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Emotion Detection Using EEG Signal Analysis

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***Abstract*— Emotion has an important role in interaction and communication between people. In this paper, we recognized the emotions by using EEG signal with different feature extraction: power, entropy, variance, standard deviation, power spectral density are used, and in classification methods support vector machine and navie bayes classifiers are used. In this work, we used SEED dataset to detect emotions. The EEG signals of 15 subjects are saved in separate file and in this 15 experiments are perform in each 1555 experiments. Objectives and contributions of this system are: to recognize emotions using efficient techniques, and to get the emotions without flaws.**

***Keywords*— EEG data, SEED dataset, Support vector machine and navie bayes classification methods.**

I. Introduction

A. Emotions

Emotion is a mental state and an affective reaction towards an event based on subjective experience [1]. It is essential to the human's daily communication and behaviors. Normally, we identify others' emotions by their facial expressions, voice or body language. For neuroscience, researchers aim to find out the neural circuits and brain mechanisms of emotion processing. This emotion is essential to the daily human communication and behaviors. Emotion is a psycho-physiological process that affects the behavior of an individual with respect to a particular situation, and plays an important role in human communication. Emotions are affect the responses of many types of biological systems in which including muscle, facial expressions, and voice, activity of the Nervous System [2] [3]. For psychology, there exist many basic theories of emotion from different researchers and it is important to build up computational models of emotion. For computer science, we focus on developing practical applications such as estimation of task workload [4] and driving fatigue detection [5]. The detection and modeling of human emotions are the primary studies of affective computing using pattern recognition and machine learning techniques. Although affective computing has achieved for emotion recognition the development in recent years, there are still many open problems to be solved [6], [7] developing practical applications such as estimation of task workload [4] and driving fatigue detection [5]. The detection and modeling of human emotions are the primary studies of affective computing using pattern recognition and machine learning techniques. Although affective computing has achieved for emotion recognition the development in recent years, there are still many open problems to be solved [6], [7]

B. Electroencephalography (EEG)

The term Electroencephalogram or Electroencephalography derived from the concepts of

Electro- this word referring to registration of electrical activities of the brain,

Encephalo- this word referring to the emission of signals from the head, and

Gram (or Graphy) - which is referring to drawing or writing.

Therefore these three terms are combined to frame Electroencephalogram to denote the electrical and neural activity of the brain.

EEG uses the electrical activity of the neurons inside the brain. It is one of the most commonly used methods to record the brain signal. EEG regarded as direct and simple invasive method to record the brain electrical activity, which is represented as voltage fluctuation from current flow within the neurons of the brain.

C. Relation between Emotion and EEG Signal

The EEG data could also used complement to emotion data, which is collected from voice or facial expression to improve the emotions recognition rates. These EEG signals are constantly emitted for emotion recognition. EEG signals are also helps to improve the quality of life of patients with brain disorders.

D. EEG Signal Generation

The EEG signal is the current measured between the dendrites of nerve cells in the cerebrum region of the brain. This current consists of electric field detected by electroencephalography (EEG) equipment and the magnetic field quantified by electromyogram (EMG) devices [8]. The brain structure is divided into three regions, first is cerebrum, second is cerebellum and third is brain stem. In this cerebrum region defines the initiation of movement, state of mind and conscious sensation. Second brain structure is cerebellum region in brain structure plays a role in voluntary actions like movements of muscle. And the brain stem region which controls the respiration functioning, heart regulation, and neural hormones [8], [9]. Therefore it is clear that the EEG signals are generated from brain and it can determine the status of whole body and brain disorders [8], [9].

