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Research Paper

Detection of human emotions using features based on discrete wavelet transforms of EEG signals

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Abstract

Affective computing is an emerging area of research in human computer interaction where researchers have developed automated assessment of human emotion states using physiological signals to establish affective human compute interactions. In this paper wepresent an efficient algorithm for emotion recognition using EEG signals for the data acquired by audio- video stimuli. The desired frequency bands are extracted using discrete wavelet transforms. The Statistical features, Hjorth parameters, differential entropy and wavelet features are extracted. Artificial neural networks, Support Vector Machine (SVM) and K- nearest neighbor are used on the extracted feature set to develop prediction models and to classify into four emotion states like clam, happy, fear and sad . These Artificial neural network models are evaluated on the acquired dataset and emotions are classified into four different states with over all accuracy of 86.36%. The classification rate of calm, happy, fear and sad states are 90.9%, 63.63%, 90.90 and 100 % respectively.

Keywords: *Affective Computing; EEG Signals; DWT; ANN; SVM; KNN.*

1. Introduction

The Brain Computer Interface (BCI) systems are used to enable unblessed people to operate devices and applications through their mental activities [1]. In the BCI techniques the Electro-Encephalogram signals are acquired from a subject's brain and the knowledge is extracted from the acquired signal to determine the intention of the subject. BCI system has a wide range of applications like assisting devices for physically challenged persons, Emotional stress recognition, Detecting epilepsy or detection of epileptic seizures, Classification of abnormal brain activity etc. One such application is Emotion recognition through EEG is used largely in the field of affective computing. The BCI systems involves in accessing brain activity which can provide significant insight into the user's emotional state. This information can be used to provide the user with more options of controlling BCI through affective modulation. [2].
Emotions play an important role in daily life human life for human interaction, decision making and human intelligence. Emotion classification aims to develop and improve the intellectual brain computer interface (BCI) system. From the psychological aspects, the emotion states can be represented using discrete model or dimensional model. In discrete model, a set of finite number of discrete states are used to define the emotion states. They include anger, fear, disgust, happiness, surprise and sadness or combination of the above. The emotion states are defined in spatially with basic dimensions such as valence and arousal and the emotion states are interpreted through the levels of each dimension. The application of emotion classification includes many areas in medical science like as neurology and psychology, entertainment, e-learning, marketing etc.
The change in emotion state of human can be detected by a number of ways which includes speech, body postures, facial expressions, the central nervous system, autonomic nerve physiological activities etc. People can deliberately hide emotion states on some social occasions when detected using speech and facial expressions. Therefore human emotion through physiological signals became popular. Out of physiological signals, use of electroencephalogram (EEG) signals for emotion recognition has become popular. EEG is a non-invasive method to record the electrical activity of the brain from the scalp by placing the electrodes as per the standard 10-20 International system. The recorded waveforms show the cortical electrical activity of the subject. Changes in inner emotion states are directly reflected in EEG signals.
In this paper, an efficient algorithm is developed to recognize 4 emotion states calm, happy, fear and sad using EEG signal acquired by the defined protocol. Our aim is to improve the accuracy rate of the classifier using the combination of time domain, time–frequency domain features.
This paper is organized as follows: Section II briefs out the related work for emotion recognition. In Section III the proposed methodology, extracted features and classifiers are explained in detail, followed by the performance of our proposed system in Section IV. The conclusion is given in Section V.

2. Related work

Raja et. al. [4] proposed a LPP-based feature extraction algorithm to detect four emotion states happy, calm, sad and scared using

IAPS database. EEG signals were acquire using Emotive epoch headset with 16 channels (AF3, T7, CMS, P7, F7, F3, FC5, O1, O2, P8, DRL, T8, FC6, F4, F8, and AF4). ERP method along with Band pass filtering is used to remove artifacts. Statically features and frequency domain features of each band were extracted and applied to KNN and SVM classifiers. Their average recognition rate of all the subjects was 55% and 58% respectively. Jingxin Liu et. al. [5], used time domain, frequency domain, time-frequency domain and multielectrode feature on DEAP dataset EEG data. To classify emotions into valance and arousal states they used KNN and RF. The performance accuracy of the classifiers for valance and arousal states is 66.1% and 65.7% respectively and by using MMR, the performance was increased to 71.23% and 69.97% respectively.
Ateke et. al. [6], Recurrence Quantification Analysis (RQA) is done, using MATLAB Toolbox for EEG signals used from eNTERFACE 06. They were able to recognize arousal/valance with the rates of 73.06%, 62.33% and 45.32% for 2, 3, and 5 classes, respectively. John et. al. [7], proposed a novel approach that combines minimum-Redundancy Maximum-Relevance (mRMR) based on feature selection tasks and SVM kernel classifiers for emotion recognition. Bhatti et.al. [8], used audio tracks to elicit emotions using a single channel EEG headset (Neurosky). Thirteen extracted features from different domains are classified into four different emotions (happy, sad, love and anger) using k-NN and SVM classifier. Tong et.al. [9], proposed a novel deep learning framework to recognize emotion states for SEED database using differential entropy feature which is calculated for five bands. Their algorithm classified for 4 kinds of emotion states like anger, happiness, sadness and surprise with an accuracy rate of more than 90%. Adrian et.al. used time-frequency and wavelet transform features for emotion recognition using EEG signals. They acquired data by placing the electrode at FP1 and FP2 and two time-domain features, two frequency-domain features, as well as discrete wavelet transform coefficients were extracted. The selected features were applied on ANN classifier and their classification rate was 81.8 %
To improve the accuracy of the classifier, combinations of the above feature extraction methods have been proposed. To acquire data the protocol is developed on the basis of DEAP [11] and SEED [12].

