Human Emotion Classification from Brain EEG Signal Using Multimodal Approach of Classifier

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ABSTRACT
To deeply understand the brain response under different emotional states can fundamentally advance the computational models for emotion recognition. Various psychophysiology studies have demonstrated the correlations between human emotions and EEG signals. With the quick development of wearable devices and dry electrode techniques it is now possible to implement EEG-based emotion recognition from laboratories to real-world applications .In this paper we have developed EEG-based emotion recognition models for three emotions: positive, neutral and negative. Extracted features are downloaded from seed database to test a classification method. Gamma band is selected as it relates to emotional states more closely than other frequency bands. The linear dynamical system (LDS) is used to smooth the features before classification. The classification accuracy of the proposed system using DE, ASM, DASM, RASM is 97.33, 89.33 and 98.37 for SVM (linear), SVM (rbf sigma value 6) and KNN(n value 3) respectively.

CCS Concepts
• Human-centered computing → Human computer interaction (HCI)

Keywords
EEG-based emotion recognition; LDS; SVM; KNN

1. INTRODUCTION
EEG signals have low Signal to Noise Ratio. (SNR) and are often mixed with much noise when collected. The more challenge problem is that, unlike image or speech signals, EEG signals are temporal asymmetry and non-stationary [1]. With the fast development of wearable devices and dry electrode techniques, it enables us to record and analyze the brain activity in natural settings. This development is leading to a new trend that integrates brain-computer interfaces (BCIs) with emotional factors. Emotional brain computer interfaces are closed-loop affective computing systems, which build interactive environments. Emotional brain-computer interfaces consist of the following six main phases. First, users are exposed to real world stimuli. The brain activities , EEG are recorded. Then the raw data will be pre-processed to remove noise and artifacts. Some relevant features will be extracted and a classifier will be trained based on the extracted features. After identifying user current emotional states, a feedback can be implemented to respond to the users. This model is then can be used in implementing various applications. In this paper we used seed database for testing classification model. Arrangement of the section is mentioned below.

In this paper section 2 is used to describe details of seed database. We have downloaded extracted features test a classification method. In section 3, proposed system is explained. Section 4 is classification modeling. In section 5 quantitative analysis is included. Conclusion is stated in section 6.

2. DATABASE
SEED Database is developed for emotion recognition. To develop this database 15 subjects, 7 males and 8 females were selected of age group 23 to 27. About 15 Chinese film clips including three emotions (positive, neutral and negative emotions) are shown to the subjects. [2]. The duration of each film clip is about 4 minutes. EEG signals of 15 subjects were recorded while they were watching the emotional film clips. There are totally 15 trials for each experiment. In order to investigate neural signatures and stable patterns across sessions and individuals, each subject is required to perform the experiments for three sessions. The time interval between two sessions was one week or longer. There are totally 45 experiments in this dataset. ESI NeuroScan System is used to record at a sampling rate of 1000 Hz from 62-channel active AgCl electrode cap according to the international 10-20 system. Data set is created for the further analysis [3].

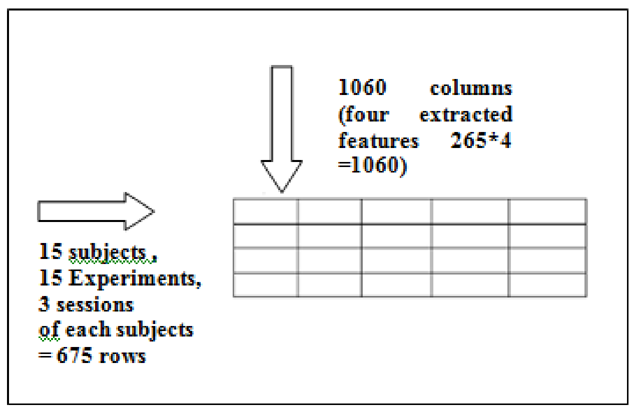

Figure 1. Dataset representation.

