

# EEG Feature Extraction for Classifying Emotions using FCM and FKM

M.Murugappan, M.Rizon, RNagarajan, S.Yaacob, I.Zunaidi, and D.Hazry

**Abstract**— The Electroencephalogram (EEG) is one of the useful biosignals detect the human emotions. This paper discusses on a research conducted to determine the changes in the electrical activity of the human brain related to distinct emotions. We designed a competent acquisition protocol for acquiring the EEG signals under audio-visual induction environment. The EEG data has been collected from 6 healthy subjects with in an age group of 21-27 using 63 biosensors. From the subjective analysis on each emotion, three emotions have been identified with higher agreement. After preprocessing the signals, discrete wavelet transform is employed to extract the EEG parameters. The feature vectors derived from the above feature extraction method on 63 biosensors form an input matrix for emotion classification. In this work, we have used Fuzzy C-Means (FCM) and Fuzzy k-Means (FKM) clustering methods for classifying the emotions. We have also analyzed the performance of FCM and FKM on reduced number of 24 biosensors model. Finally, we compared the performance of clustering the discrete emotions using FCM and FKM on both 64 biosensors and 24 biosensors. Results confirm the possibility of using wavelet transform based feature extraction for assessing the human emotions from EEG signal, and of selecting a minimal number of channels for emotion recognition experiment.

**Keywords**— EEG, Emotions, Wavelet transform, Fuzzy C-Means Clustering, Fuzzy K-Means Clustering.

## I. INTRODUCTION

Emotion recognition is one of the key steps towards Emotional intelligence in advanced human-machine interactions. The research of emotion recognition consists of facial expressions, vocal, gesture and physiological signal recognition and so on. An effort on emotion classification in EEG signals is rather difficult. Other efforts are relatively

easier, but they can not detect the underlying emotional states. Detection of emotions through EEG signals requires special equipments [1], [2]. The recognition rate of emotions through EEG highly depends on selecting an optimal subset of features to detect emotion.

In neuropsychological works [3] – [5] the signals measured from the central nervous system will give a relationship between psychological changes and emotions. The electrical potential measured by electrodes on the scalps is rich in information on the brain activity, and proper signal processing would allow us to collect global information about mental activities and emotional states. Brain activity of EEG signals is divided into four main frequency rhythms. Delta waves, slowest EEG rhythms, generally have the highest amplitude EEG waveforms observed (about 250-325  $\mu$ V) with all the frequencies below 4 Hz. Theta waves are typically of even greater amplitudes and higher frequencies, 4 Hz - 8 Hz. Alpha waves, which occur during relaxed and alert stages, are regular rhythms of 8 Hz - 12 Hz. Beta waves are defined as low voltage and high frequency rhythms (14 to 32 Hz, some times as 50 Hz) [6].

Recently, the areas of research in neurophysiology, psychology and Brain Computer Interface (BCI) have been converging on the important implications of emotions. Individual emotional state may be influenced by different kind of situations, and different people have different subjective emotional experiences even responses to the same stimulus. One of the hallmarks in that emotion theory is whether distinct physiological patterns accompany each emotion [7]. Ekman et al [8] and Winton et al [9] provided some of the first findings showing significant differences in autonomic nervous system signals according to a small number of emotional categories or dimensions, but there was no exploration of automated classification. In general emotions are existing for few micro second to few milli second) [10], [11].

This paper is organized as: Section 2 describes acquisition protocol for EEG recording. In Section 3, wavelet transform based feature extraction is portrayed. The results are presented in Section 4. The conclusions are given in Section 5.

