Feature Extraction from EEG for Emotion Classification.

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ABSTRACT

Emotion has an important role in interaction and communication between people. Emotion can be expressed either verbally through emotional vocabulary, or by expressing non-verbal cues such as intonation of voice, facial expressions and gestures.In recent years, estimation of human emotions from Electroencephalogram (EEG) signals plays a vital role in developing intellectual Brain Computer Interface (BCI) devices. In this work, we have analyzed the EEG signals of the 4 different participants from the dataset.The Data set is provided on the enterface06 site, but this data is raw EEG data. The paper describes how to extract data in text form from this raw form using EEGLAB.This extracted data is then decomposed in subbands with the help of the wavelet transform in MATLAB. Features useful for emotion classification are then extracted.

KEYWORDS: EEG, Emotions, Discrete Wavelet Transform & Features Extraction.

1. INTRODUCTION

Emotions are believed to be extremely potential for analyzing condition of mind. Recognition of emotions by physiological means is a subject of interest for both psychologists as well as engineers [1]. Gaulin, Steven J. C. *et.al* suggested that the Physiology of emotion is closely linked to Arousal of the Nerves [2].

Most of the researchers have focused on facialexpression recognition and speech signal analysis for assessing emotions [3, 4]. The human brain is a complex system, and exhibits rich spatiotemporal dynamics. Among the non-invasive techniques for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with millisecond temporal resolution. Our emotional state plays an important role in how we experience and interact with our environment. The information retrieved from the brain signals related to human emotion is one of the key steps towardsemotional intelligence. In recent years, assessment of human emotions from Electroencephalogram (EEG) has development of intellectual man-machine interfaces. In the present work,we considered different frequency ranges of EEG signals such as alpha, beta, gamma, theta &delta for classifying two classes of emotions named as High arousal(HA) and Low arousal(LA). EEG signals are collected from the ENTERFACE site (http://www.sccn.ucsd.edu/eeglab/).

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│  DISCRETE WAVELET TRANSFORM │
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│  DECOMPOSITION INTO SUBBANDS│
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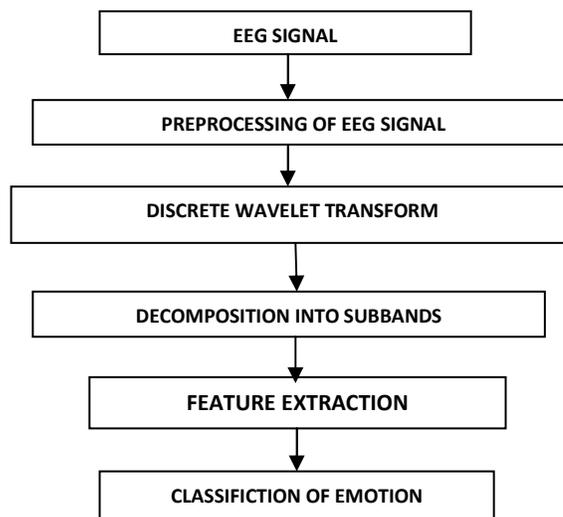
Figure 1 Flowchart for emotion classification

EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands. Interestingly the different research workrefers to these bands in different ways in this work we have chosen the bands in following manner: delta (0–4 Hz), theta (4–8 Hz),
 alpha (8–16 Hz), and beta (16–32 Hz).

In 1980 a powerful method called the discrete wavelet transforms (DWT) was introduced.Since early days, work done for frequency subband separation of EEG signal for emotion classification is based only on the decomposition of the signal to certain levels. This is followed by feature extraction from these subbands. Classification of emotions is done on the basis of these features. Methodology of this research is given figure1 in the flow chart.

2. Data Collection

A lot of work has already been done, but only few EEG signal data which can be used for detection of emotion have been made available for further exploration. Luckily, there is one available from the enterface website. This EEG data is obtained from different participants using EEGCAP. Stimulation is given by showing IAPS (International Affective Picture Set) pictures. It provides sufficient data for us to do some further work on the feature extraction and emotion classification.

We have collected all our raw EEG signals from the database of Enterface'06 (referred to as the Enterface database) that was built by Savran *et al*. As our initial dataset.AS an experimental protocol, each participant was made to undergo three sessions. In each session the participant was shown 30 picture sets each picture set pertains to one class of emotion named as POS, NEG and CALM and contains fine images. These five images are shown for 12.5 seconds each, thus total to 12.5 second exposure. In between the two picture sets, we have a black screen for 10 seconds. The participant gives self assessment of the picture set period. These self-assessments are measured because emotions are known to be very subjective and dependent on previous experience, one can never be sure that the person feels the emotion that was intended by the pictures, and this self-assessment gives a good possibility to compare the results between persons. However, self-assessments are known to be very subjective, and hard to compare. For example, some persons tend to give extreme scores where others always choose the center.
Some problems with this experimental design are given by Savran *et al*:
- Participants reported a headache at the end of each session, due to the different caps (they also wore a functional magnetic resonance imaging (FMRI) cap)
- Positive responses were not always felt, but the negative images were a bit too hard.
- Several participants said that the effects of the images decrease after viewing many images [5].

