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Human Emotion Classification using Wavelet Transform and KNN

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***Abstract*- 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. In this paper we presented the classification of human emotions using Electroencephalogram (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. An audio-visual (video clips) stimuli 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 (delta, theta, alpha, beta and gamma) using Wavelet Transform (WT). We have considered three different wavelet functions namely: *"db4", "db8", "sym8"* and *"coif5"* for extracting the statistical features from the preprocessed signal. In this work, we have investigated the efficacy of emotion classification for two different set of EEG channels (62 channels & 24 channels). The validation of statistical features is performed using 5 fold cross validation and classified by using linear non-linear (KNN - K Nearest Neighbor) classifier. KNN gives a maximum average classification rate of 82.87 % on 62 channels and 78.57% on 24 channels, respectively. Finally we present the average classification accuracy and individual classification accuracy of KNN for justifying the performance of our emotion recognition system.**

***Keywords:* EEG, Surface Laplacian filtering, Wavelet transform, KNN.**

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 addition, this emotion detection is also to be useful for designing neuro marketing system to estimate the people interest on buying a new product from the market, e-learning system to understand the student emotional state during the lectures and call centers to estimate the workers emotional states. 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, gestures and speech signal analysis [1] [2]. Another possible approach for emotion recognition is physiological signal analysis. 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 central nervous system (CNS). Indeed, the subjects have no ways to control or hide their emotional experience. 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 extensive survey on previous works using peripheral signals, EEG signals and fusion of peripheral and EEG signal 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 have 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 order to evaluate the potentiality of the emotion recognition system with different set of channels, we have compared the efficacy of emotion classification using original set of channels (62 channels) with reduced set of channels (24 channels) which is used in [4].

In this work, we have used audio-visual stimuli (video clips) for evoking five different emotions such as disgust, happy, fear, surprise and neutral. A set of linear and non-linear statistical features have been derived using wavelet transform over five different frequency bands (delta, theta, alpha, beta and gamma). The statistical features are extracted using the following three wavelet functions namely: *"db4",* *"db8"*, *"sym8"* and *"coif5"*. These numerical features are classified using a non-linear classifier called KNN. Finally, we have compared the classification rate of discrete emotions on different channel combinations over five frequency bands by combining wavelet features and KNN.

The rest of this paper is organized as follows. In Section II, we summarize the research methodology by elucidating the data acquisition process, preprocessing, and 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.standford.edu).

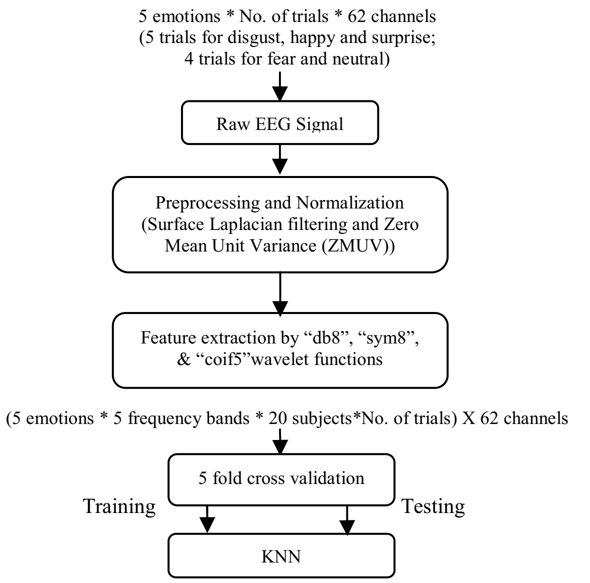

Fig.1. Systematic procedure of our work on emotion recognition using EEG signals

The selection of video clips is based on self assessment questionnaires mentioned in [9]. The subjects who have participated in the pilot study did not consider for data collection. 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.

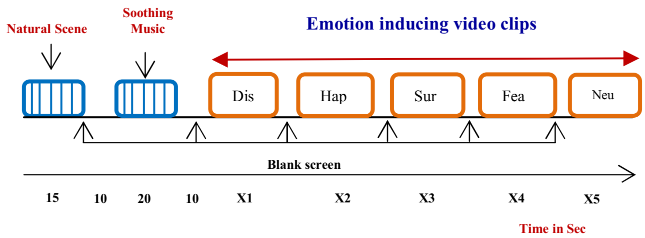

Fig 2. EEG data acquisition protocol using audio-visual stimulus

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 (Fig 3). The 24 channel EEG electrodes are heighted in Fig 3. 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.