As figure 1 show, SEED dataset representation in excel sheet. The files in the dataset contain a down sampled, pre-processed and segmented version of the EEG data in Matlab (.mat file). The data was down sampled to 200Hz. A band pass frequency filter from 0-75Hz was applied. We extracted the EEG segments corresponding to the duration of each movie. There are totally 45 .mat (Matlab) files, one for per experiment. Each subject performed the

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experiment three times with an interval of about one week. Each subject file contains 16 arrays. 15 arrays contain segmented pre-processed EEG data of 15 trials in one experiment (eeg_1~eeg_15, channel × data). A array name labels contains the label of the corresponding emotional labels (-1 for negative, 0 for neutral and +1 for positive). For the simplicity we relabel it as 1,2,3 respectively. The detailed order of the channels can be downloaded.

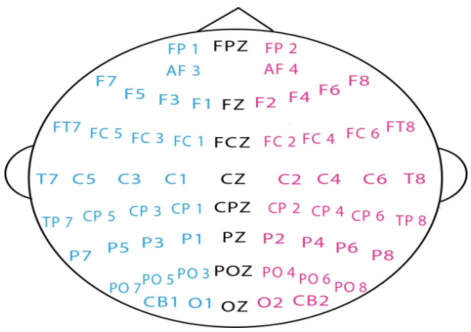

Figure 2. Ten-Twenty Electrode placement system.

Figure 2 shows EEG cap according to the international 10-20 system for 62 channels [3] and [4]. The files contain the extracted differential entropy (DE) features of the EEG signals [3]. These data is well-suited to those who want the file format is the same as the Data pre-processed. The differential asymmetry (DASM) and rational asymmetry (RASM) features are also computed. It is the differences and ratios between the DE features of 27 pairs of hemispheric asymmetry electrodes. All the features were further smooth with conventional moving average and linear dynamic systems (LDS) approaches. Each subject performs the experiments twice at the interval of a few days.

3. PROPOSED SYSTEM

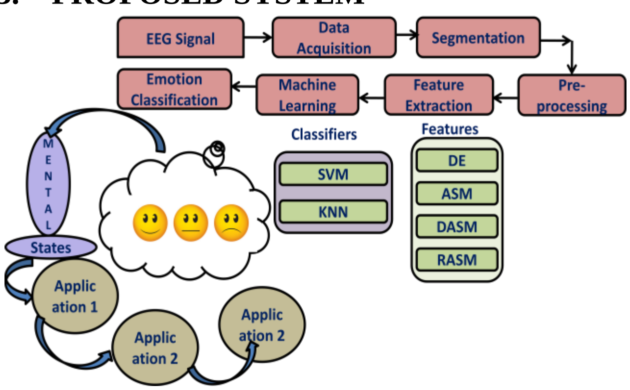

Figure 3. Proposed system model.

Figure 3 is Proposed System Model.

3.1 Algorithm

•First we downloaded the seed database with extracted features.

•Each experiment had (electrode X data X band) matrix where electrodes may be individual or pair type.

•We extracted the data of the gamma band of FT7, FT8, T7, T8 electrodes of features ASM, DE, RASM, ASM as the location of these electrodes is practically possible to be place in real life situation.

•Gamma band is selected as relates to emotional states more closely than other frequency bands

•Linear Dynamical System (LDS) is selected from extracted features as LDS method is more effective when smoothing the feature sequence. Then we took average of the electrodes data and then we placed the whole data in an excel sheet which is placed horizontally in the order DE, ASM, DASM, RASM. Then we had the corresponding labels which we used to train machine learning model.

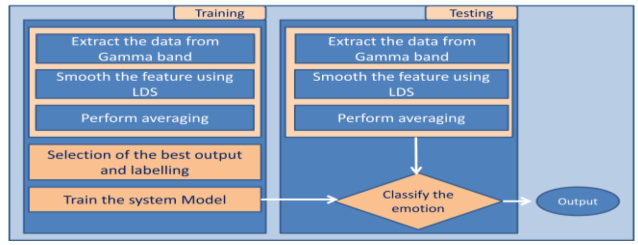

Figure 4. Process flow of automatic emotion classification system.

