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Procedia - Social and Behavioral Sciences 27 (2011) 299 – 305

Procedia
Social and Behavioral Sciences

Pacific Association for Computational Linguistics (PACLING 2011)

Analyzing Brain Activity in Understanding Cultural and Language Interaction for Depression and Anxiety

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Abstract

Human brain has always been considered as a black box and is the source of all emotions. Analyzing cultural and language role through human emotion by looking at the brain activity can thus help us understand depression and stress better. This paper focuses on understanding and analyzing undergraduate students' emotions with different background and culture after completing their semester final examination. Brain wave signals were captured using EEG device and analyzed through proposing an affective computation model. EEG signal was collected from 8 healthy subjects from different states of Malaysia with different dialects where each subject was emotionally induced with audio and video emotion stimuli using the International Affective Pictures and System (IAPS). Features were extracted from the captured EEG signals using Kernel Density Estimation (KDE), which was then categorized into four basic emotions of happy, calm, sad and fear using the Multi-layer Perceptron (MLP). Results of the study show potential of using such analysis in understanding stress, anxiety and depression.

Key Words: Kernel Density Estimation (KDE); Multi-layer Perceptron (MLP); electroencephalogram (EEG); basic emotions; brain activity.

1. Introduction

Emotion is an important factor and plays a crucial role in our daily life especially in interacting and communicating with people. Since a large portion of communication now- a -days takes place with

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1877-7058 © 2011 Published by Elsevier Ltd. Selection and/or peer-review under responsibility of PACLING Organizing Committee.
doi:10.1016/j.sbspro.2011.10.611

computer or other electronic devices, recognizing human emotion in human-computer interaction has become an active research area in recent studies [1]. Most of the time human being uses the non-verbal communication when interacting with each other more prominently but not while communicating with computer [2]. Thus, emotion recognition also known as affective computing in understanding human behavior is important in human-machine interaction and the use of brain activity in recognizing emotion is becoming popular [3].

Many researchers have been trying to recognize human emotion through speech [4] and facial expressions [5] by proposing different methods in emotion recognition. In addition human emotion can also be measured from physiological signals such as brain signal, heart beat rate or skin conductivity. In this paper we propose the use of electroencephalogram (EEG) to understand the neural activities of the Human brain. EEG signals captured from the scalp that relates to consequence of cognitive process can approximately reveals the human response to emotional stimuli [6]. The rhythmic signals captured through the EEG machine reflect the brain activities through several frequency bands from delta (up to 3Hz), theta (4-7 Hz), alpha (8-12 Hz) to beta (13-30 Hz) band.

The objective of this Study is to analyze the undergraduate students' affective state after their final examination. In this case their EEG signals were captured after their final examination and using stimuli from four basic emotions of happy, calm, sad and fear were used as reference. These basic emotions provide a better understanding of the perceived emotion of human brain exposing to different emotional stimuli based on sound and pictures.

2. Related Works

Several works done on understanding emotion from EEG signals have shown great potential in understating human stress from the analysis of emotions considering the brain as the main source of all emotions.

Horlings presented an EEG-based emotion recognition system and classified emotion into two dimensions, valence and arousal [7]. Experiment subjects were emotionally stimulated by pictures, which enabled the study to draw a relationship between the characteristics of the brain activity and the emotion. The EEG features were extracted and classified into emotion. In fact some studies have shown the potential of using the EEG to understand stress from the eye blinking artifacts of a driver using a driving simulator [8].

Cultural diversity of external environment has influence on the process of developing human brain and it differentiates in the pattern of human behavior, perception and personality [9]. Ample cross-cultural research studies show that, anxiety and depression disorder occur worldwide but the social and interpersonal reaction responses to this syndromes varies widely. Lewthwaite conducted a study on 12 international postgraduate students in New Zealand to discover students' ability in adapting to the new culture and linguistic environment [10]. Study result shows that students from culture different than New Zealand reported high level of stress and depression. Lack of intercultural communication capability is considered to be the reason of this emotional disposition that leads to depression.

3. Methodology

In this section, the proposed methodology in recognizing basic emotions was introduced.

3.1. Data collection using EEG

In capturing brain signal, subject was exposed to emotional stimuli of four basic emotions. Stimuli were taken from IAPS, Bernard Bouchard's synthesized audio and video clips [11]. During the experiment, subject was briefly explained about the design protocol of the experiment and was asked to fill personal information which includes their background details; DASS-21and PSS-4 to measure the stress level [12, 13]. Finally, subject was exposed to all emotional stimuli with duration for 1 minute each.

