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Emotion Detection Using EEG Signal Analysis

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Abstract:

This paper focus on various techniques for emotion extraction and emotion classification methods using EEG analysis, and various database for EEG are summarized. In the feature extraction techniques, discrete wavelet transformation, higher order crossing, and short time Fourier transform and mutual information methods are studied. In the feature classification techniques, principal component analysis, linear discriminant analysis, and support vector machine are studied. In this paper, DEAP databases, IAPS and IADS databases, Reading-Leeds database, Belfast database, CREST-ESP database, and CREMA database EEG database, this various databases are also studied for detection of emotion using EEG signal.

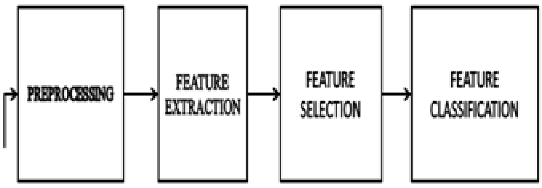
I. INTRODUCTION:

Emotion is a mental state and an affective reaction towards an event based on subjective experience [1]. 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 affect the responses of different biological systems, including facial expressions, muscles, voice, activity of the Nervous System and the Endocrine System [2] [3]. Electroencephalogram (EEG) is one of the methods to recognize the emotion. Additionally, EEG-based emotion recognition could make the human computer interface more intelligent and they are applied in many fields such as E-learning, games and marketing also.

Electroencephalograph (EEG) was first recorded by Berger in 1929 by externally attaching several electrodes on the human skull [4]. Various discrete categorizations of emotions have been proposed in [5] and [6]. Other dimensional scales of emotion have also been proposed, like the valence-arousal scale by Russell [7]. Each emotional state in valence- arousal space can be placed on a two-dimensional plane with arousal and valence as the horizontal and vertical axes. Emotion assessment is carried out through the analysis of a user’s emotional expressions and/or physiological signals. Therefore most of the studies on emotion assessment is focused on the facial expressions for analysis and speech to determine a person’s emotional state. This emotion can be expressed either verbally through emotional vocabulary or by expressing nonverbal cues such as intonation of voice, facial expressions, and gestures. A major challenge in emotion recognition from EEG signals relates to interpersonal variance in emotion induction and recognition also. It is not in general that which features are most appropriate. Different people show different emotional responses and therefore, these different emotion gives the features of the EEG data carry the best information for recognition. In this project, there are six emotions recognized with human facial expressions: anger, disgust, fear, happiness, sadness and surprise.

II. PROPOSE METHOD for Emotion DETECTION USING EEG

The EEG data were analyzed using several procedures, including signal preprocessing, feature selection, feature extraction, and feature classification methods are used to find the emotions.



a. INPUT:

The input of the system consists of measured EEG signal.

b. PREPROCESSING:

Raw EEG data is generally a mixture of environmental noise. After the data has been collected, the preprocessing step is meant to remove all unneeded noise and artifacts from the signal, and only keeping the interesting part of the signal, the brain activity.

c. NOISE AND ARTIFACTS:

In order to remove most of the noise from the measured signals, a band-pass filter is used that will remove frequencies below 2Hz and above 40Hz. This filter will also remove most of the artifacts, because their frequencies are far below 2Hz. We will not use any more sophisticated form of artifact removal.

d. FEATURE EXTRACTION AND SELECTION:

After the data is filtered and artifacts are removed, there is still a huge amount of data. Because a lot of this data is unnecessary to recognize emotion, and it would take too much time to use all this data to perform the job, some features are extracted from the data. The goal of feature extraction is to find those features that contain all the information needed to recognize emotion. Feature extraction is the process of extracting useful information from the signal.The requirements for feature extraction are:

i. reduce the size of the data by selecting appropriate features,

ii. selected features should be minimally redundant and the expected results should maximally depend on these features,

iii. preserve all information from the signal that is needed for emotion recognition.

e. FEATURE CLASSIFICATION:

With the selected features, the system can try to recognize emotion. We will implement different types of classifiers in our program, because we do not know the best one beforehand. The requirements for the analysis and classification are: determine the right values on the arousal and valence scale, from the selected features.

f. OUTPUT:

The output of the system will consist of two values on a 2-dimensional plane, arousal and valence. These values will be plotted real-time, so that a moving path through the arousal-valence plane will appear.

