Combining Spatial Filtering and Wavelet Transform for Classifying Human Emotions Using EEG Signals

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Abstract

In this paper, we present human emotion assessment using electroencephalogram (EEG) signals. The combination of surface Laplacian (SL) filtering, time-frequency analysis of wavelet transform (WT) and linear classifiers are used to classify discrete emotions (happy, surprise, fear, disgust, and neutral). EEG signals were collected from 20 subjects through 62 active electrodes, which were placed over the entire scalp based on the International 10-10 system. An audio-visual (video clips) induction-based protocol was designed for evoking discrete emotions. The raw EEG signals were preprocessed through surface Laplacian filtering method and decomposed into five different EEG frequency bands (delta, theta, alpha, beta and gamma) using WT. In this work, we used three different wavelet functions, namely: “db8”, “sym8” and “coif5”, for extracting the statistical features from EEG signal for classifying the emotions. In order to evaluate the efficacy of emotion classification under different sets of EEG channels, we compared the classification accuracy of the original set of channels (62 channels) with that of a reduced set of channels (24 channels). The validation of statistical features was performed using 5-fold cross validation. In this work, K nearest neighbor (KNN) outperformed linear discriminant analysis (LDA) by offering a maximum average classification rate of 83.04% on 62 channels and 79.17% 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: Electroencephalogram (EEG), Emotion assessment, Surface Laplacian filtering, Wavelet transform, K nearest neighbor (KNN), Linear discriminant analysis (LDA)

1. Introduction

Emotion is one of the most important features of humans’ day-to-day communication. Nonverbal communication through emotions, intentions and affective states are the key current research areas on developing intellectual man-machine systems. Without the ability of emotion processing, computers and robots cannot communicate with human in a 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 effort in Human Computer Interaction (HCI) is 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 emotion recognition, in that the influence of emotion on facial expression or speech can be suppressed relatively easily, while emotional status is inherently reflected in the activity of the 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 (brain) and autonomic nervous systems (peripheral).

Several approaches have been reported by different researchers on finding the correlation between the emotional changes and electroencephalogram (EEG) signals [3-5]. Most of these researchers have used the electromyogram (EMG), electrocardiogram (ECG) and skin conductive resistance (SCR) for assessing emotions [6-9]. Some researchers have considered fusion of peripheral and EEG signals for classifying human emotions [4,5,10,11]. The maximum mean emotion classification rate of 80.2% for classifying six emotions of 6 subjects using peripheral signals [7]. But, the maximum mean emotion classification rate of 79% is achieved by classifying two dimensional emotions of one subject [4]. Using EEG signals, the maximum mean emotion classification rate of 82.1% is achieved on classifying two dimensional emotions [12]. The extensive

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survey on previous works using peripheral signals, EEG signals and fusion of peripheral and EEG signal is reported in [13].

In general, emotions can be categorized into dimensional mode (valence-arousal) and discrete modes (disgust, happy, surprise, fear, anger, and sad). Assessing the dimensional mode of emotions is easier than the discrete mode of emotions. This is due to the easier emotion elicitation protocol, limited number of features, and fewer types of classification. Research on EEG-based human emotion assessment is a new area of research, and a very limited number of works on discrete emotion classification have been reported so far. In this present study, we have considered discrete mode of emotion classification for classifying five emotions (disgust, happy, surprise, fear and neutral). Some of the major issues to be addressed in this paper are: (i) efficient artifact and noise removal from the emotional EEGs; (ii) extracting efficient emotional features using discrete wavelet transform (DWT); and (iii) classification of emotions using simple linear classifiers. In order to evaluate the potentiality of the present emotion recognition system with different sets of channels, we have compared the efficacy of emotion classification using an original set of channels (62 channels) and also the reduced set of channels (24 channels) which is used in [4].

In this work, we used audio-visual stimuli (film/video clips) for evoking five different emotions. A set of linear and non-linear statistical features was derived using wavelet transform over five different frequency bands (delta, theta, alpha, beta and gamma). The statistical features were extracted using the following three wavelet functions namely: "db8", "sym8" and "coif5". The statistical features derived using the wavelet functions were classified by two simple classifiers, namely KNN and LDA. Finally, we compared the classification rate of discrete emotions on the original set of 64 EEG channels with that of 24 EEG channels [14] over five frequency bands.