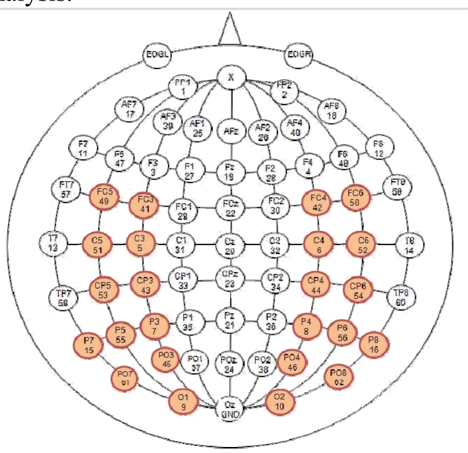

Fig 3. Electrode diagram for 62 channels based on International 10-10 system

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 Butterworth 6th Order filter for removing the noises and artifacts and Surface Laplacian (SL) filter for enhancing the characteristics of EEG channels. 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. SL filtering is used to attenuate the EEG activity which is common to all the involved channels 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

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

where X_{new} : filtered signal ; X(t) : raw signal ; N_E: 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 not used by many researchers. 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] [13]. 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.

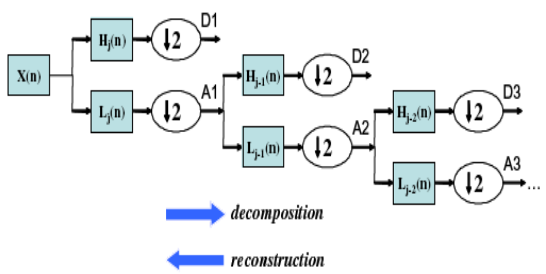

Fig 4. Filter bank implementation of wavelet decomposition

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

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

where a, b ∈ 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),

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

where ( ) is the Fourier transform of $_{a,b}$ (t).

The time-frequency representation is performed by repeatedly filtering the signal with a pair of filters namely high pass filter (H(n)) and low pass filter (L(n)), that cut the frequency domain in the middle (Fig 4). 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].

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 three different wavelet functions namely: *"db4", "db8", "sym8"* and *"coif5"* are used to decompose the EEG signals into five different frequency bands (Table 1). These wavelet functions have been chosen due to their near optimal time-frequency localization properties. Moreover, the waveforms of these wavelets are similar to the waveforms to be detected in the EEG signal. Therefore, extraction of EEG signals features are more likely to be successful [15] [16]. Table 1 also presents the bandwidth and the frequencies corresponding to different levels of decomposition with a sampling frequency f_s=256 Hz [14]. In order to analyze the characteristic natures of different EEG patterns, we derive a set of linear (power, standard deviation, and variance) and non-linear (entropy) for classifying the discrete emotions (Table 2) [8]. These features are derived from the five frequency bands of EEG.

Table 1 Decomposition of EEG signals into different frequency bands with a sampling frequency of 256 Hz

A : Approximation coefficients   D: Detail coefficients

Table 2. Statistical features used for emotion recognition and their description

Features	Description
Standard Deviation	Measures the deviation of electrodes potential from its mean value over different emotional EEG signals.
Power	Measures the squares of the amplitude of EEG signal
Entropy	Measures the useful information (nonlinearity) about the EEG signal for emotion from the intrusive noise.

D. Classification

In this work, we used non-linear classifier such as K Nearest Neighbor (KNN) for classifying the discrete emotions. KNN is 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 sample (testing and unseen 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 [17].

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. 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 8. The optimal value of K is selected for achieving the maximum classification performance among the other values of K.

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 for classifying the 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.

One of the limitations in this area of research is lack of international standard data base. Hence, all the researchers are reporting their results according to their own set of data bases. The accuracy of classification depends on the number of electrodes used, method of emotional stimuli used for

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

evoking emotions, number of subjects (male/female) participated, method of feature extraction and statistical features extracted. In addition, all these experiments are conducted under laboratory settings. Therefore, the possibility of evoking multiple emotions for unique stimuli is obvious. Hence, the emotion inducement stimuli should be efficient to induce unique emotion than multiple emotions and efficient signal processing techniques are required to enhance the emotion assessment rate.

In this work, we have used audio-visual stimuli (film/video clips) for inducing the discrete emotions. Before selecting the stimuli for the experiment, all these stimuli are presented to the subjects who are not going to take part in this study. We have asked them to fill up the self-assessment (has an option for filling their emotion with respective intensity) form by without taking the EEG data. According to the results of the self assessment report, we have shortlisted to most dominating emotional video clips with higher intensity for the original experiment. This whole study is called as pilot study. In this work, EEG signals are collected from higher number of channels will increase the recognition rate of human emotion assessment by compromising the physical burden of the subjects, time duration for placing electrodes and computational complexity.

