MENTAL STRESS QUANTIFICATION USING EEG SIGNALS

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Fares Mohammed Al-Shargie
American University of Sharjah

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Fares Al-shargie[1], Tong Boon Tang[1], Nasreen Badruddin[1], Masashi Kiguchi[2]

[1] Universiti Teknologi PETRONAS
Centre of Intelligent Signal and Imaging Research, Department of Electrical and Electronics Engineering, 32610 Bandar Seri Iskandar, Perak, Malaysia
[2] Hitachi Ltd., Research & Development Group, 2520, HATOYAMA, SAITAMA, 350-0395, JAPAN

Abstract—***Mental stress has been identified as one of the major contributing factors that leads to various diseases such as heart attack and stroke. To avoid this, stress quantification is very important for clinical intervention and disease prevention. In this study, we investigate the feasibility of exploiting Electroencephalography (EEG) signals to discriminate stress from rest state in mental arithmetic tasks. The experimental results showed that there were significant differences between the rest state and under stress at three levels of arithmetic task levels with p-values of 0.03, 0.042 and 0.05, respectively. We thus confirm the feasibility of EEG signals in detecting mental stress levels. Using support vector machine (SVM) we could detect mental stress with an accuracy of 94%, 85%, and 80% at level one, level two and level three of arithmetic problem difficulty respectively.***

Keywords—***Stress, EEG, Wavelet transform, SVM.***

I. INTRODUCTION

People suffer from stress in their daily life. Stress has been defined as “the non-specific response of the body to any demand for change” [1]. Stress can change the responsiveness of central-peripheral regulatory systems rendering them less efficient in supporting health. It has been recognized as one of the major factors contributing to chronic disorders and productivity loses. It influences the desire to work, performance at work and attitude toward life. Chronic stress has been linked to a range of health problems [2]. Previous studies have shown a correlation between long-term exposure to stress and risk factors such as cardiovascular diseases [3, 4].
Stress response can be evaluated from perceptual, behavioural and physical responses to mental stress task. Evaluation of perceptual responses to stress involves subjective estimations and perceptions. Self-report questionnaires are one of the most commonly used methods to measure an individual’s level of stress [5]. However, evaluating the stress using questionnaires is subjective method [6]. Therefore, clinicians evaluated the stress by measuring cortisol and α-amylase levels [7]. Stress response involves the activation of hypothalamus-pituitary-adrenocortical axis (HPA) and sympathetic nervous system (SNS) causing an increase in the glucocorticoid/cortisol secretion in the adrenal cortex.

Beside the release of cortisol, stress can be quantified from human bio-signals [8]. Studies have found a relationship between salivary cortisol levels and physiological variables changes such as heart rate variability (HRV), skin temperature (ST) and blood pressure (BP) [9]. Heart rate variability refers to the beat-to-beat alternations in heartbeat intervals. Stress causes a decrease in the high frequency components of the heart beat interval and an increase in the low frequency components of that heartbeat interval signals respectively. Thus, heart rate variability analysis has been established as an instantaneous quantitative measure of ANS activity associated with mental stress. Skin conductivity on the other hand varies with the changes in skin moisture level revealing the changes in sympathetic nervous system. Skin conductivity has been reported to increase with stressful task and can be acquired simultaneously using galvanic skin response (GSR) [10].

Furthermore, the changes in ANS can be effectively represented by electroencephalography (EEG) signals [11]. Electroencephalogram (EEG) is one of the most common sources of information used to study brain functions and conditions. It is a very complex signal and can be recorded non-invasively using surface electrodes from the scalp. EEG is the most studied non-invasive brain imaging device due to its excellent temporal resolution, ease of use, and low set-up cost. Additionally, EEG benefits from its high temporal resolution, enable it to measure the changes in cognitive activity within millisecond scale [12]. EEG signals are categorized by frequency bands; Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz) and Beta (14-30 Hz). Each of the frequency band represents a state of the person. An increase of EEG power spectra in the Beta frequency band associated with increase in the alertness and arousal; Alpha increased with relaxation and Theta occurred during the sleep state [13].