The rest of this paper is organized as follows. In Section 2, 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 3 illustrates the overview of the results and discussion of this present work, and conclusions are given in Section 4.

2. Materials and methods

2.1 EEG data acquisition

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 EEG device. From our earlier experiment, it was found that audio-visual stimulus is superior in evoking the discrete emotions than visual stimulus method [15,16]. Hence, we 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 was 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).

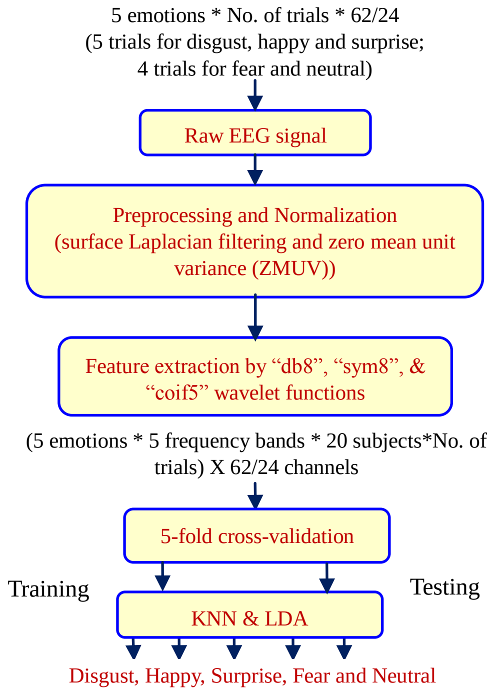
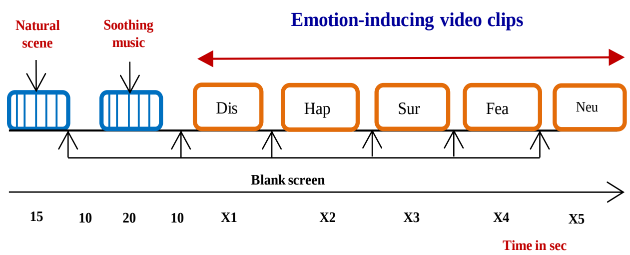


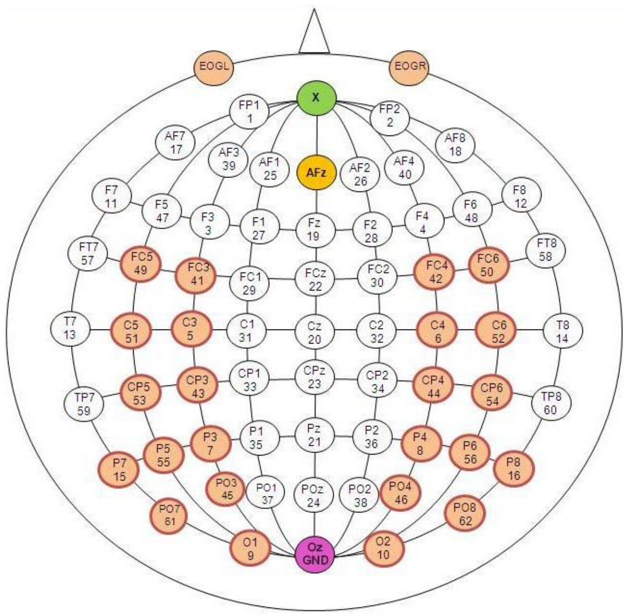
Figure 1. Systematic procedure of our work on emotion recognition using EEG signals.

The selection of video clips is based on self assessment questionnaires mentioned in [17]. The subjects (university students) who had undergone this panel study did 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 were changed in a random manner. X1 to X5 denote time periods of selected video clips. The time duration of video clips varied 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 out, the subjects were given a simple introduction about the research work and stages of emotion recognition experiment. The recording of EEG signal was done via Nervus EEG (Iceland) with 64-channel electrodes at a sampling frequency of 256 Hz and online 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 were placed over the entire scalp using the International Standard 10-10 system (Fig. 3). In addition, we also recorded the activity of subject eye blinks and eye ball rotations through two EoG (electrooculogram) electrodes (EoG_L and EoG_R). The 24-channel EEG electrodes are highlighted in Fig. 3. The impedance of the electrodes was kept below 5 kΩ. Between each emotional video clips, under self assessment section, the subjects were informed to answer the emotions they have experienced [17]. Finally, 5 trials for disgust, happy and surprise emotions and 4 trials for fear and neutral emotions are considered for further analysis.



