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# Modified Energy Based Time-Frequency Features for Classifying Human Emotions using EEG

M.Murugappan, R.Nagarajan, S Yaacob
School of Mechatronic Engineering, Universiti Malaysia Perlis (UniMAP)
02600, Jejawi, Arau, Kangar
Perlis, MALAYSIA

***Abstract*- In this paper we summarize the emotion recognition from the electroencephalogram (EEG) signals. The combination of surface Laplacian filtering, time-frequency analysis (Wavelet Transform) and linear classifiers are used to detect the discrete emotions (happy, surprise, fear, disgust, and neutral) of human through EEG signals. EEG signals are collected from 20 subjects through 62 active electrodes, which are placed over the entire scalp based on International 10-10 system. All the signals are collected without much discomfort to the subjects, and can reflect the influence of emotion on the autonomic nervous system. An audio-visual (video clips) induction based protocol has been designed for evoking the discrete emotions. The raw EEG signals are preprocessed through Surface Laplacian filtering method and decomposed into five different EEG frequency bands using Wavelet Transform (WT). In our work, we used "db4" wavelet function for extracting the statistical features for classifying the emotions. A new statistical features based on frequency band energy and it's modified from are discussed for achieving the maximum classification rate. The validation of statistical features is performed using 5 fold cross validation. In this work, KNN outperforms LDA by offering a maximum average classification rate of 78.4783 % on 62 channels and 73.6087% on 24 channels respectively. Finally we present the average classification accuracy and individual classification accuracy of two different classifiers for justifying the performance of our emotion recognition system.**

***Keywords:* EEG, Surface Laplacian filtering, Wavelet transforms, KNN, LDA.**

## I. INTRODUCTION

Traditional Human Machine Interaction (HMI) is normally based on passive instruments such as keyboards, mouse, etc. Emotion is one of the most important features of humans. Without the ability of emotions processing, computers and robots cannot communicate with human in natural way. It is therefore expected that computers and robots should process emotion and interact with human users in a natural way. In recent years, research efforts in Human Computer Interaction (HCI) are focused on the means to empower computers to understand human emotions. Although limited in number compared with the efforts being made towards intention-translation means, some researchers are trying to realize man-machine interfaces with an emotion understanding capability. Most of them are focused on facial expression recognition and speech signal analysis [1, 2]. Another possible approach for emotion recognition is physiological signal analysis. We believe that this is a more natural means of emotions recognition, in that the influence of emotion on facial expression or speech can be suppressed relatively easily, and emotional status is inherently reflected in the activity of nervous system. The traditional tools for the investigation of human emotional status are based on the recording and statistical analysis of physiological signals from the both central and autonomic nervous systems. Several approaches have been reported by different researchers on finding the correlation between the emotional changes and EEG signals [3-5]. The past works on emotion recognition using EEG signals is reported in [6]. One of the major limitations on this area of research is *"curse of dimensionality"*. The dimensionality of the data vectors extracted from the EEG data needs to be reduced because for most classification algorithms it is very difficult to reliably estimate the parameters of a classifier in high dimensions when only few training examples are available. In order to provide a simplified emotion recognition system, in our earlier work, we proposed asymmetric ratios based channel selection for reducing the number of channels from 62 to 8 and to 4 channels [7]. Since, the reduction of channels does minimize the physical burden, mental fatigue during electrode placement, computational time and complexity.

In our work, we have used audio-visual stimuli (video clips) for evoking five different emotions such as disgust, happy, fear, surprise and neutral. The new statistical features based on energy have been derived using wavelet transforms over five different frequency bands (delta, theta, alpha, beta and gamma). These numerical features are classified using two different linear classifiers namely K Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA). Finally, we have compared the classification rate of discrete emotions on different channel combinations over five frequency bands by combining wavelet features and linear classifiers.

The rest of this paper is organized as follows. In Section II, we summarize the research methodology by elucidating the data acquisition process, preprocessing, feature extraction using wavelet transform, and classification of emotions by linear classifiers. Section III illustrates the overview of the results and discussion of this present work, and conclusions are given in Section IV.

## II. METHODOLOGY

### *A. EEG Data Acquisition*

This section describes the acquisition of EEG signals for emotion stimulation experiment. In the human brain, each individual neuron communicates with the others by sending tiny electrochemical signals. When millions of neurons are activated, each contributing with a small electrical current, they generate a signal that is strong enough to be detected by an electroencephalogram (EEG) device. From our earlier experiment, we found that audio-visual stimulus is superior in evoking the discrete emotions than visual stimulus method [8]. Hence, we have used an audio-visual induction based protocol for eliciting the discrete emotions in this present work. The structural flow of emotion recognition using EEG signals is shown in Fig 1. A pilot panel study is conducted on 25 university students to select any 5 video clips (trials) for each emotion from 115 emotional video clips including from the international standard emotional clips (www.stanford.edu).