E. Frequency Bands of Signals

Most of EEG waves ranges from 0.5-500 Hz, however following five frequency bands are clinically relevant: (i) delta band, (ii) theta band, (iii) alpha band, (iv) beta band and (v) gamma band.

i. Delta band:

The delta band is the frequency band, its frequency is up to 3Hz. Delta band activity is mainly seen in deep sleep.

ii. Theta band:

The theta band gives the frequencies between 4Hz and 7Hz. This theta band activity can be observed with drowsiness or meditation.

iii. Alpha band:

The alpha band is also called as `basic rhythm' and contains the frequencies between 8Hz and 12Hz. This alpha band seen when people are awake, and it is known to be more apparent when eyes are opened.

iv. Beta band:

The beta band gives the frequencies between 13Hz and 30Hz. This Beta band is apparent with active thinking or concentration in EEG signal.

v. Gamma band:

The gamma band contains frequency from 30 Hz and up. This rhythm is sometimes defined as having a maximal frequency around 80 Hz or 100 Hz. It is associated with various cognitive and motor functions.

II. RELATED WORK

Nowadays, the EEG-based emotion recognition researches are highly active. The goal of these emotions detection is to find the suitable technique and giving a good result.

Soleymani et al.[10] proposed a user independent emotion recognition method with EEG and eye gaze data and they used logarithms of the power spectral density as EEG features .

Duan et al. [11] firstly introduced differential entropy to emotion recognition and compared discriminative properties of different features. They used SVM as a classifier and achieved average accuracy of 81.17% for emotions recognition.

Wang et al.[12] systematically compared three kinds of EEG features (power spectrum feature, wavelet feature and nonlinear dynamical feature) for emotion classification. They proposed an approach to track the trajectory of emotion changes with manifold learning.

Inan Guler et al. [13] proposed a multiclass support vector machine (SVM) with the error-correcting output codes for the multiclass electroencephalogram (EEG) signals classification problem. Classification was performed in two stages; in the first stage features are extracted by computing the wavelet coefficients and the Lyapunov exponents, in stage two classifications is done using the classifiers on the extracted features.

Poornendu Prakash Tiwari et al [14] investigated the use of the Naïve Bayes classifier and Back propagation neural network for the given signals. Naïves Bayes classifier performed comparatively better.

Webb [15] carried out a comparative study of nine discretization methods and found that the lazy discretization, nondisjoint discretization and weighted proportional k-interval discretization methods can help the naïve Bayes classifier achieve better classification performance.

III. OBJECTIVES & OVERVIEW OF THE PROPOSED MECHANISM

A. Objectives

The goal of this system is it intended to recognize emotion from offline EEG signals. The input of the system consists of EEG signals and the output of the system will be some indicator about what emotion the subject experiences. The main objective of this thesis is to analyze the acquired EEG signals using signal processing tools and classify them into different classes.

Objectives and contributions in proposed system are: to recognize emotions using efficient techniques, and to get the emotions without flaws. This work detects the emotion using SVM and NBC classifier.

B. Overview ofthe proposed Mechanism

The EEG data are analyzed by using several procedures, in which including the EEG signal preprocessing, extraction of feature, and classification feature are used to find the emotions. In this proposed system input of EEG signal is given to the preprocessing block. Preprocessing removes the noisy EEG signal and given to the feature extraction block. For extracting the feature various methods are used. After that features are selected from feature selection block. After feature extraction the signals are classified into various classes using various classifiers. For classifying the feature, support vector machine and navie bayes classifier methods are used.

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a. *Input*

The input of the system consists of measured EEG signal. Firstly the EEG signal is an input of this proposes system, which is given to the preprocessed block.

b. *Preprocessing*

Raw EEG data is generally a mixture of environmental noise. After the data collected, the preprocessing block is remove the all unneeded noise and artifacts from the signal, and only keeping the interesting part of the signal, the brain activity. In this preprocessing, 15 preprocessed EEG signal is already saved, known as test EEG signal. Bandpass filter is used to remove the noise from this EEG signal. A bandpass filter frequency range from 0 to 75Hz.

c. *Feature Extraction*

Transforming the input data into the set of features is called feature extraction methods. For the emotion recognition, if the features extracted are carefully chose it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

