EEG ANALYSIS FOR UNDERSTANDING STRESS BASED ON AFFECTIVE MODEL BASIS FUNCTION

Kazi Shahzabeen Rahnuma, Abdul Wahab, Norhaslinda Kamaruddin and Hariyati Majid

Kulliyyah of Information and Communication Technology

International Islamic University, Malaysia (IIUM)

Jalan Gombak, Kuala Lumpur, Malaysia 53100

abdulwahab@iium.edu.my

ABSTRACT

Coping with stress has shown to be able to avoid many complications in medical condition. In this paper we present an alternative method in analyzing and understanding stress using the four basic emotions of happy, calm, sad and fear as our basis function. Electroencephalogram (EEG) signals were captured from the scalp of the brain and measured in responds to various stimuli from the four basic emotions to stimulating stress base on the IAPS emotion stimuli. Features from the EEG signals were extracted using the Kernel Density Estimation (KDE) and classified using the Multilayer Perceptron (MLP), a neural network classifier to obtain accuracy of the subject's emotion leading to stress. Results have shown the potential of using the basic emotion basis function to visualize the stress perception as an alternative tool for engineers and psychologist.

Keywords: Electroencephalography (EEG), Kernel Density Estimation (KDE), Multi-layer Perceptron (MLP), Valance (V), Arousal (A).

1. INTRODUCTION

Emotion is omnipresent and an important factor in human life in interacting and communicating people. Although emotion is intuitively known to everybody, it is hard to define. Scientists consider human brain as the main source of all emotions [1]. And therefore, brain signal is captured in order to study emotion. However, the precise role of brain is not so clear. Brain activity can vary person to person in a particular circumstance. And so, to satisfy this curiosity, several research works are going on where human emotions are being analyzed through different types of emotion generated stimuli. Due to the difficulty in grasping emotion, this paper uses a dimensional view in classifying and representing emotion through placing every emotion on a multi-dimensional -scale of Valance, ranging from positive to negative emotion and Arousal, ranging from calm to excited [2]. As a brain activity exploring tool, Electroencephalography (EEG) was used to measure brain signal from human scalp which shows different emotion states in alpha band and also provides information responses to the external stimuli about both

dimensions [3]. Due to higher temporal resolution, EEG was used in this experiment, 4 subjects (two female and two male) were externally induced four basic emotions – happy, calm, sad and fear when their brain signals were observed. Audio and visual stimuli were displayed to the subject as they are thought enhance emotional experience [4-5]. Collected signal then downsampled and filtered to remove unwanted artifacts. A Kernel Density Estimation (KDE), feature extraction method was implemented on the filtered data and finally, extracted features were classified using MLP to verify and identify emotion.

1.1 KDE

Kernel Density Estimation (KDE), a non-parametric method is used to extract signal features by computing density estimate using kernel-smoothing method. The probability kernel density estimation function is given in equation 1, where k(x) represents a symmetric function that integrates to 1 and h>0 is the smoothing parameter also called bandwidth.

$$\hat{\phi}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \tag{1}$$

In feature extraction, window bandwidth was chosen to 512 data point with 80% data overlapping. The density was evaluated at 100 equally spaced points that cover the whole data range of x [6].

1.2 MLP

Multi-layer Perceptron (MLP) is one of the neural networks which have been used by many researchers and it consists of multiple layers of computational units. It is one of the feed-forward neural networks and the network use the back propagation learning algorithm to obtain the weight of the network [7]. It is connected to each of the layer in the network and the output of each of the hidden neuron is distributed to all of the neuron.
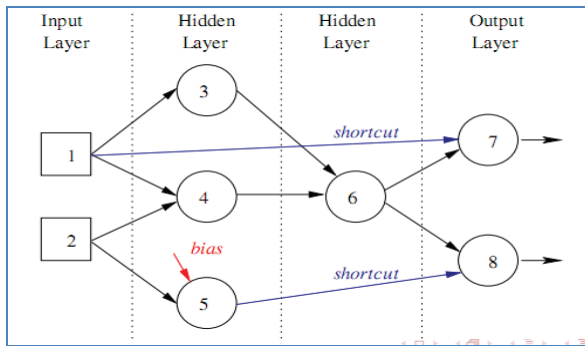
Figure 1. Multilayer Perception Network

MLP will have an input layer, hidden layer and output layer but the network can have any number of hidden layer. The number of layer in the input must be same with number of features in the database. The main goal of the training process is to find the set of weight values that will cause the output from the neural network to match the specific target values as closely as possible.

