EEG based Stress Level Identification

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Abstract— **This paper investigates detection of patterns in brain waves while induced with mental stress. Electroencephalogram (EEG) is the most commonly used brain signal acquisition method as it is simple, economical and portable. An automatic EEG based stress recognition system is designed and implemented in this study with two effective stressors to induce different levels of mental stress. The Stroop colour-word test and mental arithmetic test are used as stressors to induce low level and high level of stress respectively, and their relevant C# applications are developed in Microsoft Visual Studio to interface with Emotiv Epoc device. Power band features from EEG signals are analyzed and using the relative difference of beta and alpha power as feature along with Support Vector Machine as classifier, three-levels of stress can be recognized with an accuracy of 75%. For two-level stress analysis, accuracy of 88% and 96% are achieved for Stroop colour-word test and mental arithmetic test respectively.**

Keywords— Electroencephalogram (EEG); stress recognition;

I. INTRODUCTION

Everyone experiences diverse levels of stress in the daily life. Stress is a human body response and reaction to a challenge or stimulus that disturbs our physical or mental equilibrium [1]. The kind of challenge or stimulus that induces stress is also called as a stressor (stress factor). Stress is usually caused by human resistance towards new challenges or stressors emotionally, mentally or physically [2]. The human body is designed to experience stress and react to it. Stress can be positive ("eustress"), keeping us alert and ready to avoid danger. This positive stress can improve the performance during a presentation at work or during taking exams at school. Stress becomes negative ("distress") when a person faces continuous challenges without relief or relaxation between challenges. As a result, the person becomes overworked and stress-related tension builds which affects their lifestyle. Various health complications are also related to stress [3].

It is challenging to assess and monitor stress, because every individual experiences stress in different ways. Researchers had developed techniques to measure stress in term of questionnaire-based methods such as Cohens's Perceived Stress Scale (PSS), Stress Response Inventory (SRI) and Hamilton Depression Rating Scale (HDRS). Another alternative is by quantifying the changes of physiological signals. These works are mainly adapting physiological signals to measure stress such as Electroencephalograph (EEG) [7-9], Electrocardiography (ECG), Plethysmography, Galvanic skin response (GSR), skin temperature etc. Out of these most of the work is on EEG based stress recognition [7-12].

There are many techniques used to induce stress levels in lab settings as given in [13]. The most commonly used techniques to induce stress are the Stroop colour-word test [5], the Trier Social Stress Test (TSST) [14], the cold pressor test [15], as well as the mental arithmetic task [4,16]. Stroop colour-word test is often used as a psychological stressor [8], in which subjects are presented with lists of color words in matching and non-matching colors. It is proved to be one of the most effective methods for research in human psychophysiological reactivity under stress environment. Mental arithmetic tasks, puzzles and IQ questions can also be used to induce different levels of stress. For example, arithmetic question with varying difficulty levels are used to elicit different stress states in the experiment [12].

The work in [7] classified the subjects' mental stress level during university examination from EEG features extracted using the Higuchi's fractal dimension, Gaussian mixtures and Magnitude Square Coherence Estimation (MSCE). The results showed that using features extracted by MSCE yielded an accuracy of over 90% in classifying the stressed and stress-free groups. An accuracy of 67.06%, 75.22% and 85.71% is reported for classifying four-level, three-level and two level stresses respectively in [8]. A Stroop colour-word test is used as a stressor [8] to induce different levels of stress, and features like power feature, fractal dimension and statistical features are used for classification. The work in [12] could detect mental stress with an accuracy of 85%, and 80% at two and three levels of arithmetic problem difficulty respectively.

The works in [7, 8] used highly complex feature combinations to achieve the classification of stress levels. It is also noted that stress is been induced only by one mode of stressor [7, 8, 12]. The main objective of this study is to analyze and classify the mental stress level from EEG signals when induced by stress from multiple modes of stress. Here both Stroop-colour word test as well as mental arithmetic test are used to evoke different levels of stress. The rest of the paper is organized as follows: Section II describes the experimental procedure; Section III discusses the methodology adopted for data acquisition, signal processing and classification. The results and analysis are presented in Section IV and Section V concludes the paper.

II. EXPERIMENTAL PROCEDURE

The proposed stress detection system consists of an EEG signal acquisition unit using Emotiv Epoc neuroheadset and Matlab module for processing EEG signals to classify the amount of stress induced. The subjects are instructed to refrain from head and muscular movements during EEG data acquisition to prevent artifacts. The overall experiment is done in two phases, namely training phase and testing phase. A total of 10 subjects from Nanyang Technological University participated in this experiment. Out of 10 subjects, 9 subjects are male and 1 is female. All the subjects are healthy and of the age group 20-35 yrs. In this phase, subjects will undergo a training stage followed by a testing stage.