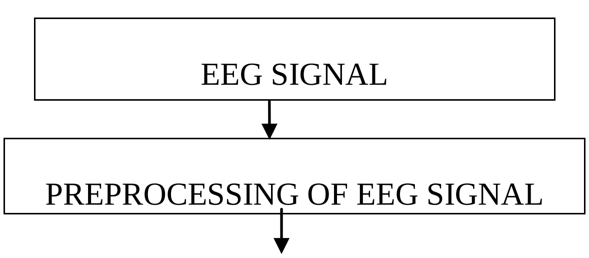
Different types of feature extraction for emotion recognition methods are used to find the features of EEG signal which are as follows:

i. Entropy

Entropy is the statistical descriptor of the variability within the EEG signal and is a strong Feature for emotion extraction. It is a numerical measure of the randomness of a signal. It can act as a feature and used to analyze psychological time series data such as EEG data. The Entropy is the statistical descriptor of the variability within the EEG signal and is a strong feature for emotion classification.

ii. *Variance*

Variance is defined as a measure of the dispersion of a set of data points around their mean value. Basically variance is a statistical parameter which gives information about data distribution from its mean or expected value. It is the one type of probability distribution which measures how far a set of numbers get spread out [16].



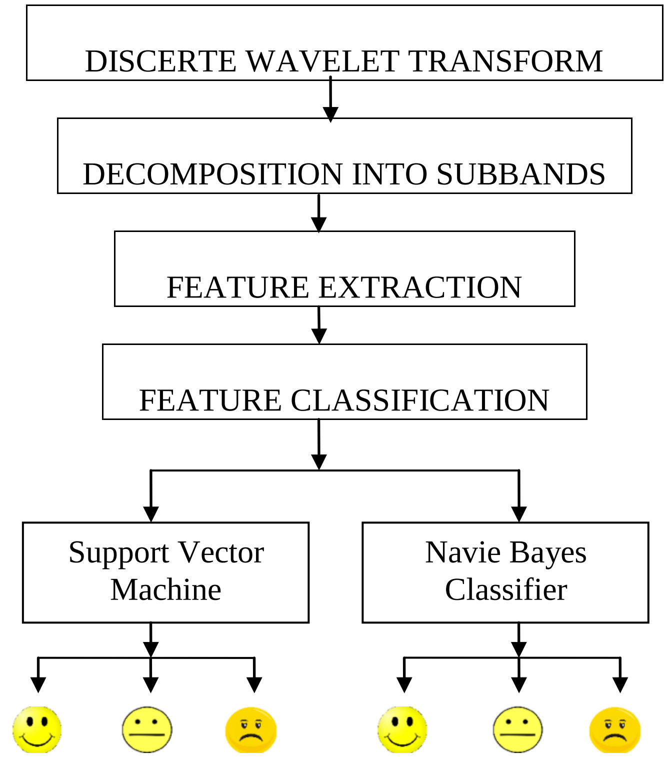


Fig.1 Flow diagram of EEG emotion detection

iii. Power

Power is Measure of the amplitude of EEG signal. Power is also defined as the amount of energy consumed per unit time. For MKS system, joule per second (J/s) is the unit of power, known as the watt. Energy transfer can be used to do the work, therefore the power is also the rate at which this work is performed.

iv. Standard Deviation

Standard deviation shows how much variation or ‘dispersion’ exists from the mean for features extraction. Standard deviation indicates that the data points tend to be very close to the mean, whereas the high standard deviation indicates that the data points are spread out over a large range of values [17].

v. Power spectral density

In order to select the correct features of the EEG signal related to the mental activity, there is proposed the use of parametric methods for power spectral density estimation for feature extraction. Power spectral density of the signal, using parametric methods, is computed as the frequency response of an autoregressive model of the signal,which is based on previous values of the signal. In [18] was found that the order of this model is very important to obtain an accurate estimation of the spectrum.

