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A Novel Approach towards Recognizing Emotions from EEG Signals

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ABSTRACT

Emotion can be recognized using different methods, among which the most commonly used method is emotion recognition from facial expressions. But this cannot be used in an effective way since persons can mimic emotions. Recognition of emotions from EEG is an effective method for emotion recognition since it cannot be manipulated intentionally. The proposed emotion recognition technique uses Support Vector Machine (SVM) for classifying emotions into eight emotional categories. A new emotional model is also proposed using Valence- Arousal- Dominance values. The proposed method is helpful in identifying the emotions of normal persons as well as paralyzed patients. Recognizing emotions of paralyzed patients will help a lot in improving Their Treatment.

Keywords : Arousal, Deap, Dominance, DWT, EEG, SVM, Valence

I. INTRODUCTION

Emotions are mental responses towards a stimulus experienced by a person. Emotions play an important role in communication between human beings. Emotions can be expressed either expressed verbally through emotional vocabulary or non-verbally through vocal tones, gestures or facial expressions. Traditional human-computer interaction systems are deficient in interpreting emotional information and suffer from the lack of emotional intelligence. The goal of affective computing is to fill this space by detecting emotions occurring during human computer interaction and thereby synthesizing emotional responses.

Emotion assessment is often carried out through analysis of users' facial expressions. Emotional expressions refer to any observable verbal or non-verbal behavior that points out a persons' state of mind. From the beginning of emotion analysis, most of the studies have focused on the assessment of facial expressions and speech recognition to determine a persons' emotion. Now, physiological signals are also known to be included in retaining emotional information that can be used for emotion assessment. Physiological signals include signal originating from central nervous system and peripheral nervous system. These signals include Galvanic Skin Response (GSR), Blood Volume Pressure (BVP), Respiration Pattern, Skin-Temperature Pressure, Electromyogram (EMG), Electrooculography (EOG) and Electroencephalogram (EEG).

The proposed system explores the possibility of deriving and classifying emotions based on the processing of EEG signals. A new emotional model was also proposed on this work. The new emotional model is based on the values of valence, arousal and dominance parameters which are calculated using the sub-band frequencies of the EEG signal.

II. RELATED WORKS

Some literature survey has been focused on the preprocessing, feature extraction, feature selection and classification of EEG signals.

O.Sourina, Y.Liu and M.K.Nguyen proposed a method based on the fractal dimensional modal for emotion recognition. They used fractal dimensional values as classification feature for recognizing emotions from EEG signals. According to this method, the new set of time series was developed from the finite set of time series [1].

D.R Chavan, M.S Kumbhar and R.R Chavan derived a relation between the obtained EEG signal and the stress level a person is experiencing. They also derived a relation between the variation in EEG signal while this stress level is decreased by the means of music therapy [2].

N. Zaware, T. Rajgure, A. Bhadang and D. D. Sapkal proposed a method that uses facial expressions for emotion recognition. Here facial curves are used as features for deriving emotions from facial images [3]. A. B. Benke, S. S. Jadhav and S. A. Joshi proposed an emotion recognition method that also uses images as input. Here the classification is based on eye and lip features [4].

The major disadvantage of using images as input is that, only emotion at a particular instance of time can be recognized. That is, real-time emotion recognition is impossible. Also this method cannot be used for recognizing emotions of paralyzed patients. Thus we move on to emotion recognition from EEG signals.

Classification of emotions from EEG signal using deep neural network was proposed by A. Al-Nafjan, A. Al-Wabil, M. Hosny and Y. Al-Ohali. They used a two-dimensional emotional model proposed by Russell. It uses two parameters namely valence and arousal, in order to classify emotions into 4 categories: Excitement, Meditation, Boredom and Frustration [5].

III. PROPOSED SYSTEM

3.1 EMOTIONAL MODEL

Generally emotions are represented using dimensional model which proposes that emotional states can be accurately represented by a small number of underlying affective dimensions. Dimensional models are incorporated with valence and arousal values.

Valence refers to the degree of 'pleasantness' associated with an emotion. It ranges from unpleasant: sad, stressed to pleasant: happy. Whereas, arousal refers to the strength of experienced emotion, i.e., inactive: bored to active: alert or excited [5]. Dominance parameter refers to the power of emotion being experienced by the person. If the emotion is uncontrollable (excitement, nervousness) then the dominance value will be negative. If the emotion is controllable then the dominance value will be positive (happiness, relaxed). Figure 3.1 shows the newly proposed three dimensional model using three parameters: valence, arousal and dominance.