In our experiment, a Stroop colour-word test- implemented using psychology experiment building language [5, 8] as well as the mental arithmetic task [4, 16] are applied as stressors to induce different levels of stress. Different targeted stress levels are induced individually to each subject.

A. Training Phase

In the experiment protocol as shown in Fig. 1 of three-level stress test, the training stage consists of 3 sections, a 3 minutes resting section, a 3 minutes Stroop colour-word test section and a mental arithmetic test section.

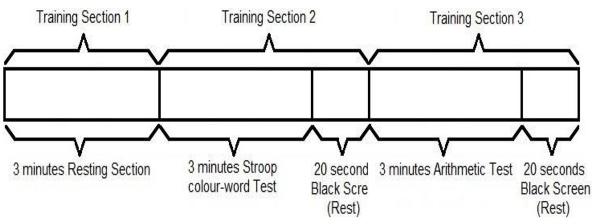

Figure 1: Timing protocol of the training.

In the resting section the person is allowed to completely relax with his eyes closed. The Stroop test is designed to induce a mild stress state. The words' font color and the words' meaning are different as indicated in Fig. 2. The subjects are required to response to the words' font color within a given time frame of 10 sec. The mental arithmetic test induces stress level higher than Stroop test. In the mental arithmetic test (Fig. 3), subjects are given problems which take more time to solve and are asked to solve that within 10 sec. There are 5 kinds of calculation, namely, addition, subtraction, multiplication, division and modulo calculation implemented in arithmetic test. The questions are randomly generated. The numbers in each question are within the range of 1 to 1000. In both the Stroop colour-word and mental arithmetic test, if the subjects can answer the question in 10 seconds, it captures the result and program will automatically proceed to next randomly generated question. If not, the program will make that particular answer unreported and will automatically proceed to next randomly generated question until 10 seconds is up. The test subjects will answer as many as they can until total time allowed for the section is up. An inter-stimulus rest interval of 20 sec is provided during training session. Each 3 minute session was divided as 18 sections of 10 sec each. After all the stress tests played, relevant features are extracted from the recordings as discussed in Section III. B. These features serve as the training data for creating a model for further classification. Once the model is created, the testing phase is executed.

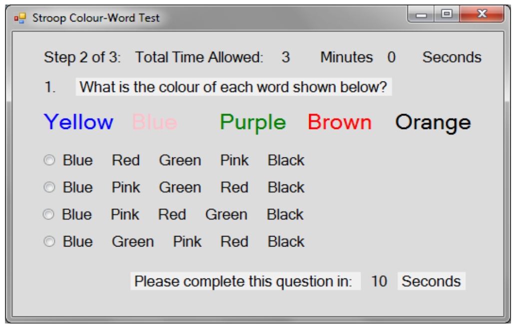

Figure 2: Stroop colour-word test.

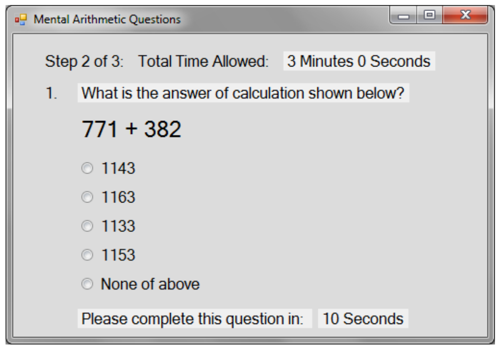

Figure 3: Mental arithmetic test.

B. Testing Phase

In the testing phase, a collection of Stroop colour-word and arithmetic tests (different from the set used above) are played in random with a rest interval of 20 seconds in between as shown in Fig. 4. In the testing stage, EEG signal is recorded for each subject for 10 stimuli consisting of resting or Stroop colour-word test or an arithmetic test in random order. Thus a total of 10 trials are there in the testing stage.

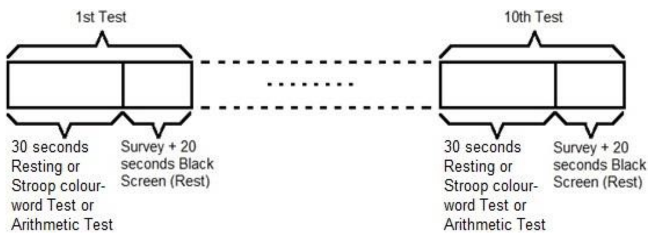

Figure 4: Timing protocol of the testing.