d. Feature classification

The key task of this stage is to choose an efficient method to provide accurate predicted results for emotion recognition. Each classifier requires an initial phase in which it is trained to perform a correct classification and a subsequent phase in which the classifier is tested. There are two different types of classification methods are used in this paper:

i. Support Vector Machine (SVM)

A support vector machine (SVM) [19] is a concept in computer science for a set of related supervised learning methods that analyze data and it recognize the patterns of emotions, so it used for classification and regression analysis of signals. A support vector machine [20] constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space and which is used for classification of emotions, and regression also. This separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class, therefore it is also called as functional margin. Therefore in general the larger margin of hyperplane there is lower the generalization error of the classifier.

ii. Navie Bayes Classifier (NBC)

The extracted features were used as an input to the classifier to classify the emotions in high valence and low valence using the Naïve Bayes classifier. This Naïve Bayes algorithm is based on conditional probabilities. It used Bayes' theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data. This classifier finds the probability of an event occurring given the probability of another event that has already occurred [21].

e. Dataset

To detect the emotions seed dataset (SJTU) is used [21]. To investigate critical frequency bands and channels, EEG-based emotion recognition models for three emotions: positive (happy), neutral (calm) and negative (sad). In this EEG dataset 15 subjects are already saved. and Each subject performs the 15 experiments. it train trained with differential features extracted from multichannel EEG data. The three different EEG-based emotions are recognized by this dataset. These three emotions are: positive, negative and neutral. Positive emotions shows the happiness, negative emotions shows sadness, and neutral emotion shows there is no emotion.

V. PERFORMANCE EVALUATION

The main objectives of this work are: a) to improve the emotion detection result efficiently, b) to improve the result of classification methods, c) to improve the result of support vector machine for emotion detection, d) to improve the result of navie bayes classifier for emotion detection. The different emotions are compared by different classifiers, and compare the accuracy of these classifiers.

After completing training parts, the EEG signals are selected from testing part. When EEG signal is selected, then output of test emotion is displayed. It shows in figure 2.

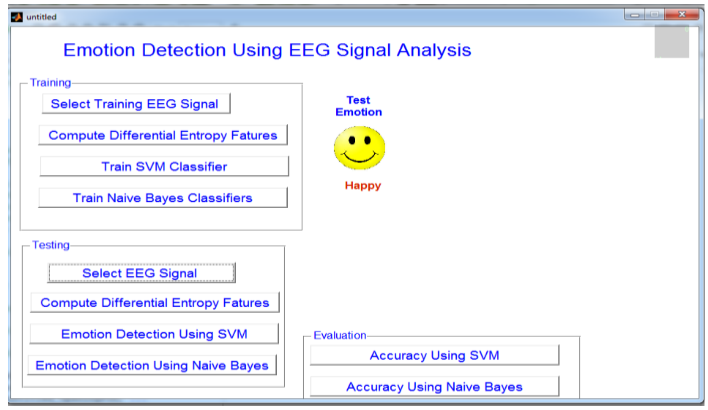


Figure.3 EEG signals are selected

After selecting the EEG signal, features are computed by using different feature extraction methods. After that, this test emotion is classified by the support vector machine classifier. It is shown in figure 4.

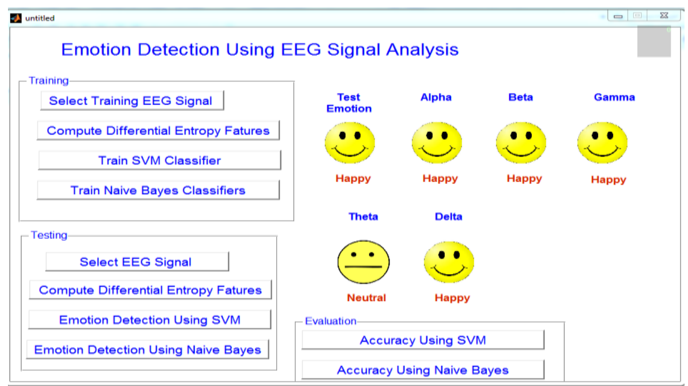


Figure.2 emotion detection using SVM classifier

After that, those features are tested by using navie bayes classifier, which is shown in figure 4.