To construct the EEG database, emotion had to be elicited with the participants. The researchers have chosen to use images for emotional stimulation, in particular images from the International Affective Picture System (IAPS). The subset of images used in this experiment could be divided into three different emotional classes: calm, exiting positive (POS) and exiting negative (NEG).
 Data which is downloaded from enterface site have 2 files, one is BDF file and other is mark file
MRK file containsthe index of samples for each block of images. These files are named as following
PART**A**_IAPS_SES**B**_EEG_fNIRS_**DDMMAAAA**.bdf
PART**A**_IAPS_SES**B**_EEG_fNIRS_**DDMMAAAA**.mrk

Here A is the participant number (1-4), B is the session number (1-3) and DDMMAAAA represents the date of the recording.
EEG data from different electrodes is available in multiple text formats. The challenge here is to correlate the data with the time when the picture is shown to the subject. The data is first down sampled at 256 samples per second to reduce the size. The mark file has information of pictures shown. Since the data has 12.5 seconds of first picture set viewing, it means that the first 256X12.5=3200 samples correspond to EEG signal when the picture are being shown. The EEG data for next 10 seconds is for assessment when the black screen is shown. It means that next 256X10=2560 samples need not be analyzed. Similarly next 3200 samples are in a class of emotion given in mark file, while the next 2560 samples need to be ignored one emotion set of 12.5 second i.e. 3200 sample is processed for feature extraction. The features extracted are to be used for classification of emotion.
There is one other folder named as common data in downloaded data, which contain the files given below.
• IAPS_Images_EEG_fNIRS.txt, contains three columns, one per session, with the names of the IAPS pictures used in this study;

• IAPS_Eval_Valence_EEG_fNIRS.txt and IAPS_Eval_Arousal_EEG_fNIRS.txt contain in three columns the valence or arousal value for each image;
• IAPS_Classes_EEG_fNIRS.txt list in three columns the associated classes we considered for each block of pictures. Labels can be "Calm", "Pos" or "Neg". This can be useful if one does not want to take into account self-assessment of participants.

Delorme, Arnaud *et.al*(2003) in their paper "**EEGLAB"(an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis**) describes the development of an open source toolbox that works on the MATLAB platform in which an EEG data from a channel can be imported for processing and analyzing operations. It includes the functions to perform preprocessing operations like baseline removal, change of sampling rate, Artifact removal and filtering as well as operations like independent component analysis (ICA) and statistical analysis. The data analyzing operations can be performed by using a graphic user interface. Other flexible attributes are provided for the ease of users. EEGLAB is freely available at http://www.sccn.ucsd.edu/eeglab/ under the GNU public license for noncommercial use and open source development, together with sample data, user tutorial and extensive documentation [6]. From this lab we select the data according to our need, that is, for high arousal and low arousal values we changed its sampling rate from 1024 to 256.

3. Electrode Data Selection

Of 64 electrode data available in EEGLAB, we chose the data from Cz, Fz, C3, C4, P3 and P4 this chick is based on the recommendation [7].

4. Preprocessing of EEG signal

Preprocessing is a state of preprocess EEG signal in such a way to remove baseline and we perform this by subtracting its average of the signal from the original signal.

5. Discrete Wavelet Transform

There are no general methods of EEG analysis. Traditionally time and frequency domains have been considered for analyses of EEG signals. In both time and Frequency methods, an EEG signal is considered as a realization of a random process. Random processes are characterized by probability distributions and their moments (e.g. Power, entropy, means, variances, power spectral densities, skewness).The discrete wavelet transform (DWT) is quite an effective tool for Time-Frequency analysis ofsignals. Wavelet transform can be defined as a spectral estimation technique in which any general function can be expressed as a sum of an infinite series of wavelets [8]. The decomposition of the signal results in a set of coefficients called wavelet coefficients.Wavelet transforms has the advantages of time frequency localization, multi-rate filtering, and scale-space analysis. Wavelet transform uses a variable window size over the length of the signal.

5.1. Analysis Using DWT
DWT successfully analyses the multi-resolution signal at different frequency bands, by decomposing the signal into approximation and detail information. The method for frequency band separation for EMOTION recognition is implemented in MATLAB 2011a. EMOTION recognition using EEG requires feature extraction from the acquired signal in specific frequency range of delta, theta, alpha, beta, and gamma. Though some researchers have mentioned the use of DWT decomposition to obtain these bands. Bands which are decomposed are given in table I.
 After a first level decomposition, two sequences representing the high and low resolution components of the signal are obtained. The low-resolution components are further decomposed into low and high resolution components. After a second level decomposition, three more decompositions are done as shown in figure 2.
 CA1,CA2,CA3,CA4 and CA5 are the approximate coefficients.
And CD1,CD2,CD3,CD4 and CD5 are the detailed coefficients obtained after successive decomposition.
The multi-resolution analysis, using five levels of decomposition, yields five separate EEG sub-bands. The main objective of the proposed method of is Wavelet Transformthe division of the original EEG signals into different frequency bands.