2. RELATED WORK

Several projects have been done on analyzing human stress using basic emotional stimuli. These studies also talked about influence of personal control on stress and coping process [8].

Human brain is considered as important source emotion recognition though its brain signals, blood flow and possibly others. Paper [9] studied on detecting stress (stress monitoring) from the eye blink artifacts using EEG involving the subjects with a car driving simulation and finally correlating eye blinking frequency with the experienced level of stress. Finally, signals were classified, using the selected features as eye blinks in the signal.

A technique called near-infrared spectroscopy (NIRS) has been proposed in study [10] to analyze mental state and compared with other conventional techniques such as Peripheral Arterial Tonometry (PAT) and Electroencephalography (EEG). 'Active electrode' technology provides EEG a significant improvement in measurement. PAT has been used to measure Heart Rate (HR) throughout the experiment. The main purpose of this study is to focus on simultaneous recording of brain activity using NIRS, EEG and PAT during stress and healing tasks and develop a better diagnostic technique for evaluating mental condition.

2.1 Neurophysiology Perspective

Stress has been empirically related to greater Right Frontal Activity (RFA). It is predicted that cortisol mediate either the relationship between examination stressor and right frontal asymmetry or between right frontal asymmetry and negative health. The main purpose of this study [11] is to use an examination stressor to elevate cortisol levels and psychological stress levels and test the effect of these elevators on frontal asymmetry and health. An examination stressor was used to elevate cortisol levels. Stress was measured through both psychological inventories and hormonal assessment for cortisol.

2.2 Approaches in Understanding Emotion

Two common and most promising approaches in understanding emotion have been proposed in study [12]. Dimensional approach states that, emotion can be described through a number of independent factors and on the other hand, Categorized approach is formed based on distinct emotions. This study used Russell's Affective Space Model in illustrating dimensional approach (figure-2) in which emotion is literally described through two-dimension space of Valence and Arousal [13].
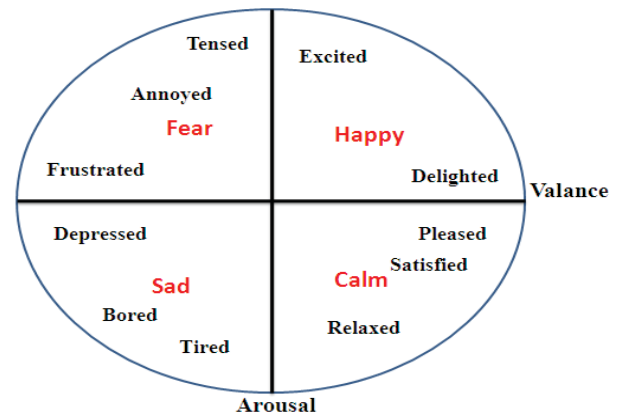

Figure 2. Russell's circumplex model of affect

In this paper, we are more interested in looking into the cognitive aspect of emotions from dimensional approach using Russell's two-dimensional Affective Space model. Understanding and analyzing the brain- waves should be able to allow us to see the brain activation in dynamic approach.