3. Methodology

From the survey it is seen that to detect emotions through EEG some have used available databases like DEAP data base, SEED, etc. and some have acquired EEG signals through their experiment setup. They have extracted features and using neural networks, SVM and KNN classifier to classify into discrete or dimensional emotion states. The classification accuracy is up to 80 %. In this our proposed work we aim to improve the classification accuracy. The proposed methodology is shown in figure 1.

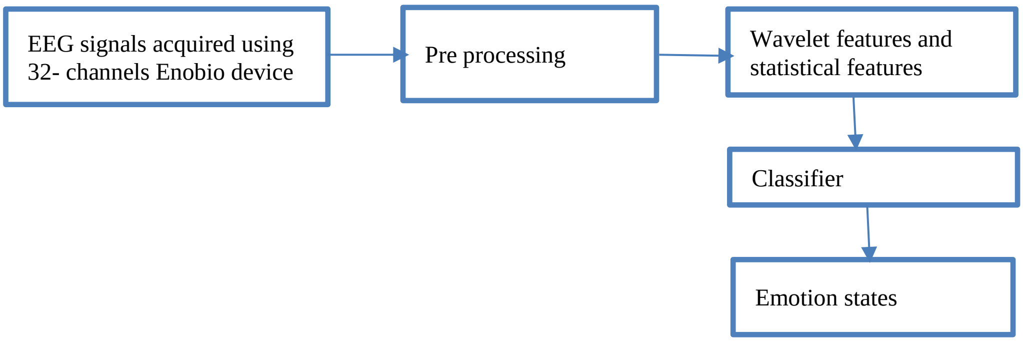

Fig. 1: Proposed Methodology.

3.1. Experiment set up

The EEG signals were acquired from 37 healthy subjects aged between 20 to 45 years (mean age: 35). The subjects involved were the undergraduate students, postgraduate students and even research scholars of SGGSIT, Nanded. A 32 –channels wireless EEG device Enobio with sampling rate of 500 Hzs is used for data acquisition. Since the prefrontal cortex plays signicant role in impulse control and in many other emotions The electrodes used for the setup are FP1, FP2, FC1, FC2, FC5, FC6, F3, F4, F7, F8, FZ, AF3, AF4, CZ, CP1, CP2, CP5, CP6, C3, C4, PZ, P3, P4, P7, P8, PO3, PO4, O1, O2, FPZ, T7, T8. The CMS & DRL are used as reference electrodes. Before starting the experiment, the procedure of the protocol was e made familiar to the subjects. After connecting the electrode cap, the subject is allowed to relax for 60 sec. Four video clips are used to elicit four emotion states like calm, happy, fear and sad. The experiment procedure for data acquisition using audio - Videos is shown in Figure 2. The experiment procedure is explained and instructions are as follows.

- The four stages are:

1) Relaxation stage [RS]: In this set-up, the subject is made to relax by closing his/ her eyes for 60 sec.
2) Base line: The trail No. is displayed.(2 sec)
3) Emotion state: In this set up, the subject is made to watch videos for 2 to 4 mins duration.
4) This is followed by self-assessment and relaxation 1 min where the subject is asked to close his eyes.

