Comparison of Human Emotion Classification through different set of EEG channels

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***Abstract*:** Assessing human emotional state through EEG is one of key research area in developing intelligent man-machine interfaces. EEG signals are collected using 64 channels from 20 subjects in the age group of 21~39 years for determining discrete emotions. An audio-visual induction based protocol has been designed for evoking the discrete emotions (happy, surprise, fear, disgust, neutral). The raw EEG signals are preprocessed through Surface Laplacian filtering method and decomposed into five different EEG frequency bands using Wavelet Transform. The main objective of this present work is to develop the emotion recognition system with lesser number of channels. Therefore, we have compared the efficacy of original set of channels (64 channels) with reduced set of channels (24 channels), which is proposed by the earlier work based on localization of brain region for assessing emotions. In our work, "db4" wavelet function is used to derive a new set of statistical features based on frequency band power for classifying the emotions. In this work, KNN outperforms LDA by offering the average classification accuracy of 79.783 % for 24 channels and 82.898 % for 62 channels. 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*:** - Human emotion, EEG signals, Wave transform, Features extraction

1. INTRODUCTION

The estimation of emotional changes from electroencephalogram (EEG) signals has recently gained attention among BCI and Human Computer Interaction (HCI) researchers for developing the BCI/HCI devices. 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 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 power have been derived using wavelet transforms over three different frequency bands (alpha, beta and gamma). These numerical features are classified using two different linear classifiers namely K Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA). The main objective of this work to compare the efficacy of discrete emotion classification of original set of channels (62 channels) and reduced set of channels (24 channels) which is proposed in [4] based on localizing brain activity in EEG signal for different emotions. The required EEG data for this reduced number of channels are derived from the EEG data of original set of channels for classifying emotions. Finally, we have compared the classification rate of discrete emotions on two different channel combinations over three frequency bands by combining wavelet features and linear classifiers. Figure 1 shows the human emotion recognition system using EEG.

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.

2. MATERIALS AND EXPERIMETAL DESIGN

2.1 EEG Data Acquisition

This section describes the acquisition of EEG signals for emotion stimulation experiments. From our earlier experiment, we found that audio-visual stimulus is superior in evoking the discrete emotions than visual stimulus method [7]. 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 Figure 2. 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).

The selection of video clips is based on self assessment questionnaires mentioned in [8]. 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 Figure. 3. 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.

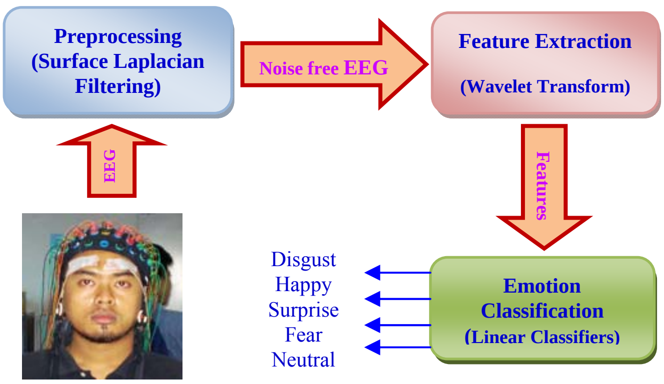

Figure 1. Emotion Recognition system overview

The selection of video clips is based on self assessment questionnaires mentioned in [8]. 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 Figure. 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. Totally, we have used 62 active electrodes, one each for reference (AFz) and ground (Oz). 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.

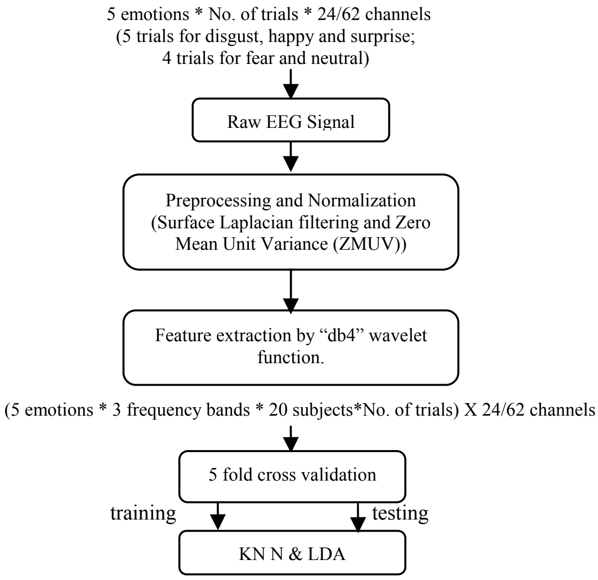

Figure 2. Systematic procedure of our work on emotion recognition using reduced set of EEG channels

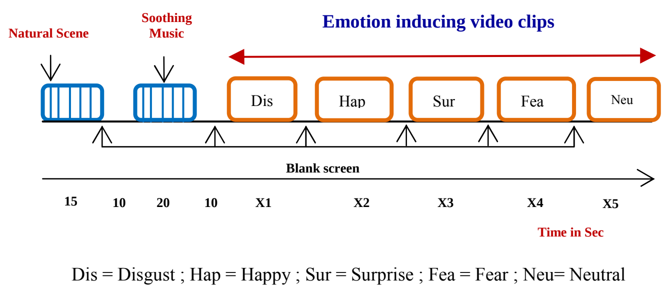

Figure 3. EEG data acquisition protocol using audio-visual stimulus

Between each emotional video clips, under self assessment section, the subjects were informed to answer the emotions they have experienced [8]. Finally, 5 trials for disgust, happy and surprise emotions and 4 trials for fear and neutral emotions are considered for further analysis.