EEG signals have been previously used in the assessment of variation in the state of the subjects during cognitive tasks. Compared to HRV and blood pressure, EEG gives more information about relaxation and alertness condition [12, 14]. In literature, both decreased and increased in alpha and beta power have been found as a sign of mental stress [15]. EEG has successfully classified stress from the rest state in [16] with an average accuracy of 85.55% using Yule Walker and in [17] with average classification rate of 90%. Another studies have combined EEG signal with several physiological signals to study mental stress. Skin conductance, heart rate variability and EEG signals combined to classify stress in [18] resulted in average accuracy of 84.1% using psychological signals and 82.7% using the EEG signals. Blood pressure, skin conductance, heart rate variability and EEG signals in [19] model the stress with high classification rate of 95% using all physiological signals and 91% using EEG signals.

According to previous studies, no stress levels has been studied yet. Stroop colour word test [20], mental arithmetic task[21], public speaking [22], cold pressor [23], computer work [24] and videos [25] have been successfully used in previous studies as stress stimuli. In this study, we developed a stress stimuli to elucidate three levels of stress using arithmetic task. The aim of this study is to discriminate between stress levels and rest state based on EEG signals collected while performing mental arithmetic tasks. We simulated the brain using mental arithmetic task with three levels of difficulty as proposed by [26]. In this study, we proposed wavelet transform (WT) for feature extraction. According to previous study, [27] WT has the ability to deal with stationary and non-stationary signals. As EEG signals are non-stationary, WT may give good features that highly correlates with mental stress levels.

II. Methodology

A. Subjects

Twelve healthy male right-handed adults with an age ranges from 20-24 years participated to this study. All subjects were informed prior to the experiment and they gave written consent, in accordance with the declaration of Helsinki and ethical approval granted by local ethics committee at Unversity Teknologi PETRONAS. None of these participants had a history of psychiatric, neurological illness or psychotropic drug use. The participants were asked to minimize their head movements and to keep calm during the entire experiment.

B. Experimental Set-up and Protocol Design

We measured EEG signals from the frontal cortex using BrainMaster 24E system with seven active electrodes [FP1, F3, F7, Fz, FP2, F4, and F8] and one reference A1 attached to the earlobes. All the electrodes placed on the surface scalp based on the international 10-20 system of electrode placement. The sampling frequency for EEG was set to 256 Hz. The impedance of EEG was minimized using small amount of gel directly to the scalp.

The mental stress experiment was designed based on Montreal Imaging Stress Task (MIST) [26]. The experiment protocol were performed in four steps. First, brief introduction was given to the participants to be familiar with the proposed tasks. Second, the participants were trained for five minutes at each level of difficulty in the mental arithmetic (MA) task to estimate time taken to answer each question. Third (i.e. control phase), the participants had their EEG signals recorded for total duration of 15 minutes while solving arithmetic problems at three levels of difficulty *without any time limit per question*. After the EEG recording, a questionnaire was filled by the participants self-reporting about task loading according to NASA-TLX rating scale. Fourth (i.e. stress phase), the average time recorded during the training phase was reduced by 10% to induce stress on the participants. Similar as in the control phase, the EEG was recorded for 15 minutes and the participants completed another questionnaires about the task loading. The task in level one (L1) involved 3-one digit integer (ranging from 0 to 9) and used the operands of + or – (example 7+2-4). In level two (L2), the task involved 3 integers (ranging from 0 to 99) with at least 2 two-digit integers using the operands of +, –, and × (example 14×3-39). In level three (L3), the task involved 4 integer numbers (ranging from 0 to 99) and the operands include +, –, ×, / and ÷ (example 7-99/3+35). In this experiment, we developed the control technique by sending marker via channels 23-24 of EEG BrainMaster as '1' to mark the start of the task and '0' for the end of the task for each block. The entire record which had a total of nearly 1 hour, consisted of four blocks. Figure 1, gives an overview of the experimental protocol and the block design. Each block consisted of 40 seconds of mental arithmetic task and 30 seconds of rest.