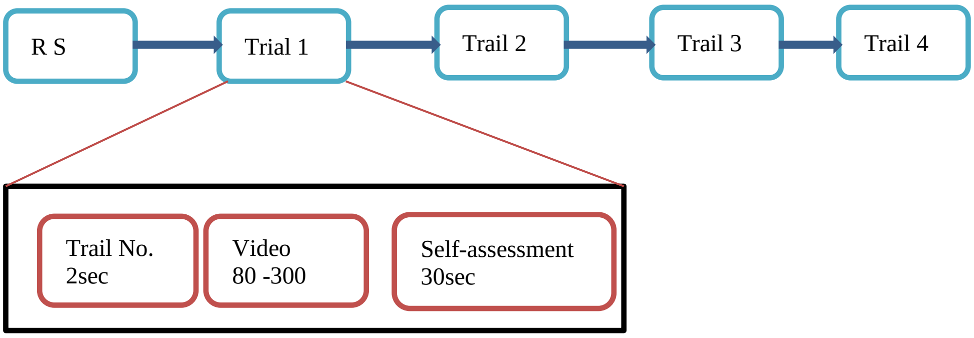

Fig. 2: Protocol for Data Acquisition Using Normal Videos.

3.2. Preprocesing

There are some noises like power line interface, external interference and some other artifacts present in the recorded EEG signals. For removing of noise a 20^{th} order FIR band pass filter with a bandwidth of 1 to 50 Hzs is been used as well as zero has digital filtering is done using the MATLAB command “filtfilt”. The 50Hzs notch filter is used during the EEG recording only to remove power line interface.

3.3. Feature extraction

For the preprocessed data, the features in time domain and time-frequency domain are extracted. It is been found from the literature review that using wavelet transforms gives better resolution in both time and frequency domain as compared with FFT and STFT. Hence Discrete Wavelet Transforms is used to segregate desired frequency bands as shown in Figure 3. To obtain signals in the desired frequency bands delta (1-3Hz), theta (4-7Hz), alpha (8-13 Hz), beta (14-30Hz), gamma (31-50Hz) bands DWT with 4 level of decomposition and wavelet function “db8” is used as shiwn in figure 3. [3] proposed a secure hash message authentication code. A secure hash message authentication code to avoid certificate revocation list checking is proposed for vehicular ad hoc networks (VANETs). The group signature scheme is widely used in VANETs for secure communication, the existing systems based on group signature scheme provides verification delay in certificate revocation list checking. In order to overcome this delay this paper uses a Hash message authentication code (HMAC). It is used to avoid time consuming CRL checking and it also ensures the integrity of messages. The Hash message authentication code and digital signature algorithm are used to make it more secure. In this scheme the group private keys are distributed by the roadside units (RSUs) and it also manages the vehicles in a localized manner. Finally, cooperative message authentication is used among entities, in which each vehicle only needs to verify a small number of messages, thus greatly alleviating the authentication burden.
The wavelet features such as energy spectrum, differential entropy are extracted in each of the five frequency bands. Average energy of each band i.e alpha (e_a), beta (e_b), gamma (e_g), delta (e_d) and theta (e_t) are calculated. Energy Spectrum is the average energy taken in the five bands. Statistical features like Mean, Standard deviation, First difference, normalized first difference, Second difference, normalized second difference, Kurtosis, Hjorth parameter such as complexity and mobility are computed for all the channels

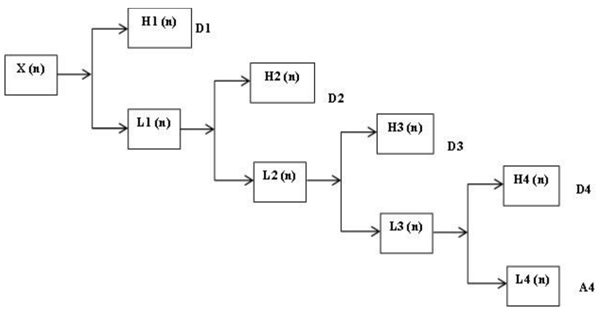

Fig. 3: The Corresponding Frequency Bands for Alpha, Beta, Gamma, Theta and Delta.