Dis: disgust Hap: happy Sur: surprise Fea: fear Neu: neutral

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



X: No electrode; AFz: Reference electrode; Oz: Ground electrode

Figure 3. International 10-10 electrode placement system.

2.2 Preprocessing

EEG signals recorded over various positions on the scalp are usually contaminated with noises and 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 [18,19]. A couple of methods are available in the literature to avoid artifacts in EEG recordings. However, removing artifacts entirely was impossible in the existing data acquisition process.

In this work, we used surface Laplacian (SL) filter for removing the noises and artifacts [20]. 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 [21]. 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" [21]. The mathematical modeling of surface Laplacian filter is given as

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

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, and (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 is based on multi-resolution analysis of wavelet transform (WT). The joint time-frequency resolution obtained by WT makes it 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) [22,23]. The nonlinearity characteristics of EEG signal is analyzed by using a wavelet basis function 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

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

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 (Eq. 3),

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

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, namely high-pass filter (H(n)) and low-pass filter (L(n)), that cut the frequency domain in the middle. Specifically, the discrete wavelet transform decomposes the signal into approximation coefficients (A) and detail coefficients (D). The approximation coefficient is subsequently divided into new approximation and detail coefficients. This process is carried out iteratively, producing a set of approximation coefficients and detail coefficients at different levels or scales [24]. The filter bank implementation of wavelet transform for three-level wavelet decomposition is shown in Fig. 4.

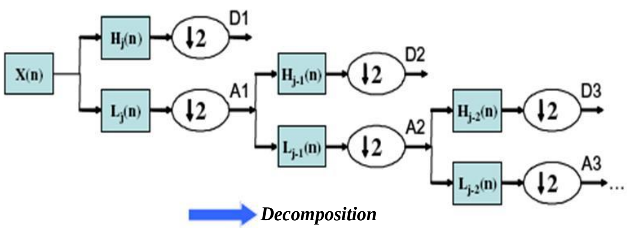


Figure 4. Filter bank implementation of wavelet decomposition.

In this work, the multi-resolution analysis of three different wavelet functions, namely db8, sym8 and coif5, were used to decompose the EEG signals into five different frequency bands (delta, theta, alpha, beta and gamma). These wavelet functions were chosen due to their near optimal time-frequency localization properties. Moreover, the waveforms of these wavelets were similar to the waveforms to be detected in the EEG signal. Therefore, extraction of EEG signals features was more likely to be successful [25,26]. Table 1 presents the bandwidth and the frequencies corresponding to different levels of decomposition with a sampling frequency $f_s = 256$ Hz [24]. In order to analyze the characteristic natures of different EEG patterns, we derived a set of linear (power, standard deviation, and variance) and non-linear (entropy) features for emotion classification (Table 2). These features were derived from the five frequency bands of EEG and were concatenated to form a feature vector.

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

Frequency range (Hz)	Decomposition label	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	Gamma	32
64 – 128	D1	Noises	64

A: approximation coefficients; D: detail coefficients

2.4 Classification

In this work, we used two simple classifiers, linear discriminant analysis (LDA) and K nearest neighbor (KNN) for classifying discrete emotions. 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. The LDA tries to find an optimal hyper plane to separate five classes (here, disgust, happy, surprise, fear and neutral emotions) [6,9].

KNN is also a simple and intuitive method of classification used by many researchers for classifying signals and images. This classifier makes a decision on comparing a newly 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, similarity voting scheme and majority voting scheme [6,8,27]. In our work, we used 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 emotion classification. In this experiment, we tried different "K" values ranging from 2 to 8. Finally, the value of "K" was selected as 6. This gave a maximum classification performance among the other values of K.