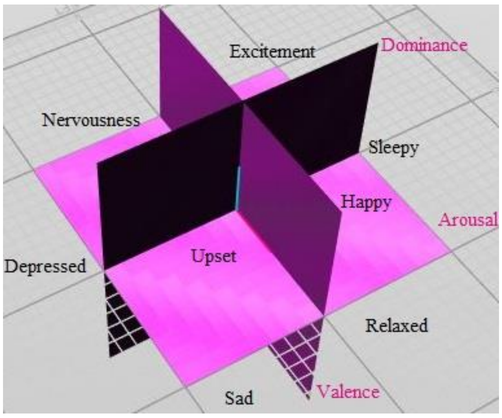
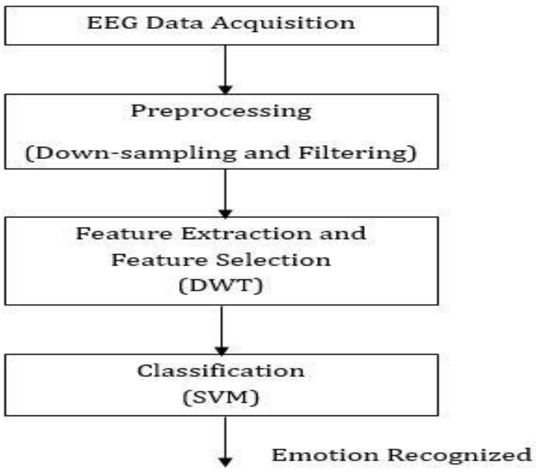


Figure 3.1. 3D Emotional Model

3.2 Data Acquisition

DEAP Dataset for emotion analysis is used in the proposed work. DEAP database was prepared by Queen Mary University of London. The database contains physiological signals of 32 participants. It was created with the goal of creating an adaptive music video recommendation system based on users' current emotion [6]. The dataset consists of two parts:

- ✓ The ratings from an online self-assessment where 120 one-minute extracts of music videos were each rated by 14-16 volunteers based on arousal, valence and dominance.
- ✓ The participant ratings, physiological recordings and face video of an experiment where 32 volunteers watched a subset of 40 of the above music videos. EEG and physiological signals were recorded and each participant also rated the videos as above. For 22 participants frontal face video was also recorded.



Figutr 3.2. Overview of the Proposed System

This dataset was used for EEG acquisition for emotion analysis and classification.

3.3 Preprocessing

Signal preprocessing is done in order to reduce noise present in the captured signal. The EEG data obtained from the DEAP dataset is already preprocessed by down sampling it to 128 Hz. The signal is filtered by passing it through a band-pass filter of frequency range 4 to 40 Hz.

3.4 Feature Extraction

Feature extraction is the method of reducing the dimensionality of the features. The characteristics of the original signal is represented by the extracted features. EEG signal features can be extracted in two different domains: Time domain and Frequency domain.

Time domain features consists of statistical calculations. These features include mean, median, mode, standard deviation, etc.

Frequency domain features include power values of each channel from the frequency band. These features consists of band power, fractal dimension, energy etc.

Discrete wavelet transform is used for feature extraction from EEG signal. Db8 wavelet transform is used for decomposing EEG signal into corresponding sub-bands. Alpha, beta, gamma, delta and theta signals are extracted from the EEG signal.

3.5 Feature Selection

Feature selection is the process of selecting relevant features by eliminating features with little or no predictive information. It is used to find a feature subset that has higher classification accuracy and used to reduce the training time. The features used in emotion recognition are sub-bands extracted from EEG signal and band power of each channel.

3.6 Classification

The classification of EEG signal is done using Support Vector Machine using multiclass classification. Recent studies proved that alpha and beta signals play a very important role in emotional analysis. Thus, we concentrate on alpha and beta signals for emotion classification. The valence and arousal values are calculated using the equations proposed in [5].

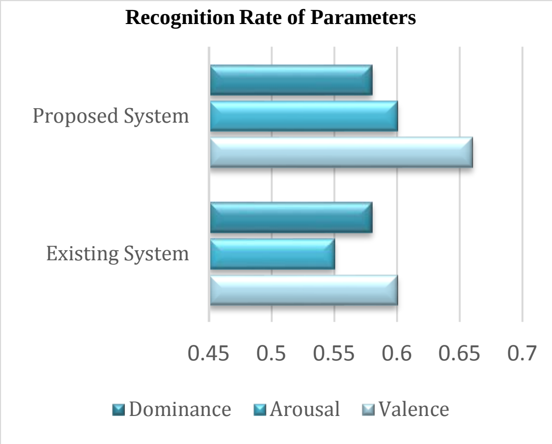
Training of EEG signals is done using the participant ratings available in the DEAP dataset. Testing phase includes classification of EEG signals to different emotions based on the trained data.

IV. PERFORMANCE EVALUATION

The performance of the proposed model was evaluated by comparing the amount of features used in the proposed system and that used in [7].

According to the recognition rate of valence, arousal and dominance values the performance of the system was estimated. It was found that the recognition rate of the proposed system is better than the system that used peripheral signals like Blood Volume Pressure, Electromyogram, Galvanic Skin Resistance measures.

Table 3.1. Comparison of Recognition Rate



V. CONCLUSION

The proposed system is based on emotion recognition from EEG signals. Using EEG signals helps to identify the emotions of paralyzed patients as well. Thus it will help a lot in the treatment of paralyzed patients. Normal persons can mimic emotions using facial expressions. Hence, using EEG signals instead of facial expressions helps to recognize the actual emotion a person is feeling.

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