III. FEATURE ETRACTION METHOD

In the first stage, from the original EEG data features are extracted using frequency domain, time domain or time–frequency domain methods. Feature Extraction is the process of identifying the particular information from EEG data and this data measured by brain activity. . Many different feature extraction methods have been proposed over the years. These Features extraction Methods are distinguished by the ability to use information about human auditory processing and perception, by the robustness to distortions, and by the length of the observation window. There are several features extraction methods, some methods are listed below:

A. Discrete wavelet Transformation
B. Higher Order Crossing
C. Short Time Fourier Transform and Mutual Information

a. DISCRETE WAVELET TRANSFORM:

DWT is a linear signal processing which is applied to the particular data. This data has the same length, and then these techniques are applied to the data reduction. Discrete Wavelet Transforms (DWTs) are orthogonal functions, this function can be implemented through digital filtering techniques and it originates from Gabor wavelets. Wavelets have energy concentrations in time and it is useful for the analysis of transient signals such as speech signals. DWT is the most promising mathematical transformation which provides both the time –frequency information of the signal and is computed by successive low pass filtering and high pass filtering to construct a multi resolution time-frequency plane [8].

Advantages:

- It analyze the signal with variable window.
- It analyze both time data and frequency data.

Disadvantages:

- There is a lacking of specific method.
- It performs the limited Heisenberg uncertainty.

Literature Review:

M. Murugappan et.al [9] proposed a discrete emotion recognition system to recognize emotions from selected frequency range of EEG signals using new statistical features. The range of frequency selected by the newly proposed feature gives a maximum average and individual classification rate compared to other conventional features. Therefore the extracted features successfully capture the emotional changes of the subject through their EEG signals regardless of the user's cultural background, race, and age. Thus, the combination of wavelet features and non-linear classifier greatly improved the emotion classification rate of the proposed system over previous works.

b. HIGHER ORDER CROSSING:

Feature extraction techniques are used in the particular time series progresses. This techniques shows that the finite zero means series; level zero can express through the zero count. Thus HOC is referred zero crossing count. HOC can be combined with spectral analysis and discriminate analysis to extract the particular feature. The feature using signal segmentation and it extract the feature using Hoc and from EEG using Hoc method. This can be combined with spectral and discriminate analysis to extract the particular feature. The emotions can be identified by using the signal segmentation and extract the feature using HOC and Cross correlation method. The features are extracted from EEG using HOC method. The features are extracted from EEG using HOC. It supports different feature extraction techniques and provides better accuracy result [10].

Advantages:

- Its performance should be high.
- Its provide optimal result.

Disadvantages:

- HOC is difficult to choose the random data.

Literature Review:

Panagiotis C. Petrantonakis [11] proposed a novel emotion recognition and EEG-based feature extraction technique. This work includes higher order crossings (HOC) analysis, employed for the feature extraction scheme and a robust classification method, namely HOC-emotion classifier (HOC-EC), was implemented testing four different classifiers [quadratic discriminant analysis (QDA), k-nearest neighbor, Mahalanobis distance, and support vector machines (SVMs)], in order to accomplish efficient emotion recognition.

c. SHORT TIME FOURIER TRANSFORMATION and MUTUAL INFORMATION

STFT is one of the methods used for feature extraction. It is used to extract from the each electrode sliding window of 512 samples and it overlapping between two consecutive windows. The mutual Information is based on how each and every electrode pair's and how those statistical dependencies the features are extracted and these extracted features are used for emotion analysis.

Advantages:

- This method has fixed slide window length.

Disadvantages:

- This method cannot denoising.
- Trade off between time and frequency.

Literature Review:

Okamura, Shuhei , [12] proposed the short time fourier transform and local signal. In this approached showed the closed-form output from several kinds of input series. In particular, just like the discrete Fourier transform, the STFT's modulus time series takes large positive values when the input is a periodic signal. One main point is that a white noise time series input results in the STFT output being a complex-valued stationary time series and it derive the time dependency structure such as the cross-covariance functions. This approach focused on the detection of local periodic signals. It presented a method to detect local signals by computing the probability that the squared modulus STFT time series has consecutive large values exceeding some threshold after one exceeding observation less than the threshold.

IV. Feature CLASSIFICATION METHOD

Classification method assigns a label representing the recognized emotion and these emotions are selected by using the features selected block. The key task of this classification method is to choose an efficient method and it provides the accurate results for emotion recognition. Features extracted from the EEG are used for classifier to differentiate the different types of emotion. The classification performance is mostly depends on the features that are being used to characterize the original EEG.