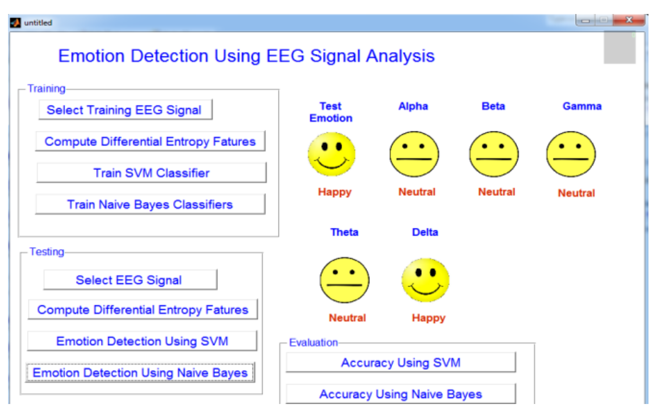


Figure.4 Emotion detection using NBC classifier

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After classifying the emotion by using support vector machine, and navie bayes classifier, the accuracy of SVM and NBC classifier is calculated:

Table I

Types of Signal	Accuracy of Signal
Alpha	59.1111%
Beta	62.2222%
Delta	85.7778%
Gamma	46.6667%
Theta	26.6667%

Table 1 shows accuracy of Support Vector machine classifier.

Table II

Types of Signal	Accuracy of Signal
Alpha	68%
Beta	85.7778%
Delta	86.6667%
Gamma	73.3333%
Theta	73.3333%

Table 2 shows the accuracy of navie bayes classifier

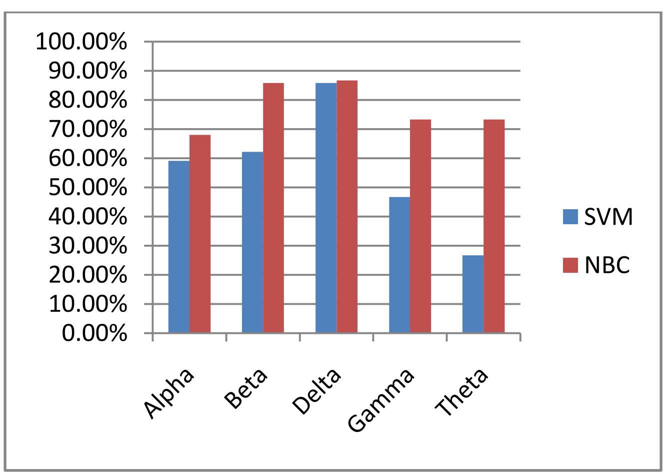

Figure.5 Accuracy with respect to EEG signal

VI. CONCLUSION

This thesis focused on construction of a program to recognize emotion using EEG signals. We have gathered theoretical information about the human brain and about emotion. Electroencephalography (EEG) seems to be the most practical way of measuring brain activity, because it is cheap and easy to use. Several researchers have shown that it is possible to measure emotional cues using EEG measurements. In this emotion research, a distinction is made between three dimensions of emotion.

This project focused on the various techniques for emotion classification using EEG signal analysis, SEED database for EEG is used to recognize emotions using efficient techniques, and to get the emotions without flaws. It recognized the three different emotion which are happy (positive), sad (negative) and calm (neutral).We receive the emotion result matched with the preprocessed EEG data through the different EEG alpha, beta, gamma, theta, delta signal. For separating this signal by using wavelet transform with finding those feature with the help of different features extraction methods. These methods are normalized power, entropy, variance, standard deviation and power spectral density. For efficient recognition support vector machine and navie bayes classifier are used. To detect the emotion using these classifier methods, navie bayes classifier gives better accuracy than support vector machine from delta feature.

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