on mental activities and emotional states. Brain activity of EEG signals is divided into five main frequency rhythms: theta, delta, alpha, beta and gamma. For this emotion recognition experiment, the alpha frequency rhythm is having higher energy over other frequency bands. Some of the important issues to be carefully discussed in the aspect of increasing classification accuracy of human emotions are: (a) proper positioning of electrodes and depth of placement of electrodes on the scalp (b) time duration of video clips and (c) proper design of acquisition protocol.

This paper is organized as: Section II describes methodology of emotion recognition system. In Section III, emotions classification using Fuzzy C-Means clustering is portrayed. The results are presented in Section IV. The conclusions are given in Section V.

II. METHODOLOGY

A. Subjects

The group of participants consisted of 6 healthy volunteers (20-27 years old, 3 males, 3 females). All subjects were informed about the aim and scope of the study and gave written informed consent according to the declaration of undergoing experiment. The participants have no history of physical or mental illness and they are not currently taking drugs or medication known to affect their EEG.

B. Experimental Setup

EEG signals were measured with 63 surface electrodes which were fixed at the standard positions on the scalp according to International 10-20 system. Reference electrode was placed between AF1 and AF2 electrodes. Ear lobe electrode was considered as ground electrode. All the electrodes impedances were kept below 5 KΩ and made up of Ag/Ag-Cl. EEG signals were registered using Nervus EEG system, USA, with a sampling frequency of 256 Hz and band pass filter of 0.05 Hz – 70 Hz.

C. Acquisition Protocol

The protocol design for our experiment is shown in Figure 1. The maximum length of the video clip is 24 sec and the minimum length is 5 sec. The x1* and x2* denote the time periods of video clips. The subjects were informed that between each movie clips they would be prompted to answer questions about the emotions they experienced under self-assessment section. In this section we posted four questions to subjects: (a) What emotion did you experience from this video clip? (b) Rate the intensity of emotion in 6 point scale (c) Did you experience any other emotions at the same intensity or higher than the stated emotion, and if so, specify (d) Have you seen these movie clips in an earlier period?

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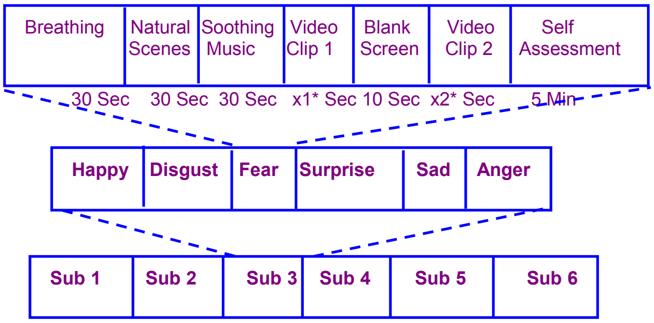

Fig.1 Acquisition protocol for EEG recording

From the above protocol, we found that, four emotions such as happy, disgust, surprise and fear have been realized strongly by the subjects among the six emotions (happy, fear, disgust, surprise, sad and anger). We consider only these four emotions in all our analysis of this work.

D. Preprocessing and Normalization

The noises due to the electronic amplifier, power line interference and external interference have been reduced by using Average Mean Reference (AMR) method. The value of mean is calculated for each channel and it is subtracted from the original raw signal value. Normalization is also carried out to reduce the effects of individual differences due to their fundamental frequency rhythms and to reduce the computational complexity. All values of the attributes are normalized to lie in some common range of [-1 to 1].

E. Feature Extraction

Various temporal and spatial approaches have been applied to extract features from the physiological signal. However, they are lacking in simultaneous time-frequency measurement with multi-resolution analysis (MRA). Wavelet analysis allows the use of long time intervals where we want more precise low- frequency information, and shorter-regions where we want high frequency information. Wavelet Transform (WT) based feature extraction has been successfully applied with promising results in physiological pattern recognition applications. A wavelet is a small oscillatory wave which has its energy concentrated in time. It has an ability to allow simultaneous time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying signals [4,5]. This is a next logical step on applying variable window size on the signal to analyze. The main objective of using this transform in our work is to extract the proficient information from the signal under certain frequency bands and to have an ability to handle the signal under noisy environment. The equation for the mother wavelet (prototype function) is given as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

where a, b ∈ R (a>0), R is the wavelet space. Parameter 'a' is the scaling factor and 'b' is the shifting factor. The only limitation for choosing a prototype function as mother wavelet is to satisfy the admissibility condition given as

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty \qquad (2)$$

where $\phi(\omega)$ is the Fourier transform of the $\phi_{a,b}(t)$.