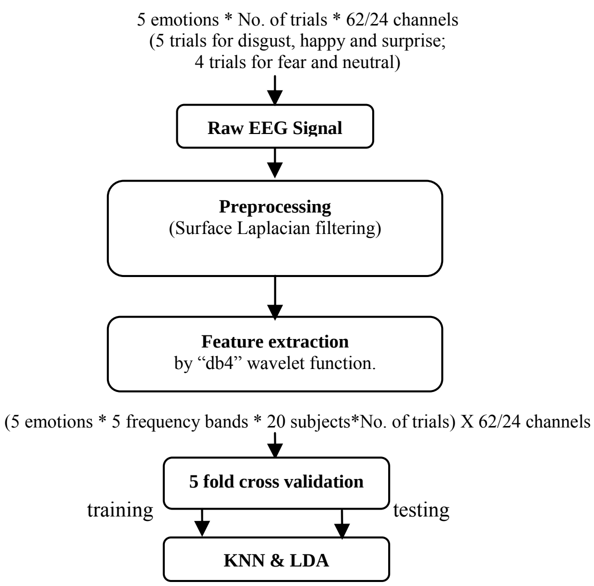


Fig.1. Systematic procedure of our work on emotion recognition using EEG signals

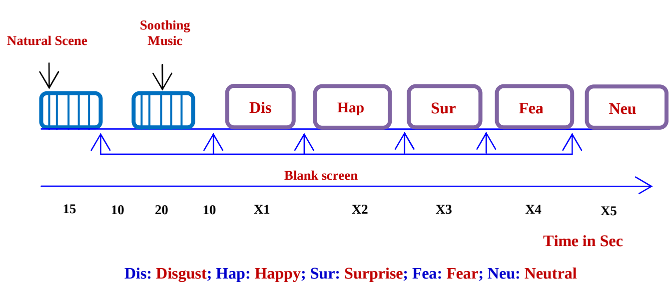


Fig 2. EEG data acquisition protocol using audio-visual stimulus

The selection of video clips is based on self assessment questionnaires mentioned in [9]. The subjects who have undergone for this panel study does not take part in the data collection experiment. The audio-visual stimulus protocol for Trial 1 of our experiment is shown in Fig. 2. From Trial 2 to Trial 5, the orders of the emotional video clips are changed in a random manner. X1 to X5 denote time periods of selected video clips. The time duration of video clips vary from one another. Three females and seventeen males in the age group of 21-39 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 and band-pass filtered between 0.05 Hz and 70 Hz. In our work, we used 62 active electrodes and one each for ground (Oz) and reference (AFz) electrode. All the electrodes are placed over the entire scalp using International standard 10-10 system. The impedance of the electrodes is kept below 5 kΩ. Between each emotional video clips, under self assessment section, the subjects were informed to answer the emotions they have experienced [9]. Finally, 5 trials for disgust, happy and surprise emotions and 4 trials for fear and neutral emotions are considered for further analysis.

### *B. Preprocessing*

EEG signals recorded over various positions on the scalp are usually contaminated with noises (due to power line and external interferences) and artifacts (Ocular (Electroocculogram), Muscular (Electromyogram), Vascular (Electrocardiogram) and Gloss kinetic artifacts). The complete removal of artifacts will also remove some of the useful information of EEG signals. This is one of the reasons why considerable experience is required to interpret EEGs clinically [10, 11]. A couple of methods are available in the literature to avoid artifacts in EEG recordings. However, removing artifacts entirely is impossible in the existing data acquisition process.

In this work, we used Surface Laplacian (SL) filter for removing the noises and artifacts. The SL filter is used to emphasize the electric activities that are spatially close to a recording electrode, filtering out those that might have an origin outside the skull. In addition, it also attenuates the EEG activity which is common to all the involved channels in order to improve the spatial resolution of the recorded signal. The neural activities generated by the brain, however, contain various spatial frequencies. Potentially useful information from the middle frequencies may be filtered out by the analytical Laplacian filters. Hence, the signal "pattern" derived from SL filters is similar to "spatial distribution of source in the head".

The mathematical modeling of Surface Laplacian filter is given as

$$X_{new}(t) = X(t) - \frac{1}{N}\sum_{i=1}^{N} X_i(t) \qquad (1)$$

where $X_{new}$ : filtered signal ; X(t) : raw signal ; N: number of neighbor electrodes.