## II. MATERIALS AND METHODS

### A. Acquisition Protocol

To elicit the target emotions in our study, we used two commercial movie clips out of 10 for each emotion. A pilot panel study has been conducted to select any 2 movie clip from the entire video clips set from the subjects, who are not taking part in the experiment. The selection criteria followed for video clips are as follows: (i) the length of the scene should

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TABLE 1 HIT RATIO OF PILOT PANEL STUDY RESULTS FOR VIDEO CLIP 1

EMOTIONS SUBJECTS	ANGER	DISGUST	FEAR	HAPPY	SAD	SURPRISE
	Sda : Sa	Sda : Sa	Sda : Sa	Sda : Sa	Sda : Sa	Sda : Sa
Subjects	6 : 6	5 : 6	4 : 6	3 : 6	3 : 6	2 : 6

TABLE 2 HIT RATIO OF PILOT PANEL STUDY RESULTS FOR VIDEO CLIP 2

EMOTIONS SUBJECTS	ANGER	DISGUST	FEAR	HAPPY	SAD	SURPRISE
	Sda : Sa	Sda : Sa	Sda : Sa	Sda : Sa	Sda : Sa	Sda : Sa
Subjects	6 : 6	1 : 6	0 : 6	1 : 6	3 : 6	3 : 6

Sda : Subject Disagreement

Sa : Subject Agreement

be relatively short. (ii) The scene is to be understood without explanation and (iii) the scene should elicit single target emotion in subjects and not multiple emotions. The protocol design for our experiment is shown in Fig 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. Three female and three male in the age group of 21-27 years were employed as subjects in our experiment. Once the consent forms were filled-up, the subjects were given a simple introduction about the research work and stages of experiment. The recording of EEG signal has been done through Nervus EEG, USA with 64 channel electrodes at a sampling frequency of 256 Hz. The subjects were informed that they would be watching the scenes from various movies geared to elicit emotions. They were also told 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?

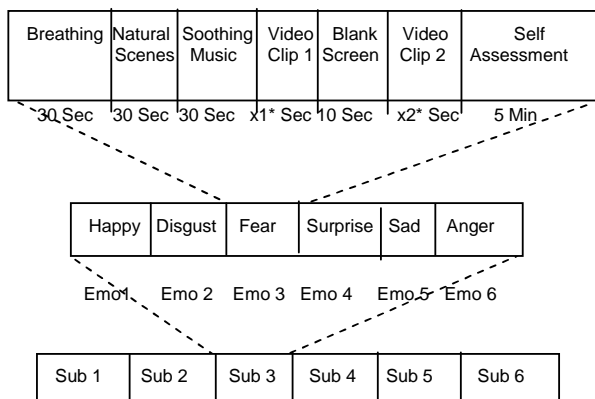


Fig 1 Acquisition protocol for EEG recording

From the Table 1 and Table 2, we found that, the Table 2 has minimum amount of disagreement over three emotions

(disgust, happy, fear). Hence we consider only three emotions say happy, disgust and fear in all our future analysis of this work.

### B. Preprocessing

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 zero to one.

### C. Wavelet Transform

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 [12], [13]. The non-stationary nature of EEG signals is to expand them onto basis functions created by expanding, contacting and shifting a single prototype functions ( $\Psi_{a,b}$ -Mother wavelet), specifically selected for the signal under consideration.

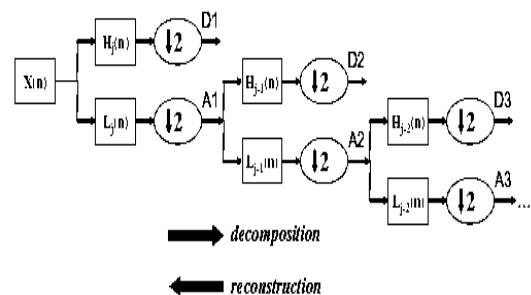


Fig 2 Filter Bank structures of discrete wavelet transform

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

where  $a, b \in \mathbb{R}$  ( $a > 0$ ),  $\mathbb{R}$  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. It is given as

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

Where  $\Psi(\omega)$  is the Fourier transform of the  $\psi_{a,b}(t)$ . 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 producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal [14], [15]. The filter bank structure of the wavelet transform is shown in Fig 2. where  $H(n)$  and  $L(n)$  are the low pass and high pass filter bank coefficients. "j" represents the number of decomposition levels and A and D denotes the approximation and detail space.