3. METHODOLOGY

This section describes a proposed methodology to verify EEG signal in time domain (figure-3). EEG was used to capture electrical brain signal from frontal (F), Central (C), and Parietal (P) lobe of scalp. Once the signal 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. Decimated data were then fed into a feature extraction method called Kernel Density Estimation (KDE).
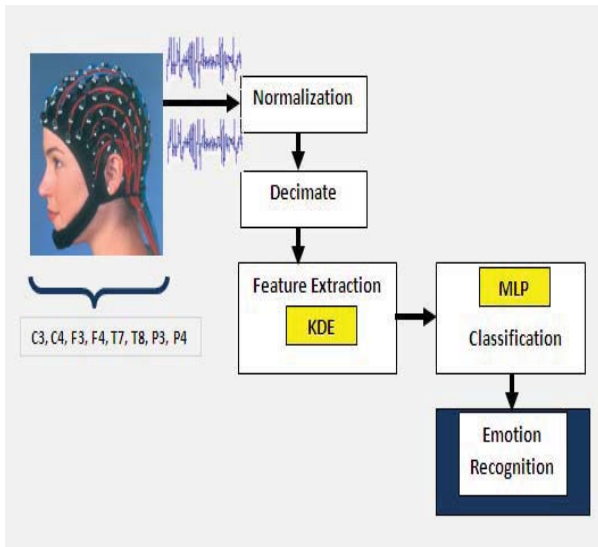
Figure 3. Methodology

KDE was used to extract feature from the downsampled data with a window size of 512 and an overlapping data of 80%. KDE yields 100 estimate feature points through data signal in each frame signals. The mean and standard deviation of this KDE are used as features that are fed to the MLP classifiers. Finally, emotion was classified using MLP from the features extracted.

4. EXPERIMENT ANALYSIS

4.1 Experiment Design

Data will be collected using EEG of international 10-20 system that describe and apply the location of scalp electrodes in the experiment. [14].

In this experiment the test participant is required to watch IAPs stimuli [15] of four basic emotions while an EEG recording is made of his brain activity. Complete experiment procedure includes following steps –
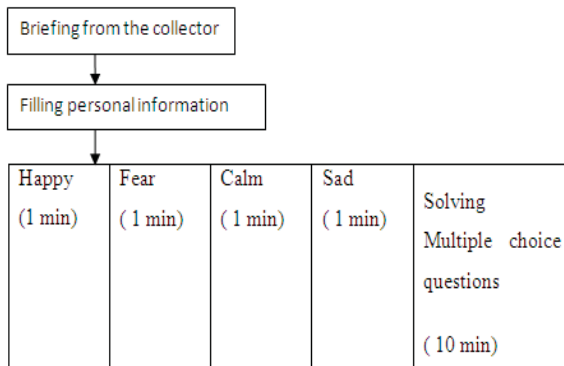

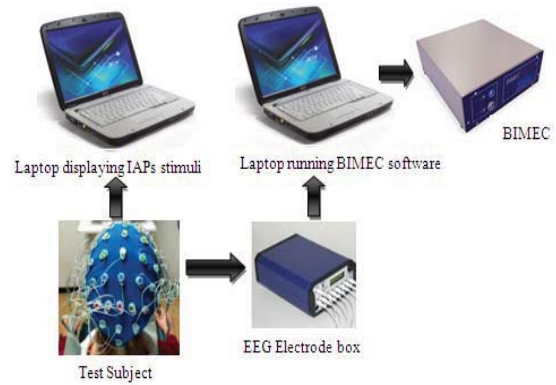**Figure 4.** Experiment design protocol

4.2 Experiment Setup

Figure 5. Experiment Setup

The Biometrischcentrum (BIMEC) machine is adopted for collecting data. It must be connected to the computer in order to capture the brain signals. The experiment need to be done in a quiet room, with a controlled temperature and lighting. Electrodes were pasted using Nuprep conducted gel and plugged into respective EEG channel port. Before the experiment begins, subjects will be briefed about the experiment. Subject requires filling some personal information and will be displayed emotional stimuli for 1 minute followed by a MCQ test in a time constraint environment.

5. RESULTS & DISCUSSION

This section describes the experimental study on the EEG-based emotion recognition system using the data processing steps described in Figure 3.