Table 1. Position of EEG Electrodes

Anatomical Regions	Left	Right
Frontal (F)	F3	F4
Central (C)	T3, C3	C4, T4
Parietal (P)	P3	P4

Brain signal was captured using EEG international 10-20 standard. For this study, 8 channels (electrodes) were used to capture brain signal in emotion recognition (Table 1). Experiments were conducted on 8 healthy subjects of ages between 22 and 24.

In this experiment, the Biometrischcentrum (BIMEC) machine was adopted for collecting data with a sampling rate of 250 Hz. During the experiment, subjects had to be seated steadily in a quiet room, with a controlled temperature and lighting. The impedance of recording electrodes was monitored for each subject prior to data collection to be below 5 kΩ.

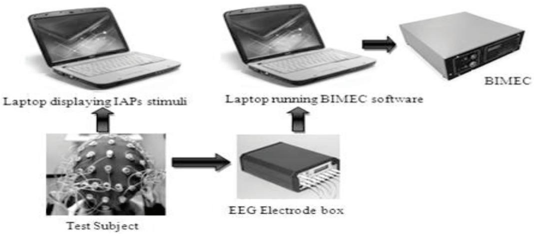

Fig. 1. Experiment Design Setup

3.2. Data Processing

Once the data was collected using EEG on eight channels, it was normalized to a length of 1 and decimated with a factor of 3 that reduces the sample rate of the signal to 83.33Hz.

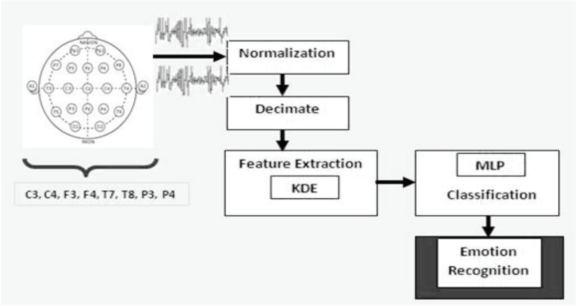

Fig. 2. EEG Data Processing

3.3. Feature Extraction

Features were extracted from the decimated data using Kernel Density Estimation (KDE) also known as non-parametric method [14] [f,xi] = ksdensity(data signal)

Above equation computes a probability density estimate of the sample in data signal where f is the vector of density values evaluated at the points in xi. The default number of equally spaced points in xi is 100. A 512 data point was used as a window size with 80% data overlapping in this feature extraction method.

3.4. Emotion Classification

Table 2. MLP Network Parameters

Parameters	Values
Number of neuron	10
Number of hidden layer	2
Number of epoch (Max)	1000
Mean square error goal	[0.1-0.5]

Multilayer Perception MLP is a neutral network, which consists of multiple layers of computational units. It is one of the feeds forward networks that use back propagation learning algorithm to obtain the weight of the network [15]. In this experiment, the chosen network training parameters were shown in Table 2.

4. Experiment Results

This section explained the experiment study based on EEG signals obtained through the procedures proposed in methodology.

4.1. KDE feature distribution

Fig. 3 shows the histogram of a channel's signal distribution along with signal's extracted feature distribution in mesh plot, presenting the normal distribution and estimated density for each emotion. KDE is based on a normal kernel function that provides a smooth kernel density estimation distribution of the discreteness of histogram where x- axis represents number of instances, y-axis represents time and z-axis represents frequency occurrences.

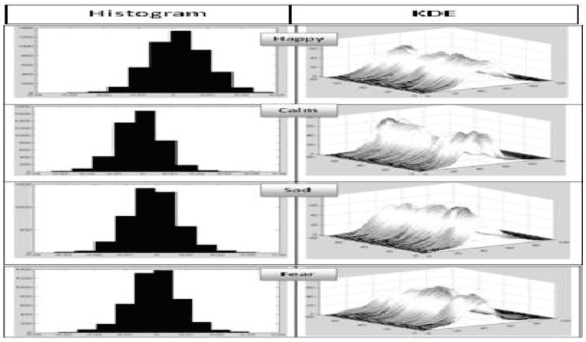

Fig. 3: Histogram and KDE distribution

4.2. Homogeneous and Heterogeneous Analysis of Emotion

Table 3. Accuracy level of 4 distinct emotions verification in percentage

Emotion Recognition (%)	Expected Emotion (%)				
	Emotions	Happy	Calm	Sad	Fear
	Happy	76.62	9.09	15.58	16.88
	Calm	16.88	75.32	11.69	7.792
	Sad	0	12.99	62.34	3.90
	Fear	6.49	2.60	10.39	71.43