#### D.Feature Extraction

In this study, Daubechies order 4 wavelet transform ("db4") is used in the wavelet analysis 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 [16]. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Table 3 presents frequencies corresponding to different levels of decomposition for "db4" with a sampling frequency (fs) of 256 Hz [17]. It can be seen from Table 3, the components A5 decomposition are in the  $\delta$  range (0 – 4) Hz, D5 decomposition are in the range of  $\theta$  range (4-8) Hz, D4 decomposition are in the range of  $\alpha$  range (8-12) Hz., D3 decomposition are in the range of  $\beta$  range (12-32) Hz. Lower level decompositions corresponding to higher frequencies have negligible magnitudes in a normal EEG. The frequency bandwidth of above frequency bands are lies within the range of standard frequency.

**Energy:** The energy content in the EEG signal can be partitioned at different resolution levels in varied ways depending on the frequency bands. The three special properties of selecting the energy distribution for emotion classifications are:

a) The "db4" wavelet function was adopted to perform DWT, the resulting in the larger energy distributions of the decomposition level 4. However, using different wavelet functions may generate similar or different results.

b) The energy distribution remains unaffected by the duration of emotion elicited.

TABLE 3 FREQUENCIES CORRESPONDING TO DIFFERENT LEVELS OF DECOMPOSITION FOR "DB4" WAVELET WITH A SAMPLING FREQUENCY OF 256 Hz

Frequency Range (Hz)	Decomposition levels	Frequency Bands	Frequency Bandwidth (Hz)
$0 - (fs/2^{j+1})$	A5	Theta	0-4
$(2fs/2^{j+1}) - (3fs/2^{j+1})$	D5	Delta	4 – 8
$(2fs/2^{j+1}) - (4fs/2^{j+1})$	D4	Alpha	8 – 16
$(2fs/2^{j+1}) - (5fs/2^{j+1})$	D3	Beta	16 – 32
$(2fs/2^{j+1}) - (6fs/2^{j+1})$	D2	Gama	32 – 64
$(2^{j-1})fs/2^{j+1} - fs/2$	D1	Noises	64 – 128

c) The outline of energy distribution remains the same despite variations in amplitude of EEG signal of the same emotion.

**Entropy:** The recording of EEG signal normally contaminated with background noises. However, the wavelet transform separates the high frequency components (noises) from the original EEG signal. There may be a chance for a tiny amount of noises that exist in the original signal. Therefore, entropy can be used for measuring the useful information about the EEG signal for emotion from the intrusive noise.

The above two statistical features were used to represent the time-frequency distribution of the EEG signals. These features on each channel have been derived by using wavelet transform. From our previous results, we found that, the alpha band has maximum energy for all emotions when compared to other frequency sub-bands. Therefore, the wavelet coefficients on fourth level decomposition (alpha band) are used to form the feature vector matrix for classifying the emotions.

### III. EMOTIONS CLASSIFICATION

From the paradigm presented in section 2, classification is performed on different data set of classes aiming at distinguishing emotions. Two classifiers, Fuzzy-C Means clustering and Fuzzy-K means clustering were performed on the EEG signal features for distinguishing the emotions. The clustering is a form of unsupervised learning that helps to find the inherent structure in the data. Using clustering, it is possible to find the similar points without actually knowing the labels. Hence those attributes may be found that contribute to the points being similar to others as well as those which make is dissimilar from others. In literature, many clustering algorithms have been developed and studied. In this paper, we have presented the results for Fuzzy C-Means [18] and Fuzzy K-means clustering [19] for 63 and 24 channel electrodes for

discrete emotions clustering. The fig 3 illustrates the 24 channel electrode placement. Both the algorithms are

implemented and stimulated in MATLAB 6.0 software.

TABLE 4 PARAMETERS USED FOR FKM CLUSTERING IN 63 AND 24 CHANNEL EEG DATA

Electrodes	Class	phi	$\ u-u'\ $	FPI	MPE	Iterations	SC	Distance
24	3	1.3	9.25E-05	0.215132	0.297061	300	0.0001	Mahalanobis
63	3	1.3	0.00008	0.21513	0.23053	300	0.0001	Mahalanobis

FPI: Fuzziness Partition Index MPE: Modified Partition Entropy SC: Stopping Criteria Phi: Fuzziness Index