Immediately after each stress stimuli is played, the test subjects are required to take a survey, to receive feedback on how they feel about the level of stress experienced. The subject has to rate the intensity of the stress state on a three point scale, 0-no stress, 1-low level stress and 2-high level stress. The stress state and intensity level specified in self-assessment questionnaire by the participants is used to validate the stress level experienced by the subject when entering resting stage or answering a specific kind of test question. If they feel a stress state that is different from the one is supposed to be induced, it is fine for them to select a different stress state and just press 'Ok' button. However, this particular test will not be considered or taken into account when computing the classification accuracy.

III. EEG BASED STRESS DETECTION

This section describes the methodology used in the proposed method. The flowchart of the proposed method is shown in Fig. 5 and basic modules are briefly explained. The experiment begins with the data acquisition phase. After data acquisition, the recorded EEG signals are passed through a signal processing phase to extract features from the signal. Once extracted, the features are then used by the Support Vector Machine (SVM) classifier in the classification phase for stress detection.

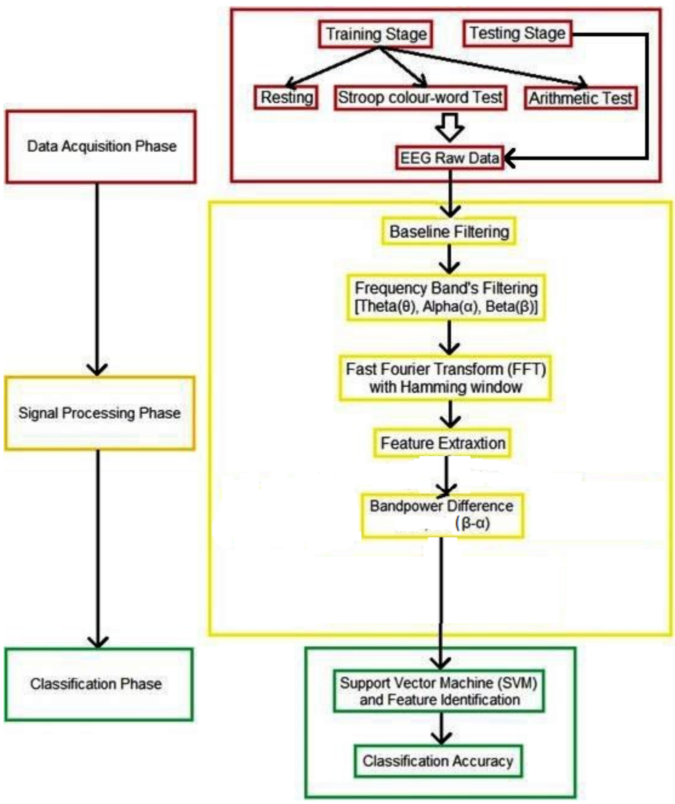

Figure 5: Flowchart of proposed method.

A. Data Acquistion Module

In our experiment, EEG data are collected from 10 subjects between the age 21 and 35 years from Nanyang Technical University. All subjects have no history of mental diseases and head injuries. A wireless EEG device Emotiv EPOC [6] is used to record EEG signals from 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4), placed on the scalp following the international 10-20 system, sampled at 128 Hz with bandwidth from 0.16 Hz to 43 Hz. The recordings are done with the subjects restricted to head movements and other muscle movements, according to the timing protocol shown in Fig. 1 and 4.

B. Signal Processing Phase

The signal processing stage comprises of baseline correction, bandpass filtering, and time window analysis. Baseline filtering is the first step in signal processing, performed by subtracting the average of the signals from all electrodes from the original signal to obtain the baseline corrected recording. Baseline correction is done to remove any offset present in the recording. This is done on all EEG channels across all the samples.

In order to compute signal power, it is necessary to convert the discrete time signal to frequency domain using Discrete Fourier Transform (DFT). Fast Fourier Transform (FFT) is used with appropriate Hamming window to convert and process the time domain EEG signal. The power spectral density (PSD) is calculated for theta (4-8 Hz), alpha (8-12 Hz) and beta (12-30 Hz) band to determine the average power in the frequency range specified.

According to [7, 8], the EEG power spectrum features are correlated with stress levels. It has been reported in literature that there are many similarities between the stressed state and negative emotion state [9]. The key parameter used here is the ratio of the relative difference of beta power and alpha power.