Figure 4 shows process flow of automatic emotion classification system. Li and Lu proposed a frequency band searching method to choose an optimal band, into which the recorded EEG signal is filtered. They used common spatial patterns (CSP) and linear-SVM to classify two emotions (happiness and sadness). Their experimental results indicated that the gamma band (roughly 30-100 Hz) is suitable for EEG-based emotion classification. The problem of electrode set reduction is commonly studied to reduce the computational complexity and ignore the irrelative noise. The identified features were primarily derived from electrodes placed near the frontal and the parietal lobes. Valenzi et al. selected a set of eight electrodes: AF3, AF4, F3, F4, F7, F8, T7, and T8, To the best of our knowledge, the popular publicly available emotional EEG datasets are MAHNOB HCI. and DEAP .[5]

3.2 Pre-processed Data

An EEG records the electrical waves of the brain. It is a safe, easy and painless test that takes approximately one hour. An EMG evaluates nerve and muscle function in the arms or legs

According to the response of the subjects, only the experiment epochs when the target emotions were elicited were chosen for further analysis. The raw EEG data was downs sampled to 200Hz sampling rate. The EEG signals were visually checked and the recordings seriously contaminated by EMG. and EOG were removed manually. EOG was also recorded in the experiments, and later used to identify blink artifacts from the recorded EEG data. In order to filter the noise and remove the artifacts, the EEG data was processed with a bandpass filter between 0.3Hz to 50Hz [6].

3.3 Feature Extraction

An efficient feature called differential entropy (DE) : measure the complexity of a continuous random variable. differential entropy is equivalent to the logarithm energy spectrum in a certain frequency band. So differential entropy can be calculated in five frequency bands (delta: 1-3Hz, theta:4-7Hz, alpha:8-13Hz, beta:14-30Hz, gamma:31-50Hz)with time complexity O (KN logN), where K is the number of electrodes, and N is the size of samples. For a specified EEG sequence, we used a 256-point Short-Time Fourier Transform with a non-overlapped Hanning window of 1s to extract five frequency bands of EEG signals. Then we calculated differential entropy for each frequency band. Since each frequency band signal has 62 channels, we extracted differential entropy features with 310 dimensions for a sample [7]

3.4 Extracted Data

We have downloaded the extracted feature from the seed database site. In the extracted feature folder, there are 45 .mat file. We used 40 mat files for the training the system model and 5 mat files for testing the system model [8].

Forming training and testing data: There are 15 experiments, 15 subjects and each subject attended 3 sessions of 15 experiments.

Means 1 subject have seen 45 videos.

45 mat files contain

15 subjects = 15 experiments = 15 recordings (trial 1)

15 subjects = 15 experiments = 15 recordings (trial 2)

15 subjects = 15 experiments = 15 recordings (trial 3)

Total = 45 mat files

Each subject undergo 45 experiments in 3 trials, 15 experiment each. .The data collected is a three dimensional data. Channel * data length * band. (62 channel, 265 data length, 5 bands).

Their experimental results indicated that the gamma band (roughly 30-100 Hz) is suitable for EEG-based emotion classification

3.5 Dimensionality Reduction

The third dimension is maintained as constant means 5 for gamma band. It converts three dimension data into 2 dimensional data. 1 mat file contains data from 62 electrode.

Asm = 54 electrode

Dasm = 27 electrode (pair of electrode)

Dcau = 23 electrode (pair of electrode)

De = 62 electrode

Psd = 62 electrode

Table 1. Extracted features

Extracted Features	
DE	$h(x) = \int_x f(x) log f(x) dx$
DASM	DASM = DE(Xleft) - DE(Xright) (3)
RASM	RASM = DE(Xleft) / DE(Xright);

Table 1 shows extracted features.

Where Xleft and Xright represent the pairs of electrodes on the left and right hemisphere.

Procedure

1. Input mat file from in the extracted folder(total mat files are 45)

2. t=[235;233;206;238;185;195;237;216;265;237;235;233;235;238;206]; % data length for Defrontial entropy feature.

For asm feature

asm_LDS1(4,i,5); %pair of electrode FT7,FT8

asm_LDS1(6,i,5); %pair of electrode T7,T8similarly for dasm and rasm feature

vertical(1,1:1060)=0;

horizontal=horzcat(de5,asm5,dasm5,rasm5); % horizontal concat all the features

vertical=vertcat (vertical,horizontal); % vertical concat

The dimensions of the training database 600*1060. (600= 15*40) The dimensions of the testing database is 75*1060.75=15*51060 = 265*4(maximum data length of the DE, ASM,DASM,RAMS is 265).