The time-frequency representation is performed by repeatedly filtering the signal with a pair of filters that cut the frequency domain in the middle. Specifically, the discrete wavelet transform decomposes the signal into an approximation and detailed signal. The approximation signal is subsequently divided into new approximation and detailed signals. This process is carried out iteratively to produce a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal [6,7].

In this study, we used Daubechies wavelet function with different order ("db4" and "db8") for extracting the statistical feature from the EEG signal. These wavelet functions have been chosen due to their near optimal time-frequency localization properties. Moreover, their waveforms are similar to the waveforms to be detected in the EEG signal. Therefore, extraction of EEG signals features are more likely to be successful [8]. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Table 1 presents frequencies corresponding to different levels of decomposition with a sampling frequency (fs) of 256 Hz [9]. The frequency bandwidth of above frequency bands are lies within the range of standard frequency [10]. In this work, we have selected three statistical features

Table 1 Frequency Decomposition of EEG signals with a sampling frequency of 256 Hz

Decomposition levels	Frequency bands	Frequency bandwidth (Hz)
A5	Theta	0-4
D5	Delta	4 – 8
D4	Alpha	8 – 16
D3	Beta	16 – 32
D2	Gama	32 – 64
D1	Noises	64 – 128

(i) RECOURSING ENERGY EFFICIENCY (REE):

The preprocessed EEG signal is decomposed into sequence of wavelet coefficients using Daubechies wavelet functions. In order to measure the recoursing energy efficiency of the approximation and detail coefficients, REE is defined as

$$REE = \frac{\text{Energy of the sub-band}}{\text{Total Energy of the DEV}} \times 100 \qquad (3)$$

where DEV is the decomposition coefficient vector composed of energy at all frequency subbands [11].

ii) *ROOT MEAN SQUARE (RMS):* The root mean square value of the wavelet coefficients on alpha frequency band has been calculated using the equation (4).

$$RMS(j) = \sqrt{\frac{\sum_{i=1}^{j}\sum_{n_i} D_i[n]^2}{\sum_{i=1}^{j} n_i}} \qquad (4)$$

where D_i and n_i are the detail coefficients and the number of detail coefficients at ith level. The feature vector is obtained by $rms(j)$, where j=1,2,3…N and N is the deepest level of decomposition.

(iii) *ENERGY:* The energy feature can be calculated by squaring the wavelet coefficients on each frequency sub-bands.

III. Fuzzy C-means clustering

From the paradigm presented in section II, feature extraction is performed on different data set of classes aiming at distinguishing emotions. Clustering is the task of categorizing objects having several attributes into different classes such that the objects belonging to the same class are similar, and otherwise not similar. In this paper we have used Fuzzy C-Means (FCM) clustering as a classifier for classifying the emotions from the EEG signal parameters [12]. FCM is an unsupervised clustering method based on minimizing the objective function. FCM seeks to group sampled data together so as to minimize the variance (objective function) between data in different cluster. One of the issues in using fuzzy clustering based classification is that of setting the number of clusters to use in each class. The generalization is acceptable only when large sets of samples are available for classification. In our work, the features derived for four emotions from the six subjects on 63 channels have been used as input for distinguishing emotions. In addition, we also derived the statistical features for subset of 24 channels [13] from the 63 channels for classifying the emotions using FCM. The reduced number of channels reduces the computation complexity and physical burden to the subjects. This algorithm is stimulated and implemented in MATLAB 6.

IV. Results and discussion

The five level decomposition of two wavelet functions have been performed and 4th level detail coefficients (alpha band) are used for extracting the features. In order to evaluate the selection optimal transform for efficient feature extraction in emotion recognition, we have calculated the objective function value of statistical feature over four different emotions on all six subjects. In addition, we also compared our results with 24 channels for analyzing the classification ability of emotion from the EEG signals. Figure 2 and Figure 3 show the performance of FCM on classifying the emotions of 63 channels and 24 channels EEG data using RMS feature on “db4” wavelet function.