TABLE I. decomposition of EEG signals into different frequency bands with a sampling frequency of 256 Hz

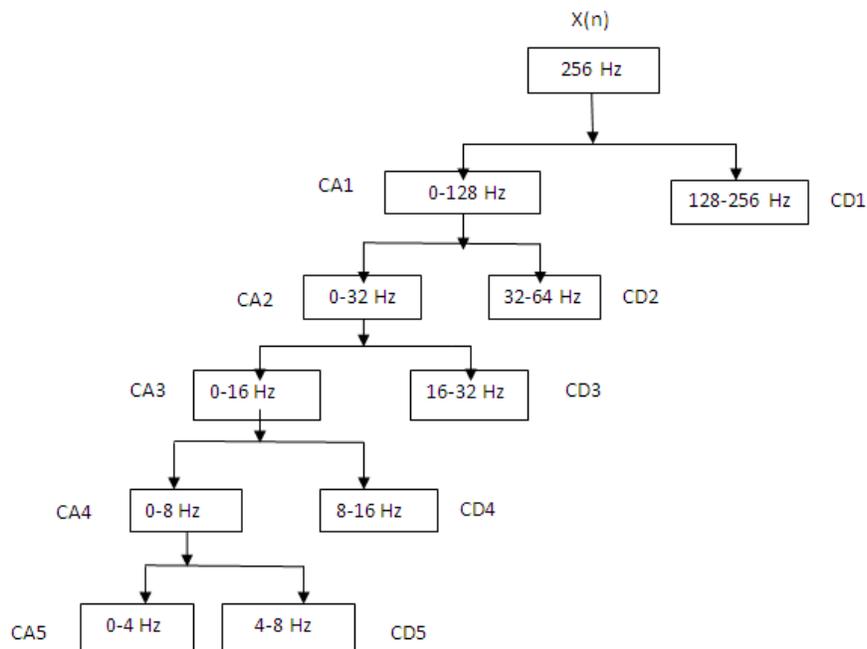| Frequency Range (Hz)	Frequency Bands	Decomposition Level	Frequency Bandwidth (Hz)
0-4	DELTA	CA5	4
4-8	THETA	CD5	4
8-16	ALPHA	CD4	8
16-32	BETA	CD3	16
32-64	GAMMA	CD2	32
64-128	NOISE	CD1	64

Figure 2: Decomposition of Signal into its approximation and detail coefficients

6. Feature Extraction

Some of the parameters derived for emotion classification are defined here under:

6.1. Entropy:

Entropy is a numerical measure of the randomness of a signal. Entropy can act as A feature and used to analyze psychological time series data such as EEG data. The Entropy can thus be calculated as:

$$e = -\sum_{1}^{n} x^2 - \log(x^2)$$

Entropy is the statistical descriptor of the variability within the EEG signal and is a strong Feature for EMOTION classification.

6.2. Power:

Power is Measure the amplitude of EEG signal andthe power can be calculated as:

$$Power = \sum X^2 / L(X)$$

X = the signal values and

L(x) = length of the signal.

6.3. Variance:

Variance is defined as a measure of the dispersion of a set of data points aroundtheir mean value. Assume some random variable X that has the sample values of each EEGsubband signal. Let the sample value of X is Xi={X1, X2 ...Xn} .Where I represent a sampleset from the subbands delta, theta, alpha, beta, and gamma. The variance can thus beexpressed as

$$Y^2 = \sum(X-\mu)^2/n$$

Where μ is the mean value of the set X and n is the number of samples in the EEG dataset.

Features mentioned above are extracted from each subband the EEG data. The subbands of EEG are (Delta, Theta, Alpha, Beta and Gamma) which are decomposed using wavelet transform.
Matlab program to extract thesefeatures, are given below:

1. Find out average value of the signal.
2. Subtract the average from the original signal.
3. Take the transpose of this pre-processed signal.
4. Apply wavelet transform to decompose this signal in different frequency bands.
5. Find the entropy in each band of the signal.
6. Normalize the entropy of each sub-band by dividing sum of entropy is all sub-bands.
7. Step 5 and 6 are repeated for power and variance calculation

Features so extracted are from 40 events 20 for High arousal events and 20 for Low arousal events. Feature extraction steps given above are performed in Matlab and we get the feature in the normalized form i.e.the values in between 0 and 1.

Conclusion and Proposed Work

This research mainly deals with the selection of electrodes and its data for emotion classification. The electrodes chosen are CZ, Fz, C3, C4, P3 and P4. And the features selected are entropy, variance and power. The EEG signals are decomposed using Discrete Wavelet Transform into Delta, Theta, Alpha, Beta, and Gamma subbands before extracting features.it is proposed that features be used of classification of emotional arousal state by employing a suitable classifier.

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