3.4. Classification

For classification, artificial neural network using a two-layer feed-forward pattern net network with sigmoid output neurons is used. Since 37 samples are used for developing a training model, 70 % of data samples are used for training reaming are used for testing the performance of the trained network. So 26 samples are used for training the network. The feature vector of size 104 x 736 is applied to three kinds of classifiers Multi-Class Support Vector Machine (SVM), artificial neural networks and K-NN to classify the features into four states.
The neural network classifiers are best for classification of multiple classes using neural pattern recognition. In this paper neural networks toolbox is used to implement neural networks.”nnstart” MATLAB neural network start function is used to develop NN architecture as shown in Figure 4. The network using 10 and 20 nodes in the hidden layers were used. From the features extracted pattern recognition network used 70% of the data is used for training, 15 % for testing and 15% for validation. The overall performance of the network is 86.36%.
The SVM and KNN classifiers are implemented using “Statistics and Machine Learning tool box” available in MATLAB. A 10 fold cross validation is used. The classification accuracy of 80 % obtained for both SVM and KNN classifiers. [10] discussed about a method, Sensor network consists of low cost battery powered nodes which is limited in power. Hence power efficient methods are needed for data gathering and aggregation in order to achieve prolonged network life. However, there are several energy efficient routing protocols in the literature; quiet of them are centralized approaches, that is low energy conservation. This paper presents a new energy efficient routing scheme for data gathering that combine the property of minimum spanning tree and shortest path tree-based on routing schemes. The efficient routing approach used here is Localized Power-Efficient Data Aggregation Protocols (L-PEDAPs) which is robust and localized. This is based on powerful localized structure, local minimum spanning tree (LMST). The actual routing tree is constructed over this topology. There is also a solution involved for route maintenance procedures that will be executed when a sensor node fails or a new node is added to the network.

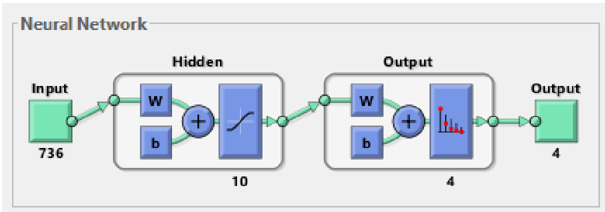

Fig. 4: Neural Network Architecture.

4. Results

In this paper, for 37 subjects data is used for analysis of their emotion states using EEG signals. The 736 features are calculated for 26 subjects so total of 104 x 736 features are applied on 3 different classifiers. With the help of confusion matrix, the results of the various classification processes are calculated and this gives us the accuracy of the model. Ten-fold cross validation is done on training and testing data to obtain the most accurate outputs. The training was done using 70% of the data samples and remaining 30% was used for testing the trained network. So 26 data samples are used for training and 11 data samples are used for testing the trained model. The average classification rate of the network is 86.36%. The trained network classified the test data samples in to four states like calm, happy, fear and sad with an accuracy of 90.9%, 63.63%, 90.90 and 100 % respectively. The confusion matrix of onetest signal is shown in figure 5. The performance of test signals is shown in Table 1.
It is seen that the neural networks classifier provides much better accuracy compared to the multiclass SVM for three emotional states.

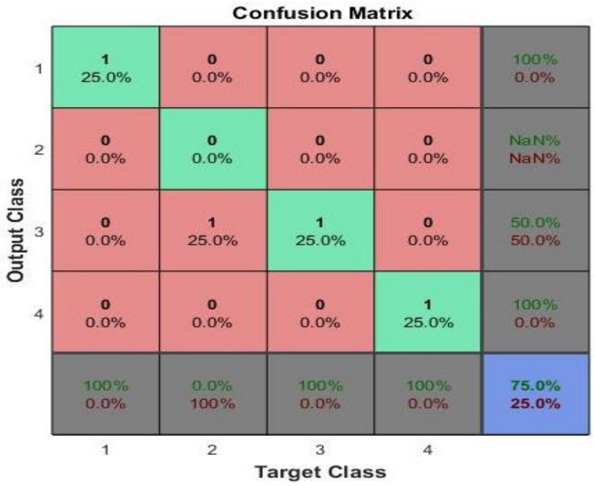

Fig. 5: Confusion Matrix for One Test Signal.

Table 1: Perfomance of Test Data

Subject	Calm	Happy	Fear	Sad	Overall accuracy
1	25	25	25	25	100
2	25	25	25	25	100
3	25	25	25	25	100
4	25	0	25	25	75
5	25	25	25	25	100
6	25	25	25	25	100
7	25	0	25	25	75
8	25	0	25	25	75
9	25	25	25	25	100
10	25	0	25	25	75
11	0	25	0	25	50
Average Accuracy	90.9	63.63	90.9	100	86.36

5. Conclusion

In this paper, a machine learning algorithm using wavelet transforms is developed to detect four emotional states form the acquired data. The combined features from time and time- frequency domain are extracted and are applied to the three types of classifiers. The ANN classifier is further used for testing the data. The classification rates of ANN classifier is 86.36%. The four emotion states were calm, happy, fear and sad were classified with an accuracy of 90.9%, 63.63%, 90.90 and 100 % respectively.

This model works best for the acquired dataset and in the future the model can be tested on various other EEG signals and results are can be compared. Further by combining different classification method and adding more features a robust system to detect emotion states can be developed in order to increase the performance of the network. The different pre-processing techniques can also be applied for better performance of the system. Research can be further extended to find other emotion states given in the literature and also to develop some applications of emotion detection.

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