C. Classification

The key features from the training phase are fed into a Support Vector Machine (SVM) Classifier to obtain a model for further classification in the testing phase. SVM is widely used in emotion and stress recognition systems [8].The data files containing extracted features from the training stage are fed into SVM to generate an SVM classifier model. The EEG features extracted from the testing stage are fed into the trained SVM classifier to determine the level of stress induced. 4-fold cross validation is used to calculate the accuracy. First, the data are partitioned to 4 folds in which three folds are used as the training data and one fold is used as the testing data. Each fold of the data has a chance to be the testing data, the entire process runs for 4 times and an average accuracy is obtained. Depending on the degree of stress, a subject may feel the stress instantly or within a certain time. Hence, for proper detection of stress, different overlapping windows in time need to be analyzed. The chosen windows are 2, 4 and 10 sec with overlapping of 1, 3 and 5 sec.

IV. RESULTS AND ANALYSIS

Ten subjects, named as Sub 1 to Sub 10 in the sequel, have participated in this experiment and their performance in terms of classification accuracy with and without time window analysis is discussed here.

As explained in Section III. B., bandpower features are used for stress classification. Three key features extracted are relative bandpower values of high frequency component (β) compared to the low frequency components (α and θ). Based on the EEG data acquired from all fourteen channels, it is observed that during resting section, alpha bandpower is higher than the theta and beta bandpower. It is also noticed that both during Stroop colour-word test and arithmetic test, beta bandpower are relatively higher than the theta and alpha bandpower. This observation also corresponds to the known theories and concepts in literature. It indicates that the subject is in alert condition during Stroop colour-word test and arithmetic test, as shown by their higher beta value when compared to resting section as shown by their higher alpha value. Therefore, the effective stress feature is indicated by the decrease of alpha power and increase of beta power. Therefore, the beta-alpha bandpower difference is extracted and used to train SVM and the classification results for two-level (resting vs Stroop colour-word test and resting vs arithmetic) and three-level classifications are discussed.

A. Two-level classification

In this section, the classification accuracy for two-level stress test is computed. Classification accuracy is calculated for Stroop colour-word test vs resting stage as well as for arithmetic test vs resting stage, separately. Fig. 6 shows the two-level classification accuracy for the five subjects both for Stroop test as well as for arithmetic test. This accuracy is taken without considering any specific time-window of the stress stimuli, i.e., based on the entire 10 sec. duration for each stimulus.

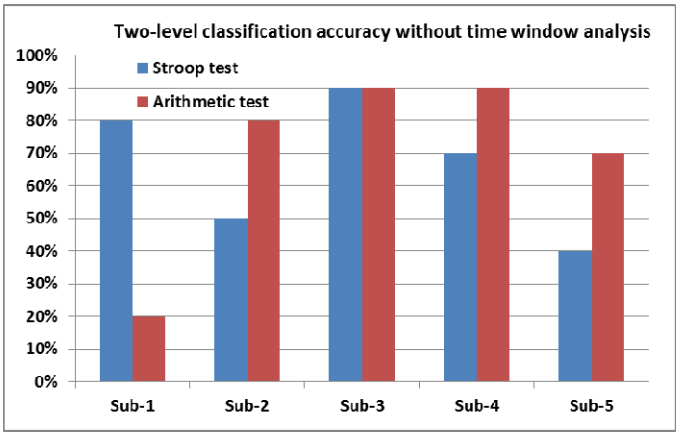

Figure 6: Classification accuracy of two-level stress test without time window analysis.

From Fig. 6, it can be noted that average classification accuracy for the Stroop test is 66% and that of arithmetic test is 70%. As the subjects are exposed to 10 sec of stress stimuli during the experiment, there can be a chance that they experienced stress after few seconds elapsed. This can be the reason of lower accuracy across the total 10 sec window. In order to have a proper detection of stress, different overlapping windows in time need to be analyzed.

In Table 1, average accuracy of five subjects is shown after undergoing through a time-window analysis. The chosen windows are 2, 4 and 10 sec with overlapping of 1, 3 and 5 sec. It has been noticed that the average accuracy for Stroop test increases from 66% to 88%, for the sliding window of 4 sec with 3 sec as overlap. For arithmetic test, the average accuracy increases from 70% to 96%, for the sliding window of 2 sec with 1 sec as overlap.

TABLE I. TWO-LEVEL STRESS TEST ACCURACY AFTER TIME WINDOW ANALYSIS

Sliding Window	Overlap	Average Accuracy (Stroop test)	Average Accuracy (Arithmetic test)
2 sec	1sec	80%	96%
4 sec	3sec	88%	88%
10 sec	5sec	84%	88%

It is noted that compared with the classification results obtained from Stroop colour-word test and mental arithmetic test, the classification accuracy of mental arithmetic test is higher than classification accuracy obtained from Stroop colour-word test. Therefore, the stress intensity induced in Stroop colour-word test is relatively lower than the level of stress induced in mental arithmetic test. On this basis, three-level classification is implemented with high stress level as mental arithmetic and medium stress as Stroop-colour word test.