### *C. Feature Extraction*

There are two important aspects of feature extraction: (a) extracting the features using the most salient EEG channels (b) extracting the features only from the selected EEG channels. In the emotion recognition research using EEG signals, the non-parametric method of feature extraction based on multi-resolution analysis of Wavelet Transform (WT) is quite new. The joint time-frequency resolution obtained by WT makes it as a good candidate for the extraction of details as well as approximations of the signal which cannot be obtained either by Fast Fourier Transform (FFT) or by Short Time Fourier Transform (STFT) [12, 12]. The non-stationary nature of EEG signals is to expand them onto basis functions created by expanding, contracting and shifting a single prototype function ($\Psi_{a,b}$, the mother wavelet), specifically selected for the signal under consideration.

The mother wavelet function $\Psi_{a,b}(t)$ is given as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (2)$$

where a, b $\in$ R, a>0, and R is the wavelet space.

Parameters 'a' and 'b' are the scaling factor and shifting factor respectively. The only limitation for choosing a prototype function as mother wavelet is to satisfy the admissibility condition (Eqn. 3),

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty \quad (3)$$

where $\psi(\omega)$ is the Fourier transform of $\psi_{a,b}(t)$. 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 coefficients (CA) and detailed coefficients (CD). The approximation coefficient is subsequently divided into new approximation and detailed coefficients. This process is carried out iteratively producing a set of approximation coefficients and detail coefficients at different levels or scales [14].

TABLE 1
DECOMPOSITION OF EEG SIGNALS INTO DIFFERENT FREQUENCY BANDS WITH A SAMPLING FREQUENCY OF 256 HZ

| Frequency Range (Hz) | Decomposition Level | Frequency Bands | Frequency Bandwidth (Hz) |
|---|---|---|---|
| 0 - 4 | A5 | Theta | 4 |
| 4 – 8 | D5 | Delta | 4 |
| 8 – 16 | D4 | Alpha | 8 |
| 16 – 32 | D3 | Beta | 16 |
| 32 – 64 | D2 | Gama | 32 |
| 64 - 128 | D1 | Noises | 64 |

A : Approximation coefficients D: Detail coefficients

Commonly, brainwaves are categorized into 5 different frequency bands, or types, known as delta, theta, alpha, beta and gamma. In this work, the multi-resolution analysis of *"db4"* wavelet function is used for decomposing the EEG signals into above five different frequency bands. This wavelet function has been chosen due to their near optimal time-frequency localization properties. Therefore, extraction of EEG signals features are more likely to be successful [15]. In Table 1, A5, D5, D4, D3, and D2 represents the five EEG frequency bands. In order to analyze the characteristic natures of different EEG patterns, we proposed one energy based feature called *Recoursing Energy Efficiency (REE)* in our earlier work [7]. In that work, we used the Fuzzy C Means (FCM) and Fuzzy K-Means (FKM) for clustering the human emotions. The equation for deriving REE for five frequency bands is given in Eqn (4) to Eqn (9). In this present work, we used the same feature and two modified form of REE namely *Logarithmic REE (LREE) and Absolute Logarithmic REE (ALREE)* for classifying emotions using two linear classifiers. The equations for calculating LREE and ALREE for theta band is given in Eqn (10) and Eqn (11), similarly the remaining frequency bands can be derived. These features are derived from the five frequency bands of EEG. Table 1 also presents the bandwidth and the frequencies corresponding to different levels of decomposition for "db4" wavelet function with a sampling frequency $f_s$=256 Hz [12].

$$E_{total} = E_{alpha} + E_{beta} + E_{gamma} + E_{delta} + E_{theta} \quad (4)$$

$$REE_{theta} = \frac{E_{theta}}{E_{total}} \quad (5) \qquad REE_{delta} = \frac{E_{delta}}{E_{total}} \quad (6)$$

$$REE_{alpha} = \frac{E_{alpha}}{E_{total}} \quad (7) \qquad REE_{beta} = \frac{E_{beta}}{E_{total}} \quad (8)$$

$$REE_{gamma} = \frac{E_{gamma}}{E_{total}} \quad (9)$$

$$LREE_{theta} = \log_{10}\left[\frac{E_{theta}}{E_{total}}\right] \quad (10)$$

$$ALREE_{theta} = abs\left(\log_{10}\left[\frac{E_{theta}}{E_{total}}\right]\right) \quad (11)$$

### *D. Classification*

In this work, we used two simple linear 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 five classes (here, disgust, happy, surprise, fear and neutral 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 time series in the training data set and assigns X to the class that appears most frequently in the neighborhood of k time series. There are two main schemes or decision rules in KNN algorithm, that is, similarity voting scheme and majority voting scheme [16]. In our work, we used the majority voting for classifying the unlabeled data. It means that, a class (category) gets one vote, for each instance, of that class in a set of K neighborhood samples. Then, the new data sample is classified to the class with the highest amount of votes. This majority voting is more commonly used because it is less sensitive to outliers. Besides the training and testing samples, LDA does not require any external parameter for classifying the discrete emotions. However, in KNN, we need to specify the value of "K" closest neighbor for emotions classification. In this experiment, we try different "K" values ranging from 2 to 6. Finally, the value of "K" is selected as 6. This gives a maximum classification performance among the other values of K.