Therefore, optimal selection of the feature plays an important role in the performance of an emotion classifier. Each classifier requires an initial phase and it is trained to perform a correct classification and a subsequent phase in which the classifier is tested. There are several features classification methods in which three methods are listed below:

A. Principal Component Analysis
B. Linear Discriminant Analysis
C. Support Vector Machine

a. Principal Component Analysis (PCA)

PCA is known a principal component analysis. It is a statistical analytical tool that is used to explore, sort, and group data. It takes a large no. of correlated (interrelated) variables and transforms this data into a small no. of uncorrelated variable while retaining maximal amount of variation, therefore it is easier to operate a data and make prediction. PCA is used to reduce multidimensional data to lower dimension while retaining most of the information. Principal component analysis (PCA), also known as Karhunen-Loeve expansion, is a classical feature extraction and data representation technique widely used in the areas of pattern recognition and computer vision such as face recognition [13]. PCA used for reduce dimension vector to better recognize images [14].

Advantages:

- PCA can be used to compress data, by reducing the no. of dimension, without loss of any information.
- Reduction of noise since the maximum variation basis is chosen and so the small variations in the back ground are ignored automatically [15].
- Reduction of noise since the maximum variation basis is chosen and so the small variations in the back ground are ignored automatically [15].
- Smaller database representation since only the trainee images are stored in the form of their projections on a reduced basis [15].

- There is no knowledge of geometry and reflectance of faces is required.
- Lack of redundancy of data given the orthogonal components [15, 16].
- Reduced complexity in images' grouping with the use of PCA [15, 16].

Disadvantages:

- PCA is very sensitive to scale, therefore, a low-level preprocessing is still necessary for scale normalization.
- The Eigenface representation is, in a least squared sense, faithful to the original images, its recognition rate decreases for recognition under varying pose and illumination.
- Due to its "appearance-based" nature. First, learning is very time-consuming, which makes it difficult to update the face database.
- The simplest invariance could not be captured by the PCA unless the training data explicitly provides this information.
- The covariance matrix is difficult to be evaluated in an accurate manner [15].

Literature Review:

Myoung Soo Park et.al [17] proposed two dimensional PCA for face recognition In this approach image projection technique developed for image feature extraction. As compared to PCA, it is based on 2D matrices rather than 1D vector so the image matrix does not need to be transformed into a vector prior to feature extraction. J. Yang, D. Zhang et.al [18] proposed an image covariance matrix is constructed directly using the original image matrices. Also the size of the image covariance matrix is much smaller in 2DPCA as compared to that of PCA. Therefore, 2DPCA has two important advantages over PCA. First, it is easier to evaluate the covariance matrix accurately. Second, less time is required to determine the corresponding eigenvectors.

b. Linear Discriminant Analysis (LDA)

LDA is known as Linear Discriminant Analysis. LDA is used in many applications such as face recognition, image retrieval, and micro array data classification. LDA provides the extremely fast evaluation of unknown inputs, and it performed this input by distance calculations between a new sample and training data sample in each class weighed by their covariance matrices. LDA is very simple but elegant approach to classify the different types of emotion. It does not require any external parameters for classifying the discrete emotion. LDA also known as Fisher's discriminant analysis. It has been used widely in many applications such as face recognition [19], image retrieval [20]. The goal of LDA is to maximize the between-class scatter matrix measure while minimizing the within-class scatter matrix measure [21].

Advantages:

- 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.
- LDA is a very simple but elegant approach to classify various emotions.
- LDA does not require any external parameter for classifying the discrete emotions.

Disadvantages:

- An intrinsic limitation of classical LDA is the socalled singularity problem; therefore LDA is fails when all scatter matrices are singular.
- However, a critical issue using LDA, particularly in face recognition area, is the Small Sample Size (SSS) Problem. This problem is encountered in practice since there are often a large number of pixels available, but the total number of training samples is less than the dimension of the feature space. This implies that all scatter matrices are singular

and thus the traditional LDA algorithm fails to use.

Literature Review:

Satonkar Suhas S. et.al [22] is proposed the emotion recognition on Holistic Approach in Facial Images Database. In this approach they use Grimance database images. The graph shows the LDA projection vector and eigenvalues, eigenvectors of these images. The success rate of classification of these samples images is 100%.The value of projection vectors is 0.0076, 0.0056, 0.0008, 0.0036 and 0.0028.

a. Support vector Machine (SVM)

Support Vector machine (SVM) is a classification method that performs classification jobs by assembling hyper planes during a dimensional house that divides situations of various class labels. SVM carries each regression and classification jobs and it handle multiple relentless and categorical variables. For categorical variables a dummy variable is formed with case standards as either none or one.