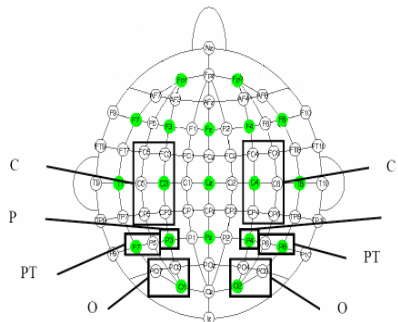


Fig 3 24 Channel electrode placement for EEG recording

#### IV. RESULTS

We briefly reported the multi-resolution analysis of wavelet function based feature extraction of emotion recognition using EEG signals. Data base has been created for both 63 and 24 channels EEG data for three emotions using energy and entropy features. The five level decomposition of “db4” wavelet function has been performed and 4<sup>th</sup> level detail coefficients (alpha band) are used for extracting the features. All the figures given in these results belong to energy feature. Fig 4 and Fig 5 show the FKM based clustering of three emotional data of 63 channels and 24 channels respectively. Similarly, Fig 6 and Fig 7 shows the FCM based clustering of three emotional data for 63 channels and 24 channels. The table 4 describes the parameters used for clustering the EEG emotional data in FKM clustering method. Where Phi is the Fuzziness index,  $\|u-u'\|$  is the norm distance between old and new membership matrix, FPI is the Fuzziness Performance Index (FPI), MPE refers to Modified Partition Entropy (MPE) and SC denotes stopping criteria.

#### V. CONCLUSIONS

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 recoding 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 and FKM. We compared the results of FCM and FKM for 63 and 24 channels of EEG data. FKM clustering method performs well on clustering the emotional data of 24 channels than 63 channels EEG data. The centre of confident circle will have better separation between each emotion in 24 channel EEG data. The FCM based clustering

performs well on classifying both 63 and 24 channels EEG emotional data. However, the objective function of 63 channel EEG data converges to zero than 24 channel EEG data on the given number of iterations. Hence, the wavelet based feature extraction of EEG signal in alpha band activity has proved to be successful in discretizing emotions from the EEG signals.

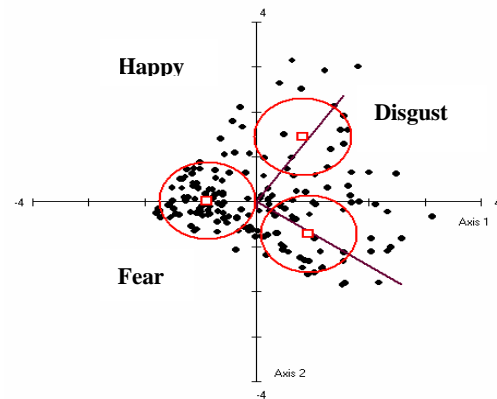


Fig 4 FKM output of 63 Electrodes for 6 subjects using Energy Feature

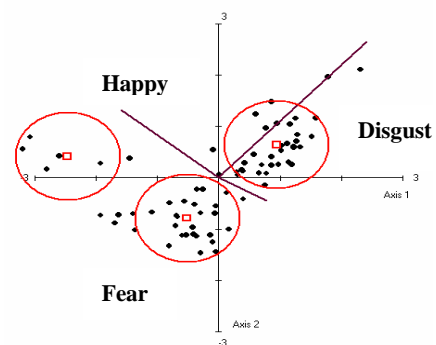


Fig 5 FKM output of 24 Electrodes for 6 subjects using Energy Feature

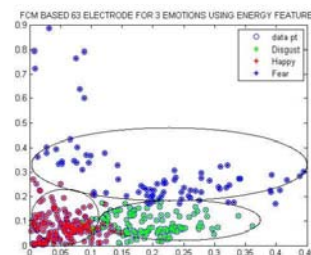


Fig 6 FCM output of 63 Electrodes for 6 subjects using Energy Feature



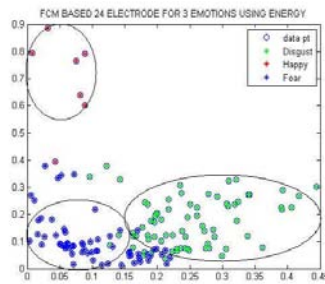


Fig 7 FCM output of 24 Electrodes for 6 subjects using Energy Feature

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