From Table 3 and Table 4, we found that, KNN gives a maximum classification accuracy of 82.87% and 78.57% using *entropy* feature on 62 channels and 24 channels, respectively. For the two different channel combinations, *entropy* performs better than the other features (*power, standard deviation and variance*). Since, the entropy feature is basically a non-linear in nature and captures the non-linearity of the EEG signals over different emotions than other statistical features. In this work, we have presented the average individual classification accuracy over five trials in Table 5 and Table 6. Table 5 and Table 6 shows the individual emotions classification rate of KNN classifiers in two different set of channels. From the above tables, we found that, the 62 channel EEG data gives the maximum individual classification rate on three emotions (surprise (76%), fear (68.75%) and neutral (96.25%)) using *sym8* wavelet function in KNN. In addition, 24 channels EEG performs well on giving the maximum classification accuracy of 89% in happy emotions using *db8* wavelet function. The classification accuracy of subsets of emotions may differ from trial to trial.

In addition, all the four wavelet functions have very minimum difference in classification rate. However, *"sym8"* wavelet function performs well on KNN classifier. 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

The preliminary results presented in this paper address the classifiability of human emotions using original and reduced set of EEG channels. The main aim of this work is to optimize the number of active channels to develop a portable emotion recognition system and to reduce the computational complexity and computational time. However, the results indicated that, there is no common emotional center for determining the human emotional changes and higher number of channel gives more accuracy than lower channels. Very few of the researchers have considered the classification of discrete emotions than dimensional emotions (valence/arousal). Most of the researchers have used multiple physiological signals for developing emotion recognition system. In this work, we have concentrated on developing a unimodal system using EEG signals for assessing the human emotions.

The results presented in this paper indicate that the multi-resolution analysis based non-linear feature works well with the context of discrete emotion classification. 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 the linear and non-linear features. 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. The experimental result on the performance of KNN is very encouraging and 62 channel EEG signals gives more classification accuracy than 24 channels. Assessing subject individual emotion recognition rate with new statistical feature will be treated in future work. In addition, the results can be extended to the development of online emotion recognition system.

Table 3 KNN based classification of emotions using two different channel combinations

Wavelet	"K"	62 Channel			24 Channel		
		Entropy	**Power**	**Std.Dev**	**Entropy**	**Power**	**Std.Dev**
db4	K=6	76.74±2.25	72.39±1.52	75.65±1.36	71.30±1.23	71.74±1.95	75.02±2.92
db8	K=6	81.96±2.09	68.30±1.21	73.52±1.46	**78.57±1.07**	74.30±1.15	77.43±2.42
sym8	K=6	**82.87±1.56**	67.78±1.39	72.65±2.46	78.43±1.33	74.13±1.74	76.78±1.82
coif5	K=6	82.52±1.09	67.61±1.51	76.61±1.31	78.17±2.77	73.22±2.49	78.17±1.24

Table 5 Individual classification accuracy of emotions in two different channel combinations on 5 frequency bands using KNN (K=6)

Feature	**Wavelet**	**62 Channel**					**24 Channel**				
		Disgust	**Happy**	**Surprise**	**Fear**	**Neutral**	**Disgust**	**Happy**	**Surprise**	**Fear**	**Neutral**
Entropy	db4	85	85	65	50	87.5	80	85	70	68.75	75
	db8	92	86	72	63.75	91.25	92	**89**	50	70	88.75
	sym8	92	87	**76**	**68.75**	**96.25**	92	88	63	75	86.25
	coif5	92	85	71	70	93.75	92	84	52	67.5	90
Power	db4	85	80	65	50	68.75	85	75	80	31.25	81.25
	db8	92	79	65	53.75	50	92	78	60	66.25	81.25
	sym8	92	78	63	57.5	53.75	92	84	61	61.25	72.5
	coif5	92	77	64	47.5	43.75	92	74	69	63.75	71.25
Std Dev	db4	80	85	65	43.75	93.75	90	85	70	56.25	81.25
	db8	92	82	71	57.5	61.25	92	83	65	60	81.25
	sym8	92	82	69	60	53.75	92	81	69	61.25	76.25
	coif5	92	83	67	62.5	68.75	92	80	70	67.5	75

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