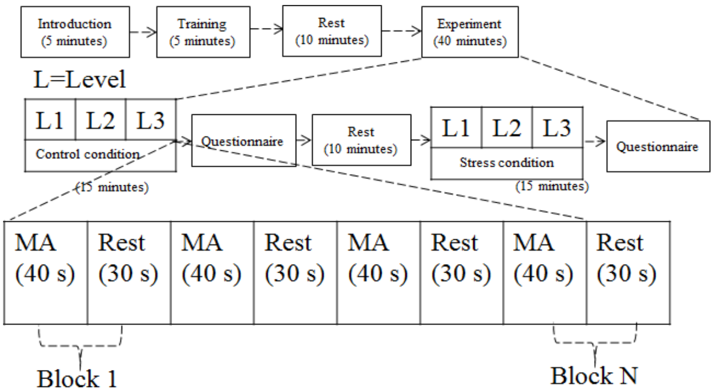

Figure 1. Experimental protocol of mental stress study. The labels L1, L2 and L3 represent the levels of mental arithmetic task and MA stands for mental arithmetic. Six recordings were performed in this experiment; three for control case and three for stress case. In each record, there were four blocks. In each block, mental arithmetic was allocated for 40 s followed by 30 s rest.

C. EEG Analysis

The Pre-processing of EEG data was performed offline. EEG data was Pre-processed with EEGLAB 2013a toolbox. First, the EEG data was bandpass filtered in the range of 0.5 Hz to 30 Hz using 3rd order Butterworth filter. Second, the artefacts were removed using independent components analysis technique (ICA).

EEG signal is a non-stationary signals which have different frequency elements at different time intervals. In this study, EEG signals was analysed using wavelet transform (WT) [28]. WT is suitable method for multiresolution time-frequency analysis. In this work, WT decomposed the EEG into four sub-frequency bands; Delta (1-4Hz), Theta (4-8 Hz), Alpha (8-12.5 Hz) and Beta (12.5-30 Hz). The wavelet decomposition level was set to 5-levels and one final approximation since we are interested in the frequency range of 0-30 Hz only. Table 1 gives a summary of the frequency distribution with wavelet decomposition levels.

Table 1. EEG frequency band decomposition levels.

Decomposition level	Frequency bandwidth	Frequency band
DL1	64 Hz -128 Hz	Noisy signal
DL2	32 Hz -64 Hz	Noisy Gamma
DL3	16 Hz -32 Hz	Beta
DL4	8 Hz -16 Hz	Alpha
DL5	4 Hz -8 Hz	Theta
AL5	0-4 Hz	Delta

From the wavelet coefficients we extracted the mean of the absolute values of the wavelet coefficient in each sub-band and the average power and energy. The power spectral density was calculated by:

$$P = \frac{1}{N}\sum_{n=k}^{k+N-1}|x(n)|^2 \quad , \qquad (1)$$

where *x(n)* represents the segmented EEG signal and *N* is the length of the recorded EEG signal. The energy of EEG frequency bands was calculated based on:

$$E = \frac{1}{N}\sum_{n=-\infty}^{\infty}|x(n)|^2 \quad , \qquad (2)$$

In this work, we used a segmentation of s time interval rectangular window to calculate the features of EEG signals.

D. Features Normalization

The features extracted from EEG signals were normalized to interval [0, 1] before feeding them into the classifier by calculating:

$$\mathrm{x}' = \frac{x - min(x)}{max(x) - min(x)} \quad , \qquad (3)$$

where *x* is the entire feature set, *min(x)* is the minimum value in the feature set and *max(x)* is the maximum value in the feature set respectively.

E. Classification

In this work, we used support vector machine (SVM) with 10-fold cross validation to classify stress from rest state. The SVM algorithm is a nonprobabilistic binary linear classifier that build a model to predict which category the new case belongs to. In this phase, only power values extracted from alpha band were used for classification. There was a total of 840 features for each subject in each recording phase (120 power values calculated from alpha frequency band multiply by 7 EEG measured electrodes). Features of one trial were used for testing and the other features (from other trials) were used for training the classifier. The formulation for obtaining SVM can be found in [29].

III. Result and discussion

The goal of this study was to discriminate between stress and rest state based on EEG signals collected while solving mental arithmetic task with three levels of difficulty. Stress levels in this experiment were based on time pressure and negative feedback. The developed mental stress stimulus in this paper induced variations in the brain cortical activities as captured by EEG signals. We investigated on the effects of mental stress levels induced by arithmetic tasks by calculating the alpha and beta rhythm power values in all electrodes for all the subjects. The obtained results of EEG records found that, subjects failed to relax and appeared less attentive when facing high level of stress. This indicates that, the cortical activation increased with low level of stress and decreased with high level of stress and time pressure. Our results demonstrated a decrease in alpha rhythm power from level one to level two and failed to drop in level three of mental stress. Beta rhythm power, on the other hand increased with response speed of mental arithmetic, suggesting that subjects needed to pay more attention to finish the task under time pressure but as they faced high level of stress their attention would reduce.