3. Results and discussions

Among all twenty subjects, we sampled and preprocessed the total of 460 EEG epochs from the five discrete emotions (20 subjects × 3 emotions of 5 trials and 2 emotions with 4 trials). The number of data points in each epoch depended on the time duration of video clips. In our experiment, the time duration of video clips varied from one another. The next stage was to train the KNN classifier with a best value of K, while the LDA classifier directly worked to classify 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 include: (a) total number of samples are

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

Features	Formula	Description
Standard deviation	$SD_j = \sqrt{\dfrac{\sum_k (d_j(k) - \overline{d_j(k)})}{k-1}}$ $\overline{d_j(k)}$ is the mean value of the wavelet coefficient; $d_j(k)$ is the detail wavelet coefficient	Measures the deviation of electrodes potential from its mean value over different emotional EEG signals.
Variance	$V_j = \dfrac{1}{N}\sum_{k=1}^{N}(d_j(k) - \overline{d_j(k)})^2$	Measures the value variation in electrical potential for various emotions.
Power	$P_j = \dfrac{1}{N}\sum_{k=1}^{N}(d_j(k)^2)$	Measures the squares of the amplitude of EEG signal.
Entropy	$H = -\sum_{j=1}^{M} p_j \log p_j$ where $p_j = \dfrac{E_j}{E_T}$ E_j = Energy at jth frequency band of decomposition E_T = Energy of all frequency band of decomposition	Measures the useful information (nonlinearity) about the EEG signal for emotion from the intrusive noise.

j = level of wavelet decomposition; k = No. of wavelet coefficients, varies from 1 to N

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

Wavelet	"K"	62 channels				24 channels			
		Entropy	**Power**	**Std. Dev.**	**Variance**	**Entropy**	**Power**	**Std. Dev.**	**Variance**
db8	K=6	82.48±2.09	68.61±1.21	73.30±1.46	67.87±1.13	78.87±1.07	74.26±1.15	77.35±2.42	72.35±0.75
sym8	K=6	**83.04±1.56**	67.91±1.39	71.74±2.46	68.39±2.18	**79.17±1.33**	75.00±1.74	76.78±1.82	74.52±2.35
coif5	K=6	82.35±1.09	68.39±1.51	76.96±1.31	67.74±1.44	78.69±2.77	72.96±2.49	77.44±1.24	71.70±1.40

Table 4. LDA-based classification of emotions using two different channel combinations.

Wavelet	62 channels				24 channels			
	Entropy	**Power**	**Std. Dev.**	**Variance**	**Entropy**	**Power**	**Std. Dev.**	**Variance**
db8	**80.52±1.61**	53.73±4.76	63.43±0.28	51.87±3.04	**74.52±0.24**	55.26±0.45	62.35±0.37	50.48±0.51
sym8	79.73±2.04	51.34±2.76	64.78±2.26	50.04±2.89	72.43±0.25	55.26±0.47	63.48±0.37	48.96±0.52
coif5	80.30±1.29	51.52±1.82	63.82±1.94	50.34±3.30	72.96±0.24	52.09±0.50	63.65±0.37	49.91±0.51

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

Feature	Wavelet	62 channels					24 channels				
		Disgust	**Happy**	**Surprise**	**Fear**	**Neutral**	**Disgust**	**Happy**	**Surprise**	**Fear**	**Neutral**
	db8	92	86	72	63.75	91.25	92	**89**	50	70	88.75
Entropy	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
	db8	92	79	65	53.75	50	92	78	60	66.25	81.25
Power	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
	db8	92	82	71	57.5	61.25	92	83	65	60	81.25
Std Dev	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
	db8	92	81	60	62.5	47.5	91	83	53	60	73.75
Var	sym8	90	81	71	56.25	41.25	92	75	59	72.5	67.5
	coif5	92	76	61	45	55	92	73	56	61.25	73.75

Table 6. Individual classification accuracy of emotions in two different channel combinations on five frequency bands using LDA.

Feature	Wavelet	62 channels					24 channels				
		Disgust	**Happy**	**Surprise**	**Fear**	**Neutral**	**Disgust**	**Happy**	**Surprise**	**Fear**	**Neutral**
	db8	92	86	59	**77.5**	86.67	92	74	46	73.75	81.25
Entropy	sym8	92	82	66	68.75	88.33	92	82	41	66.25	87.5
	coif5	91	82	61	58.75	88.33	92	78	42	73.75	85
	db8	**94**	84	23	13.75	25	89	62	15	86.25	33.75
Power	sym8	93	84	25	10	21.67	91	67	31	28.75	21.25
	coif5	**94**	80	31	25	26.67	91	57	65	6.25	11.25
	db8	88	81	56	26.25	51.67	83	61	41	60	46.25
Std Dev	sym8	89	78	59	51.25	43.33	87	64	46	66.25	48.75
	coif5	89	77	49	46.25	45	87	68	43	83.75	53.75
	db8	77	87	58	12.5	20	69	54	65	55	21.25
Var	sym8	74	84	33	12.5	13.33	77	61	45	72.5	41.25
	coif5	85	74	28	23.75	20	68	58	49	33.75	16.25