5.1 Emotion and Subject Verification

In experiment analysis, all subjects' emotion and each subject's data were tested using MLP in order to verify emotion and the respective subject. Each emotion and each subject's signal were trained and testing into MLP. Figure 6 shows 100% accuracy for each emotion – happy, calm, sad and fear that was obtained from MLP. Likewise, figure 7 shows the accuracy of subject differences when all subject's combined data were trained and each subject's data was tested into MLP. However, fourth subject's data verification result appeared to be below 100% in contrast to other subjects.
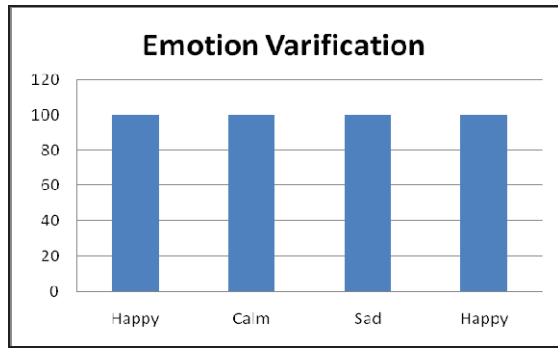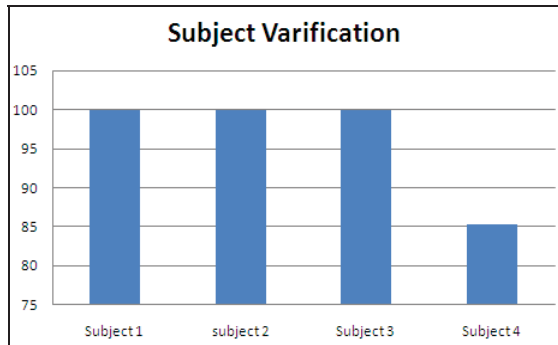
Figure 6. Emotion Verification (in percentage)

Figure 7. Subject Verification (in percentage)

5.2 K-fold Verification of Emotion

A 5-fold cross-validation was performed using MLP classifier in order to observe percentage accuracy for four emotions of all subjects through developing a confusion matrix. The results in Table-1 showed that proposed method has improved the accuracy to 71.84%.

Table 1. Accuracy level of four distinct emotions of 4 subjects using 5-fold cross validation technique

Emotion Recognition (%)	Expected Emotions (%)			
Emotions	Happy	Calm	Sad	Fear
Happy	**71.69**	14.41	1.43	17.56
Calm	15.81	**60.74**	19.04	1.61
Sad	0.36	22.35	**71.84**	14.90
Fear	9.64	2.50	7.69	**65.94**

5.3 Subject's Emotion Identification

In this analysis, each subject's emotion was tested in dimensional approach considering valance and arousal and performance accuracy was calculated for all emotions

of each subject. Table 2 shows the performance accuracy of one subject's emotion when **valence and Arousal were combined** to train and test into MLP.

Table 2. Accuracy level of four distinct emotions of 4 subjects with combined Valence and Arousal

Emotion Recognition (%)	Expected Emotions (%)			
Emotions	Happy	Calm	Sad	Fear
Happy	**73.21**	3.57	1.79	0
Calm	23.21	**87.5**	12.5	1.79
Sad	1.79	8.93	**75**	1.79
Fear	1.79	0	10.71	**96.43**

Table 3 shows the confusion matrix of performance accuracy of the emotion of the same subject when **valence and arousal were trained and tested separately** into MLP. Study Result shows an improved accuracy of 96.43% was obtained when valence and arousal were trained and tested together i.e. combined valence and arousal.

Table 3. Accuracy level of four distinct emotions of 4 subjects considering Valence and Arousal separately

Emotion Recognition (%)	Expected Emotions (%)			
Emotions	Happy	Calm	Sad	Fear
Happy	**92.86**	19.64	1.79	1.79
Calm	1.79	**55.36**	7.14	1.79
Sad	5.36	5.36	**89.29**	7.14
Fear	0	19.64	1.79	**89.29**