In particular, by studying each level of mental stress separately, we found a very significant difference between the control/rest and the stress condition. We employed two-sample t-test analysis between every pair of the tasks to study their significant differences. In the analysis part, we focused on alpha rhythm due to its negative correlation with mental stress and its significant variation with mental workload [16]. There was a significant decrease in alpha rhythm power from control condition to stress condition in level one of mental stress with mean *p-value* of 0.03. Level two however, showed a significant reduce in alpha rhythm power with mean *p-value* of *0.042*. In level three we found that, the mean difference between control and stress condition was less significant as compared to level one and level two, mean *p-value* of 0.05. By comparing the three levels of mental stress induced by arithmetic tasks, there was a great decline in alpha power from level-one-to-level-two and increased again from level-two-to-level-three. This indicates that the cortical activation increased from task level-one to task level-two and failed at task level-three, verified with questionnaires. Figure 2 showed the mean differences between each level of the control task and stress task.

NASA-TLX rating scales showed no significant differences in the three mental stress levels. The results suggested that, subjective assessment using questionnaire was not sensitive for measuring mental stress levels and revealed the effectiveness of physiological measurement using EEG signals.

Based on the repititive of the stress tasks (three times recording for three levels of mental stress), we studied the dominant brain regions to mental stress. The dominant was obtained based on the significant responses from the right and left asymmetry as calculated by two-sample t-test. The study revealed the dominant of the right prefrontal cortex (PFC) to mental stress (PFC reduce with stress) in all the three levels of mental stress. This finding is consistent with previous study [30, 31]. Furthermore, we classified the stress levels using support vector machine classifier. The mean classification accuracy obtained by the classifier was 94%, 85% and 80% for level one, level two and level three of mental stress respectively.

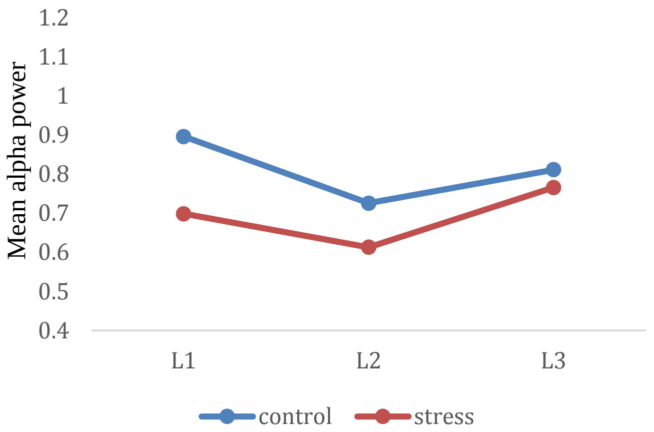

Figure 2. Mean Alpha rhythm power distribution in two mental states; control and stress. The L1-represents level one of mental arithmatic task, L2- represents level two of mental arithmatic task and L3- represents the level three of arithmatic task.

IV. Conclusion

In a study with 12 subjects, we have shown that EEG signals can be used to reliably identify mental stress levels from rest state. The study reported a significant differences between the tasks (control and stress) as measured by two-sample t-test with mean *p-values* of *0.03, 0.042, and 0.05* for level one , level two and level three of arithmetic task respectively. Furthermore, the study revealed the dominant of the right prefrontal cortex to mental stress. The questionnaire about task loading indicated that with increasing level of difficulty especially level three, the engagement of participants reduced significantly. The experimental results supported the suggestion of using EEG to detect mental stress, and reported level one of mental arithmetic task as the most suitable stress stimuli.

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Conflict of Interest

The authors have declared that no competing interests exist.

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Author: Fares Al-shargie
Institute: Universiti Teknologi PETRONAS, Centre of Intelligent Signal and Imaging Research, Department of Electrical and Electronic Engineering
Street: Bandar Seri Iskandar,
City: Perak
Country: Malaysia
Email: fares_g02737@utp.edu.my