2.2 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 [9, 10]. 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

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

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

2.3 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) [11, 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 [13].

In this work, the multi-resolution analysis of "db4" wavelet function is used for decomposing the EEG signals into three different frequency bands (alpha, beta, and gamma). This wavelet function "db4" has been chosen due to their near optimal time-frequency localization properties. Moreover, the waveforms of "db4" are similar to the waveforms to be detected in the EEG signal. Therefore, extraction of EEG signals features are more likely to be successful [14]. 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 propose a new set of statistical features based on power called: *Recoursing Power Efficiency* (RPE), *Logarithmic Recoursing Power Efficiency* (LRPE), and *Absolute Logarithmic Recoursing Power Efficiency* (ALRPE) for classifying the discrete emotions (Eqn 5 to Eqn 7). These features are derived from the three 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 [13].

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

Frequency Range	Decomposition Level	Frequency Bands	Frequency Bandwidth (Hz)
0 - 4	A5	Theta	4
4 – 8	D5	Delta	4
8 – 14	D4	Alpha	8
14 – 32	D3	Beta	16
32 – 64	D2	Gama	32
64 - 128	D1	Noises	64

A : Approximation coefficients D: Detail coefficients

$$P_{total-3b} = P_{alpha} + P_{beta} + P_{gamma} \quad (4)$$

$$RPE_{gamma} = \frac{P_{gamma}}{P_{total-3b}} \quad (5)$$

$$LRPE_{gamma} = \log_{10}\left|\frac{P_{gamma}}{P_{total-3b}}\right| \quad (6)$$

$$ALRPE_{gamma} = abs\left(\log_{10}\left|\frac{P_{gamma}}{P_{total-3b}}\right|\right) \quad (7)$$

2.4 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 hyperplane 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 [15]. 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 1 to 6. This value of "k" which gives a maximum classification performance among the other values of K is considered for emotion classification.

3. 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. 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. From Table 2, we found that, KNN gives higher average classification accuracy than LDA on all different channels sets. The maximum classification accuracy of 79.78 % and 64.92 % is obtained using Logarithmic Recoursing Power Efficiency (LRPE) feature among the three newly proposed statistical features in KNN and LDA respectively.

Among the two different channel combinations, the statistical feature (LRPE) on the original set of channels gives maximum average classification accuracy over reduced set of channels. Here, the LRPE feature measures the frequency band power variations over different emotional EEG data. And so, each emotional EEG signals have its own frequency band power variation characteristics and it can be easily found out by using the LRPE feature. Table 3 shows the individual emotions classification rate of three different statistical features over two different liner classifiers. Table 4 shows the average classification rate of emotions on original set of channels using LRPE feature on KNN and LDA [16]. From Table 3 and Table 4, we found that, the 24 channel EEG data gives the maximum individual classification rate in disgust, happy and fear emotions compared to 62 channels respectively. In addition, 62 channels EEG data performs well on achieving higher classification rate on neutral and surprise emotions than 24 channels. Therefore, the region of brain which is covered by a set of 24 channels will able to detect the three emotions (disgust, happy and fear) with higher classification rate over 62 channels. In a similar way, the original set of channels gives a maximum classification rate on neutral and surprise emotions over reduced set of channels. Over all the feature analysis, the EEG data on disgust and neutral data gives a classification rate nearly 90 % over other features. This accuracy of classification shows the potentiality of the audio-visual stimuli for evoking the emotion. In addition, the classification rates of two channels are nearly equal or we can say that, minimum in difference. However, this equivalent classification rate with lesser number of channels is more suited for the development of real-time emotion recognition system. Since, it reduces the computational complexity, physical burden to the subjects and time required for placing electrodes. 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.

Table 2: Comparison average classification rate of statistical features on KNN and LDA

Classifier	RPE		LRPE		ALRPE	
	24 Channels	62 Channels	24 Channels	62 Channels	24 Channels	62 Channels
KNN	**79.42**	**82.61**	**79.78**	**82.89**	**79.21**	**81.74**
LDA	64.71	76.88	64.92	75.58	67.24	75.72

Table 3: Subset of discrete emotion classification rate of three statistical features on KNN and LDA

Classifiers	KNN	LDA	KNN	LDA	KNN	LDA	KNN	LDA	KNN	LDA
Feature	Disgust		Happy		Surprise		Fear		Neutral	
RPE	90	78.33	75	31.66	76.67	68.33	**78.916**	58.33	93.75	68.75
LRPE	88.33	**91.67**	**80**	36.67	76.67	70	70.83	45.83	89.58	64.58
ALRPE	88.33	91.67	75	38.33	75	71.67	77.08	70.83	85.41	77.08

Table 4: Subsets of discrete emotion classification rate of 62 channels EEG data using KNN and LDA

Classifier	Feature	Disgust	Happy	Surprise	Fear	Neutral
KNN	LRPE	**91.67**	78.33	73.33	75	**95.83**
LDA	LRPE	90	65	**80**	66.67	95.83

3 CONCLUSIONS

This work addresses the classifiability of human emotions using reduced set of EEG channels. The results presented in this paper indicate that the multi-resolution analysis based newly proposed features works well with the context of discrete 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 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. In addition, the results can be extended to the development of online emotion recognition system.

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