5.4 Emotion Distribution

Subject's emotion was distributed according to Russell's Affective Space Model. Figure 8 shows emotion distribution of a test subject. It is observed from the emotion distribution that the new centroid (0.05,0.03) calculated differs from the default centroid (0,0) and places itself on 'Happy' quadrant. New centroid was calculated taking the mean of two nearest centroid of distinct emotion. This origin shift may have an impact on subject's overall emotional perspective which is an important element to consider for future work.
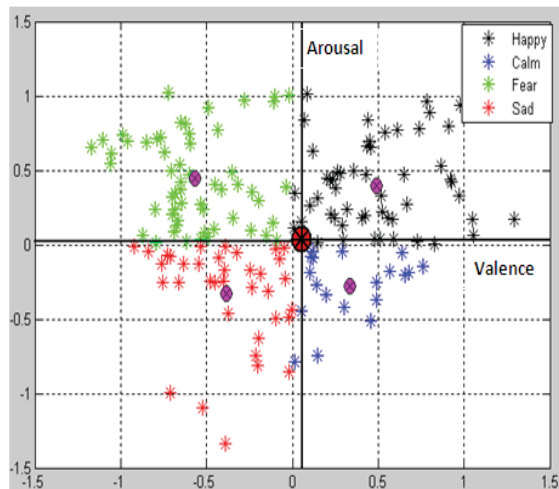
Figure 8. Emotion distribution of one subject based on Russell's Affective Space Model

5.5 Stress Analysis based on Valence and Arousal

Subject's emotional change was traced while solving multiple choice questions (MCQ) in a time constraint situation. This task was given to the subject to induce stress. Figure 9 shows the flow of valence of arousal representing the dynamic movement of stress. It is observed that subject's emotion at the beginning appears to be in calm quadrant with a positive valence and negative arousal. And at a certain point, valence turned into negative when the arousal turned to positive and place itself into fear quadrant which then moves to calm quadrant again.
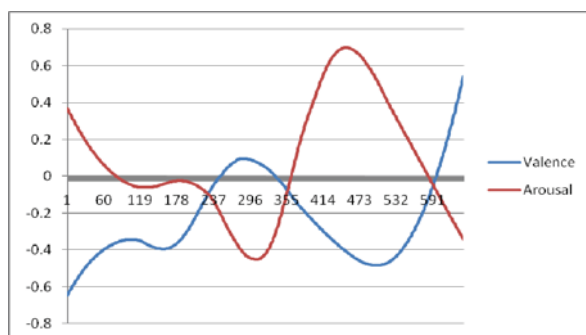

Figure 9. Dynamic movement of valence and arousal while conducting MCQ test

Following figure shows the scatter plot of subject's emotion while answering MCQ. It helps us to observe the trajectory of subject's emotion which shows subject started with a low intensity of calm emotion that gradually moves to fear with a higher intensity.
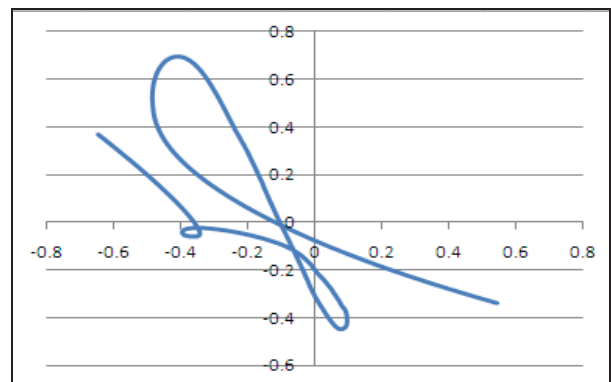

Figure 10. Trajectory of subject's emotion while conducting MCQ test

6. CONCLUSION

This paper analyzes basic emotion from captured EEG brain signal in order to understand human stress. An experiment was conducted on 4 subjects (2 male, 2 female) in an emotion induced environment. Experiment results shows that, performance accuracy of emotion considering combined valence and arousal provides better performance accuracy of 96.43% comparing to separate valence and arousal of 92.86%. It is possible to observe stress emotions from the trajectory of valence and arousal of four basic emotions. MLP classifier tends to provide inconsistent result, however results appeared to be acceptable. Therefore, a future work for this study will be testing emotion using a more effective classifier to obtain more accurate and consistent experiment results.

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