Table 2. Procedure

```
a=t(1);
b=a;c=a;d=a;e=a; % where abc is the mat file
for i=1:a
   de2(1,i)=abc.de_LDS1(15,i,5);
end
for i=1:b
   de2(2,i)=abc.de_LDS1(23,i,5);
end
for i=1:c
   de2(3,i)=abc.de_LDS1(24,i,5);
end
 for i=1:d
   de2(4,i)=abc.de_LDS1(32,i,5);
end
for i=1:e

de1(1,i)=((de2(1,i)+de2(2,i)+de2(3,i)+de2(4,i))/4);
end  %take average fo video 1,similarly for video 2 and upto 15
```

No of Electrode	Type
15	FT7
23	FT8
24	T7
32	T8

Table 2 represents procedure of dimensionality reduction.

ASM stands for asymmetry feature that is the combination of DASM and RASM. Total frequency band means that features in all the five frequency bands are used to train and test the model. The training data and the test data are from the different sessions of the same experiment. Experiments 1 - 6 refer to the first experiment of subject 1 6, and experiments 7 - 12 refer to the second experiment of subject 1 - 6, respectively (the same below). All the features used here had been smoothed by LDS, and SVM models were applied as classifiers. As we can see from the table, Gamma frequency bands perform better than other frequency bands. And it is obvious that the accuracies of classifiers trained with features calculated using DE (DE, DASM, RASM, and ASM) are higher than those trained with traditional ES features. This result confirms that the emotional states related to EEG in Gamma frequency band more closely than other frequency bands. It can be implied from this result that DE is more suited for EEG-based emotion classification. [4].

4. EMOTION CLASSIFICATION MODEL

A class is assigned to a set of features extracted from the signal in the classification stage. Every Classification technique has its own advantage and disadvantage. The choice of classifier normally depends on various factors leading to type of data and sample size. In this paper, extracted features are classified using Support Vector Machine (SVM) with linear and Radial Basis Function (RBF) and KNN. Experimental results show that the proposed system has a high classification accuracy of 98.67% with KNN.

4.1 Support Vector Machine

It is a very popular supervised learning algorithm .SVM is used to recognize pattern and analyze data. They infer a function or relationship from the given training data and recognize patterns. It is frequently applied in the field of pattern regression analysis and classification.

4.2 K-nearest Neighbor

K-NN classification is an instinctive and simple method of classification used by researchers for the classification of signals. This classifier compares a newly labelled sample means testing data with the baseline data - training data and then gives the decision accordingly. Training data set includes classes. For a given values from data set, k-NN finds the k i.e. closest neighborhood in training data set. Then it assigns a class which frequently appears in its neighborhood. [9].

5. QUANTITATIVE ANALYSIS

Researchers have developed various pattern recognition techniques to detect human emotions. M.Murugappan et al. [10]] achieved a maximum accuracy rate of 79.174 using KNN. Viet Hoang Anh et al. [11] proposed a system which employed Russell's circumflex model which could predict emotions with an accuracy of 70.5%. By using two layered Arousal-Valence model and fractal dimension based algorithm, Berkman et al. [12] achieved an accuracy of 43%. In the "EEG-based emotion classification using deep belief networks." By Zheng, Wei-Long, et al they use advanced deep learning models to classify only two emotional categories (positive and negative) from EEG data. They trained a deep belief network (DBN) with differential entropy features extracted from multichannel EEG as input. They achieved average accuracies of SVM, and KNN as 85.67%, 84.08%, and 69.66%, respectively [13]. Following are the results which we obtained by Support vector machine classifier using linear kernel, radial basis function and k-nearest neighbors classifier.

Table 3. SVM analysis

Classifier	kernel	Values	Accuracy
SVM	Linear	Linear	97.3333
	rbf	sigma	
		0.1	33.3333
		0.5	36
		1	41.3333
		2	62.6667
		3	82.6667
		4	85.3333
		5	88
		7	89.3333
		9	89.3333
		11	89.3333
		13	88
		15	88

Table 3 represents experimental results of calculation of accuracy by Support vector machine using Linear kernel and rbf.