TABLE 2
AVERAGE CLASSIFICATION ACCURACY OF THREE STATISTICAL FEATURES OVER 2 DIFFERENT CHANNELS SET USING KNN AND LDA

| Features | 62 Channels | | 24 Channels | |
|---|---|---|---|---|
| | KNN | LDA | KNN | LDA |
| **REE** | 68.2609 | 71.0896 | 65.8696 | 62.1739 |
| **LREE** | 78 | 77 | 73.5652 | 68.6957 |
| **ALREE** | **78.4783** | 77.1739 | **73.6087** | 70.4348 |

TABLE 3
MAXIMUM INDIVIDUAL CLASSIFICATION ACCURACY OF DISCRETE EMOTIONS OVER 2 DIFFERENT CHANNELS SET

| Channels | Features | Dis | Hap | Sur | Fea | Neu |
|---|---|---|---|---|---|---|
| **62** | ALREE | **92** | **85** | **67** | **61.25** | **83.75** |
| **24** | ALREE | **92** | 81 | 54 | 58.75 | 66.25 |

Dis = Disgust; Hap = Happy; Sur = Surprise; Fea = Fear; Neu= Neutral

TABLE 4
THE STANDARD DEVIATION OF AVERAGE CLASSIFICATION ACCURACY OVER DIFFERENT CHANNELS SET

| Features | 62 Channels | | 24 Channels | |
|---|---|---|---|---|
| | KNN | LDA | KNN | LDA |
| **REE** | 1.7486 | 1.7992 | 1.0494 | 2.19015 |
| **LREE** | 2.3814 | 0.80464 | 2.63394 | 2.222 |
| **ALREE** | **1.2139** | 1.4744 | **3.33467** | 2.0219 |

## III. RESULTS AND DISCUSSIONS

Among all twenty subjects, we sample and preprocess the total of 460 EEG epochs from five discrete emotions. The number of data points in each epoch depends on the time duration of video clips. In our experiment; the time duration of video clips vary from one another. The next stage is to train the KNN classifier with a best value of K while LDA classifier directly works for classifying the emotions. Among these two classifiers, LDA is of very simple but elegant approach to classify various emotions. The classification ability of a statistical feature set can be measured through classification accuracy by averaging five times over a 5 fold cross-validation. The basic stages of 5 fold cross-validation includes: (a) total number of samples are divided into 5 disjoint sets (b) 4 sets are used for training and 1 set is used for testing (c) repeat stage (b) for five times and each time the data set is permuted differently. In order to develop an reliable and efficient emotion recognition system with lesser number of electrodes, we compared the classification accuracy of the original set of channels with reduced set of channels which is used by the other researcher [4]. This reduced set of channels was obtained on the basis of localizing the frequency range of emotion over different areas of the brain though cognitive analysis. From Table 2, we found that, KNN gives higher average classification accuracy than LDA on two different channels sets. The maximum classification accuracy of 78.4783 % and 73.6087 % is obtained using *ALREE* feature on 62 channels and 24 channels respectively. Among the two different channel combination, *ALREE* performs better than the other features (*REE and LREE*). Table 3 shows the individual emotions classification rate of KNN classifier for the feature which gives the maximum average classification accuracy in two different set of channels in Table 2. From Table 3, we found that, the 62 channel EEG data gives the maximum individual classification rate on four emotions (happy, surprise, fear and neutral). Both 62 and 24 channel gives the same classification rate on distinguishing disgust emotion. In Table 4 we present the average standard deviation of classification rate over in 5 trials. All the programming was done in Matlab environment on a desktop computer with AMD Athlon dual core processor 2 GHz with 2 GB of random access memory.

## IV. CONCLUSION

This work addresses the classifiability of human emotions using EEG signals. The results presented in this paper indicate that the multi-resolution analysis based *Recoursing Energy Efficiency* features works well with the context of emotion classification. The experimental result on the performance of KNN is very encouraging. These results represent a possibility of determining the emotional changes of human mind through EEG signals. In addition, these results also confirm our hypothesis that it is possible to differentiate and classify the human emotions through *REE* and modified form of *REE* features. Compared to the *REE* and *LREE* features, *ALREE* performs well on deriving the refined information on emotional changes from the EEG signals. The results of this study provide a framework of methodology that can be used to elucidate the dynamical mechanism of human emotional changes underlying the brain structure. In addition, the results can be extended to the development of online emotion recognition system.

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