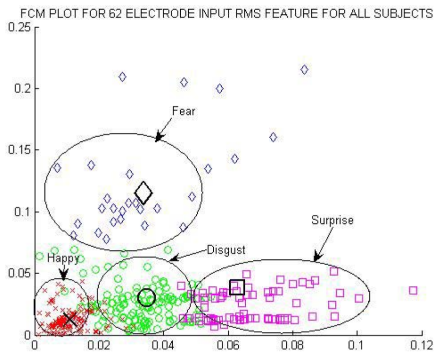

Fig. 2 FCM plot for RMS feature for 63 electrodes

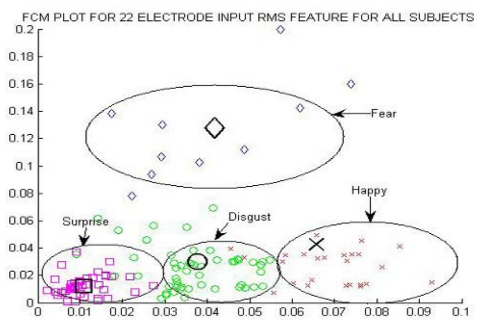

Fig. 3 FCM plot for RMS feature for 24 electrodes

V. Conclusions

We briefly reported the multi-resolution analysis of different wavelet functions based feature extraction of emotion recognition using EEG signals. This work proposes a new approach to extract the features from multi-resolution analysis of wavelet functions from the EEG signal for distinguishing emotions. An acquisition protocol for recording the EEG signal under an audio-visual induction environment is designed to acquire emotional data. The extracted features from the time-frequency analysis have been classified using FCM. We compared the results of different statistical features of 63 channels and 24 channels of EEG data using two wavelet functions (Table 2). FCM based clustering performs well on classifying 24 channels EEG emotional data using "db4" wavelet function. Hence, the wavelet based feature extraction of EEG signal in alpha band activity has proved to be successful in distinguishing emotions from the EEG signals.

Table 2 Comparison of objective function values for two discrete wavelettransforms with three statistical features for 63 and 24 channels

Fuzzy Exponent: 2.0 ; MSE: 1 X 10^{-5} ; Max No of Iterations : 100				
	db4		db8	
Features	Objective Function (OF)		Objective Function (OF)	
	63	24	63	24
Energy	2.822123	**1.062893**	2.985268	1.297523
RMS	0.132159	**0.041897**	0.174020	0.041903
REE	0.15246	**0.045783**	0.163671	0.049603

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References

1. Kim K.H, Band S.W., and Kim S.B. (2004). Emotion Recognition System using short-term monitoring of physiological signals. Proceedings on Medical & Biological Engineering & Computing, Vol 42, pp, 419-427.
2. Arikin R.C, Fujita M, Takagi T, Hasegawa R.(2001). Ethological modeling and architecture for an entertainment robot. IEEE Proceedings on Robotics and Automation, pp, 453-458.
3. Egon L, Broek V D, Schutt M H et.al. (2006). Computing Emotion Awareness Through Facial Electromyography. HCI/ECCV 2006, pp, 53-63.
4. Mallat S. G. (1989) A theory for multiresolution signal decomposition: the wavelet representation. IEEE Transactions on Pattern Anal. & Mach. Intelligence, Vol. 11(7), pp, 674–693.
5. Olivier R, Vetterli M. (1991). Wavelets and Signal processing. IEEE Signal processing Magazine, pp, 14-38.
6. DA-Zeng, Ming-Hu Ha (2004). Applications of Wavelet Transform in Medical Image Processing. IEEE Proce on Machine Learning and Cybernatics, Vol 3, pp, 1816-1821.
7. Qin S , Ji Z. (2004) Multi-Resolution Time-Frequency Analysis for Detection of Rhythms of EEG Signals. IEEE Proceedings on Signal Processing, Vol 4, pp, 338-341.
8. Glassman E L. (2005). A Wavelet-Like Filter Based on Neuron Action Potentials for Analysis of Human Scalp Electroencephalographs. IEEE Transactions on Biomedical Engineering , Vol 52(11), pp, 1851-1862.
9. Chethan P, Cox M. (2002), Frequency Characteristics of Wavelets, IEEE Transactions on Power Delivery, Vol 17 (3), pp, 800-804.
10. WRC at http://www.wordsworthcentre.co.uk
11. Manikandan M S ,Dandapat S. (2006).Wavelet threshold based ECG compression using USZZQ and Huffman coding of DSM. Journal of Biomedical Signal Processing and control, pp, 261-270.
12. Srinivasa K G, Venugopal K R, Patnaik L M. (2006), Feature Extraction using Fuzzy C- Means Clustering for Data Mining Systems, International Journal of Computer Science and Network Security, Vol 6 (3A), pp, 230- 236.
13. Channel G, Kronegg J, Grandjean D, Pun T (2006). Emotion assessment: Arousal evaluation using EEG's and peripheral physiological signals. Lecture Notes on Computer Science, Vol 4105, Springer, pp, 530-537.

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