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 Tables 3 and 4, we find that, KNN gave higher average classification accuracy than LDA for the two different channel sets. The maximum classification accuracy of 83.04% and 79.17% was obtained using entropy feature on 62 channels and 24 channels using KNN, respectively. Among the two different channel combinations, the entropy feature performed better than the other features (power, standard deviation and variance), because the entropy feature is basically non-linear in nature and captures the non-linearity of the EEG signals over different emotions better than other statistical features. Tables 5 and 6 show the individual emotion classification rates of KNN and LDA classifiers, respectively, in the two different set of channels. From the above tables, we see that the 62-channel EEG data gave the maximum individual classification rate on two emotions (surprise (76%) and neutral (96.25%)) using the sym8 wavelet function in KNN, and db8 wavelet function gave the maximum classification accuracy on the other two emotions, namely fear (77.5%) and disgust (94%) using LDA. In addition, 24-channel EEG performed well in giving the maximum classification accuracy of 89% for happy emotion using the db8 wavelet function. The classification accuracy of subsets of emotions may differ from trial to trial. We present the average individual classification accuracy

Table 7. Comparison of maximum mean emotion classification rate of the present work with that of earlier works on classifying emotions using EEG.

Reference	No of subjects	No of electrodes	Stimuli	Discrete emotions		Max % CR
				No's	**Types**	
Discrete emotion classification						
[10]	- -	3	Visual	3	Joy, Sad, Neutral	74.00
[26]	5	32	Audio	4	Joy, Anger, Pleasure, Sad	69.69
[27]	17	3	Visual	8	4 emotional and 4 mental states	82.27
Valence – arousal-based emotion classification						
[11]	5	10	Visual	3	Calm, Positively excited and Negatively excited	66.66
[30]	5	4	Visual	3	Pleasant, Neutral and Unpleasant	66.70
[31]	5	4	Visual	3	Pleasant, Neutral and Unpleasant	47.11
[32]	2	3	Visual	2	Valence – Arousal	82.11
Present Work	**20**	**64**	**Audio-Visual**	**5**	**Happy, Disgust, Surprise, Fear and Neutral**	**83.04**

(in %) over five trials in Tables 5 and 6. In addition, all of the three wavelet functions had very minimum difference in classification rate. However, sym8 wavelet function performed well on KNN classifier and db8 in the LDA classifier.

One of the limitations in this area of research is lack of an international standard data base. Hence, all the researchers are reporting their results according to their own datasets. In general, the accuracy of emotion classification mainly depends on the number of electrodes, type of emotional stimuli used for evoking emotions, and number of subjects (male/female) used for developing the dataset. A list of earlier works on discrete and dimensional modes of emotion classification using EEG is given in Table 7. Due to the limited number of emotional classes (valence-arousal), dimensional mode of emotion classification has been chosen by many researchers. However, the maximum mean emotion classification rate of 82.11% was achieved for classifying two emotional states of two subjects. All researchers have adopted visual stimuli for evoking the emotions and considered the number of subjects below 10. But, the present work showed a maximum mean emotion classification rate of 83.04% for classifying five different emotional states of 20 subjects. Also, the present data set is developed with higher number of subjects, considered higher number of emotion categories and used audio-visual stimuli for eliciting emotions. In this work, the increase in emotion recognition rate through EEG signals was achieved using higher number of channels by compromising the physical burden of the subjects and computational complexity. In addition, the accuracy of emotion classification can also be studied by combining statistical features. Since, this work completely deals with single or unique features for classifying the emotions, all the programming was done offline in Matlab 7 environment on a desktop computer with AMD Athlon dual core processor 2 GHz with 2 GB of random access memory.

4. Conclusion

The preliminary results presented in this paper address the classifiability of human emotions using original and reduced set of EEG channels. Very few researchers have considered the classification of discrete emotions rather 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 within 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 by their 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 gave 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 an online emotion recognition system.

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