Advantages:

- Adaptability in picking a closeness capacity.
- Inadequacy of result when managing
- Expansive information sets just under pin vectors are utilized to determine the differentiating hyperplane.
- Capacity to handle substantial characteristic spaces multifaceted nature does not hinge on upon the dimensionality of the characteristic space.
- Overfitting might be regulated by delicate edge approach

Disadvantages:

- It is sensitive to noise
- A relatively small number of mislabeled examples can dramatically decrease the performance.

Literature Review:

P.Shen et.al [23] proposed the support vector machine for classification of emotion recognition. This system shown to have better generalization performance than traditional techniques in solving classification problems. The accuracy of the SVM for the speaker independent and dependent classification are 75% and above 80% respectively.

V. EEG Databases:

It is the memory of the classifier; it contains sentences divided according to the emotions to be recognized. The database, also called dataset, is a very important part of a speech emotion recognizer. The role of databases is to assemble instances of episodic emotions. It is used both to train and to test the classifier and it is composed of a collection of sentences with different emotional content. Currently, the existing EEG databases are mostly about motor imaginary, sleep stages, mental tasks and epileptic. These databases mostly cover speech, visual data, or audio visual data (e.g., [24] [25], [26], [27], [28]). The visual modality includes facial expressions and/or body gestures. The audio modality covers posed or genuine emotional speech in different languages. These several databases are given as follows:

a. DEAP Databases:

There are different datasets available in DEAP database. For example, the original EEG dataset, the videos dataset which records the subjects’ facial expressions, the preprocessed EEG data, etc [29]. More details about the DEAP database could be found in [29] and [30]. The Database for Emotion Analysis using Physiological Signals (DEAP) [31] is a recent database that includes peripheral and central nervous system physiological signals in addition to face videos from 32 participants.

b. IAPS and IADS Databases:

The International Affective Picture System (IAPS) [32] and the International Affective Digitized Sound system (IADS) [33] are developed and distributed by the NIMH Center for Emotion and Attention (CSEA) at the University of Florida. IAPS intends to provide a set of standardized, emotionally visual stimuli, while IADS provides a set of acoustic emotional stimuli.

c. Reading-Leeds Database:

This project begun in 1994 to meet the need for a large, well-annotated set of natural or near-natural speeches orderly stored on computers. The essential aim of the project was to collect speeches that were genuinely emotional rather than acted or simulated [34].

d. Belfast Database:

It was developed as part of a project called Principled Hybrid Systems and Their Application (PHYSTA) [35], whose aim was to develop a system capable of recognizing emotion from facial and vocal signs. The Belfast Natural Induced Emotion Database is intended to provide examples of mild to moderately strong emotionally colored naturalistic responses to a series of laboratory based tasks [36].

e. CREST-ESP (Expressive Speech Database):

This database built within the ESP project [37]. Research goal was to collect a database of spontaneous, expressive speeches.

f. CREMA-D

It is a Crowd-sourced Emotional Multi-modal Actors Dataset, CREMA-D, a labeled data set for the study of multimodal expression and perception of basic acted emotions. The large set of expressions was collected as part of an effort to generate standard emotional stimuli for neuro imaging studies. CREMA-D explicitly distinguished between matching, non-matching and ambiguous clips. The dataset will be released with classes of emotional expressions and levels of ambiguity. These characteristics permit the development of applications needing subtle and un-prototypical emotion expressions [38].

VI. CONCLUSION

- This paper focused on the various techniques for emotion classification using EEG signal analysis, various database for EEG are studied.
- In this paper, different feature extraction methods are studied. In DWT, analysis of signal is done with variable window in time as well as in frequency domain where as in STFT analysis of signal is done with fixed window length. As compared to these two methods HOC method provides optimized results but it is difficult to choose data in HOC.
- Also this paper summarized different methods of feature classification. SVM is adaptable in picking a closeness capacity but very sensitive to noise. LDA fails when all scatter matrices are singular, but elegant approach to classify various emotions. Whereas in PCA, as the maximum variation basis is chosen there is reduction of noise and small variation in background are also ignored.
- The proposed system is intended to recognize emotion from offline EEG signal. The input of the system consists of EEG signal and the output of system will be some indicator about what emotion the subject experience

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