B. Three-level classification

The classification accuracy of three-level stress test is performed by using the same feature extracted as discussed in section III.B. Fig. 7 shows the three-level classification accuracy for the ten subjects. This accuracy is taken without considering any specific time-window of the stress stimuli, i.e., based on the entire duration of 10 sec. for each stimulus.

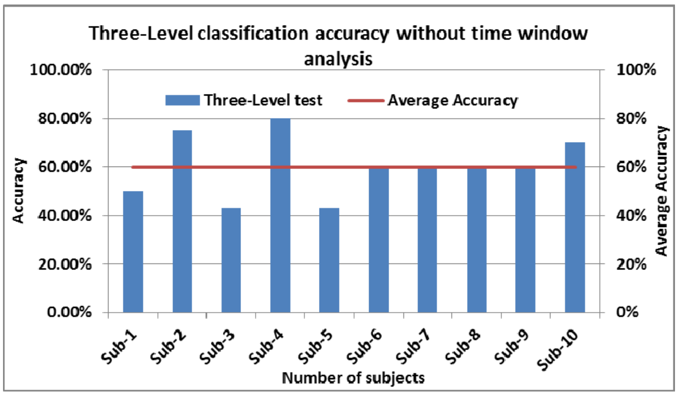

Figure 7: Classification accuracy of three-level stress test without time window analysis.

From Fig. 7, it can be noted that average classification accuracy is 60% when the subjects are exposed to entire 10 sec of stress stimuli. In order to have a proper detection of stress, different overlapping windows in time need to be analyzed. As earlier, the chosen windows are 2, 4 and 10 sec with overlapping of 1, 3 and 5 sec. Fig. 8 shows significant improvement in classification accuracy when compared to that of Fig 7. It has been noticed that the average accuracy increases from 60% to 75%, for the sliding window of 4sec with 3 sec as overlap. In [8], it is observed that the best classification is obtained by using 4 second sliding window with 3 sec overlapping. Our result revalidates the above observation with a mean significance value of p=0.0035.

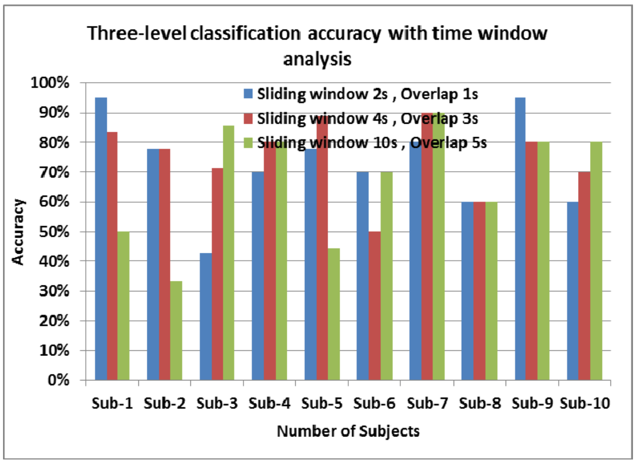

Figure 8: Classification accuracy of three-level stress test with time window analysis.

The proposed study obtained the best two-level stress classification accuracy of 88% from Stroop colour-word test, which is higher than the accuracy reported in [8]. The study also achieved classification accuracy of 96% from mental arithmetic test, which is higher than the accuracy reported in [7,12]. By combining Stroop colour- word test and mental arithmetic test to induce three different levels of stress, this study obtained the three-level stress classification accuracy of 75%. This classification result for three-level stress test in this proposed stress analysis is almost the same as in [8], but slightly lower than [12] by using only mental arithmetic test. It is to be noted that, in the proposed method the feature used is a simple power feature difference when compared to the complex combinations used in [7, 8, 12].

V. CONCLUSION

In this study, a real time EEG based stress recognition system is designed. Both Stroop colour-word test and mental arithmetic test are implemented as stressors to induce different levels of stress. The separate experiments on Stroop colour-word test; mental arithmetic test and 3-level stress test are carried out with 5 test subjects respectively. The classification results obtained from Stroop colour-word test, mental arithmetic test and three-level stress test are 88%, 96% and 75% respectively. It is also observed that the design of temporal sliding window with different overlapping increases the accuracy. As stress is a kind of emotion is very subjective to different individual's understanding and interpretation, the questions set by Stroop colour-word test and mental arithmetic test can be personalized and EEG data from more subjects will be acquired to determine a better set of stress features.

VI. ACKNOWLEGMENT

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