Table 4. KNN analysis

	Value	Accuracy	Value	Accuracy
KNN	K	Accuracy	K	Accuracy
	2	90.66667	14	97.33333
	3	94.66667	15	97.33333
	4	96	16	97.33333
	5	94.66667	17	96
	6	96	18	96
	7	98.66667	19	96
	8	97.33333	20	94.66667
	9	97.33333	21	94.66667
	10	97.33333	22	93.33333
	11	96	23	94.66667
	12	97.33333	24	94.66667
	13	98.66667	25	94.66667

Table 4 represents experimental results of calculation of accuracy by KNN

Table 5. Comparative analysis

Classifier	Accuracy
SVM(Linear)	97.33
SVM(sigma=9)	89.33
KNN (K=13)	**98.67**

Table 5 represents comparative analysis.

Table 6. SVM- Linear accuracy plot

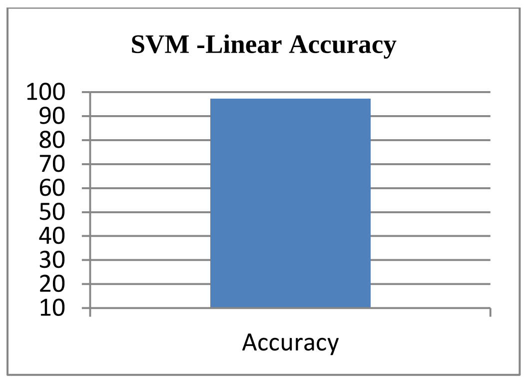

Table 6 represents plot of accuracy result by SVM.

Table 7. KNN accuracy plot

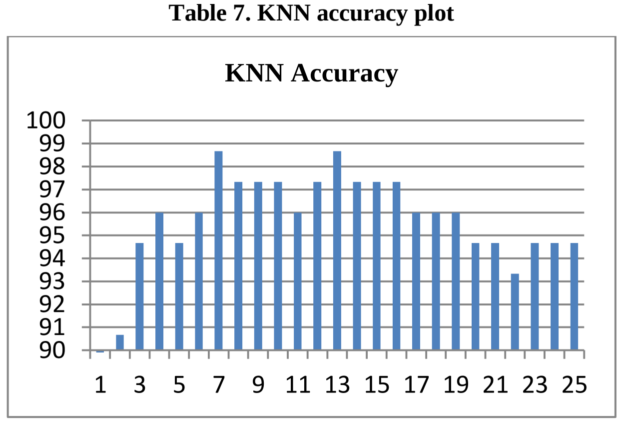

Table 7 represents plot of accuracy result by KNN.

Table 8. Comparative accuracy of the classifier plot

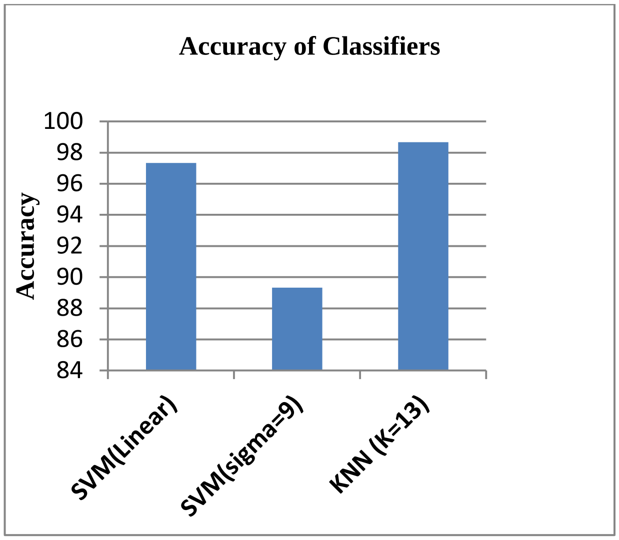

Table 8 represents Comparative accuracy of the SVM and KNN machine learning classification techniques.

6. CONCLUSION

EEG signal analysis is gaining popularity in the field of neuroscience, brain-computer interface and physiological evaluation. Accurate analysis will be helpful to recognize emotions and emotion related disorder. Applications can be extended up to teaching robots, fast identification of disease in medical applications and providing way of communication to mentally challenged people. Experimental results show that the proposed system has a high classification accuracy of 98.67% with KNN at K=13. For future work, more categories of emotions will be studied, and we will evaluate extending the generalization of our proposed approach for extracting features and labelling the data.

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