Emotion classification using MLP helps to provide the accuracy level of each basic emotion in emotion recognition. Considering 100% instances of emotion data for both training and testing into MLP, performance evaluation was obtained above 60% for all emotions with a highest accuracy of 76.62% (Table 3). Besides homogenous study, this study also performs a heterogeneous experiment where an individual subject's emotion was tested with the emotion of different subjects. This experiment is also known as Blind test [16]. Fig. 4 shows the performance accuracy in emotion verification of three subjects.

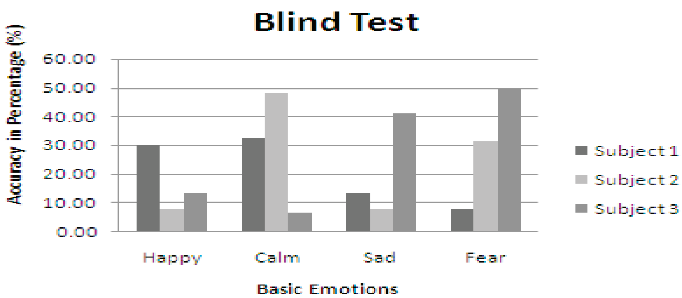

Fig. 4. Blind test for emotion detection

In blind test, performance accuracy of all emotions was below 50% while performance accuracy of emotion 'Happy' continuously appeared to be below 35% for all subjects.

4.3. DASS-21 evaluation

While analyzing EEG signal help us recognizing basic emotion such as – happy, calm, sad and fear; other emotion parameters such as depression, anxiety and stress were observed in this study for each individual subject from the obtained result of DASS-21. Stress measures a syndrome that is distinct from depression and anxiety can be illustrated as nervous, tension, irritability and difficulty in relaxing. DASS was calculated based on plastic scoring template in Table 4. Higher score represents higher intensity of emotion scale. Different values of each emotion scale were obtained from different individuals based on the DASS severity ratings shown in fig. 5.

Table 4. DASS Severity Ratings

Severity Labels	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34

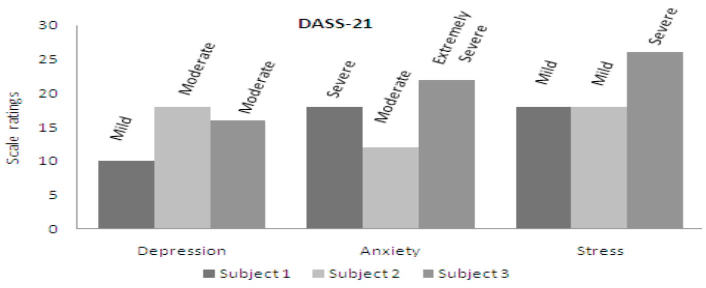

Fig. 5. DASS response to severity ratings

The severity labels in table are used to describe the full range of scores in the population, therefore, in fig. 5, 'severe' stress for third subject means that the person is above the population mean but probably still way below the typical severity. However, it says that, individual DASS score do not define appropriate interventions about subject. Score obtained needs to be discussed in conjunction with clinical information that determines appropriate treatment of that individual subject [17]. Therefore, the clinical study of this analysis is left for future work.

5. Conclusion

In this paper the proposed system was able to recognize emotion through analyzing EEG signals captured from undergraduate students of different cultural and language background. Experiments were conducted on 8 healthy subjects in an emotion-induced environment. Four basic emotions were analyzed in order to understand different emotional parameters such as stress, anxiety and depression. DASS-21 represents subject's anxiety, depression and stress level to some extend which can provide subject's appropriate intervention with clinical conjunction. Experiment results show that, performance accuracy of emotion in homogeneous test provides an improved verification accuracy of 76% comparing to Heterogeneous blind test. MLP classifier tends to provide inconsistent result, however results appeared to be acceptable. Thus, choosing a different classifier to improve the result of the experiments is left as a future work of this study.

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