

**DEVELOPMENT OF NEUROMETRIC ACUTE
STRESS ASSESSMENT BASED ON EEG SIGNALS**

SAIDATUL ARDEENAWATIE BTE AWANG

UNIVERSITI MALAYSIA PERLIS

2014

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STRESS ASSESSMENT BASED ON EEG SIGNALS**

by

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A work submitted in fulfillment of the requirements for the degree of
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**School of Mechatronic Engineering
UNIVERSITI MALAYSIA PERLIS**

2014

THESIS DECLARATION

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2014

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LIST OF ABBREVIATIONS

AAS	Alpha Asymmetry Score
AC	Alternating Current
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ANS	Autonomous Nervous System
AP	Action Potential
AR	Autoregressive
ARMA	Autoregressive Moving Average
BCI	Brain Computer Interface
BCMSI	Brain Computer Mental Stress Interface
BIS	Bispectral Index
BP	Blood Pressure
DASS	Depression Anxiety Stress Index
DC	Direct Current
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
EoG	Electrooculagraphy
ESD	Energy Spectral Density
FCM	Fuzzy C Clustering
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
fMRI	functional Magnetic Resonance Imaging

GAS	General Adaptation Syndrome
GSC	Galvanic Skin Resistance
HR	Heart Rate
HRV	Heart Rate Variability
IQ	Intelligent Question
KNN	K- Nearest Neighbors
L-O-O	Leave-One-Out
LFA	Left Frontal Asymmetry
MA	Moving Average
MAT	Mental Arithmetic Task
MLPNN	Multi Layer Perceptron Neural Network
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
MUSIC	Multiple Signal Classification
NIRS	Near Infrared Spectroscopy
PCA	Principle Component Analysis
PNS	Peripheral Nervous Sytem
PR	Pulse Rate
PS	Power Spectrum
PSD	Power Spectrum Density
PTG	Plethymography
SAS	Stress Asymmetry Score
SNR	Signal to Noise Ratio
SNS	Sympathetic Nervous System
TP	Time Pressure

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LIST OF SYMBOLS

Delta

Theta

Alpha

Beta

Gamma

P Power

E Energy

Asymmetry Score

Stress Index

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Pembangunan Neurometrik bagi penilaian Tekanan Akut Berdasarkan Isyarat EEG

ABSTRAK

Pada masa kini, tekanan perasaan adalah isu kesihatan yang serius dan membawa kepada kemurungan, keletihan dan insomnia. Tekanan boleh dibahagikan kepada dua jenis iaitu eustress dan distress. Eustress atau tekanan positif merujuk kepada tekanan yang boleh membantu untuk meningkatkan prestasi individu. Sebaliknya, Distress atau tekanan negatif boleh membinasakan seseorang dengan mewujudkan kemurungan dan merosakkan kualiti hidup. Pembangunan indeks berangka adalah penting untuk memahami tahap keseriusan tekanan tersebut. Pembangunan protokol dalam membetuk data perolehan adalah sangat penting bagi membentuk sistem data yang dapat memberikan tahap tekanan yang berbeza-beza. Dalam kajian ini, beberapa pengubahsuaian telah dilakukan kepada Tugas Mental Aritmetik yang sedia ada bagi memastikan protokol yang direka mampu untuk mendorong intensiti yang berbeza tekanan seperti rendah, sederhana dan tinggi. Protokol pengujaan dinamik dan konsep tekanan masa telah dicadangkan dalam kerja ini. Untuk tujuan pengesahan kebolehpayaan protokol, tiga cara pengesahan telah digunapakai iaitu: K Kejiranan paling hampir (KNN), Alpha Otak Asimetri dan Analisa statistik (Ujian-t berpasangan). Hasil daripada kajian ini, didapati bahawa protokol eksperimen yang dicadangkan adalah setanding berdasarkan kepada (i) Hasil ujian-t menunjukkan perubahan fisiologi pra dan pos adalah signifikan secara statistik ($p < 0.01$) (ii) Nilai purata Alpha Otak Asimetri adalah setanding dan mempunyai potensi untuk membezakan antara tahap dan (iii) ketepatan peratusan klasifikasi sebanyak 84%. Keputusan ini mengesahkan bahawa protokol yang dicadangkan mempunyai potensi dalam mengklasifikasikan tahap tekanan mental. Selain daripada itu, kaedah pra proses dengan penapis eliptik dan setiap data bingkai dengan 256 data per bingkai adalah paling sesuai. Pengekstrakan ciri dengan menggunakan lima jenis penganggar spektrum (Welch, Burg, Yule Walker, Pengubahsuaian Kovarians dan Klasifikasi Isyarat Pelbagai) dijalankan. Ciri-ciri yang diekstrak disahkan dengan menggunakan pengesahan silang 10 kali ganda dan dikelaskan menggunakan KNN dan disahkan signifikannya dengan menggunakan analisis statistik (ANOVA). Kadar klasifikasi purata peratusan maksimum 86.75 % dicapai menggunakan ciri Pengubahsuaian Kovarians diperolehi daripada gelombang alfa menggunakan KNN. Selain daripada itu, kajian menunjukkan, elektrod F3 dan F4 adalah elektrod yang paling bermaklumat dengan ketepatan klasifikasi 93.50%. Akhir sekali, idea baru telah dicadangkan berdasarkan skala yang ditubuhkan iaitu Alpha Asimetri Skor (AAS) sebagai rujukan. Pengubahsuaian telah dibuat dari segi jalur frekuensi yang berfungsi sebagai pembolehubah dalam persamaan indeks tekanan. Ketepatan klasifikasi yang dicadangkan iaitu Tekanan Asimetri Skor (SAS) adalah lebih kurang 96% di mana 10% lebih tinggi daripada AAS. Pembangunan indeks tekanan menjanjikan era baru dalam penyelidikan berasaskan tekanan mental untuk faedah manusia sejagat di masa depan.

Development of Neurometric Acute Stress Assessment Based on EEG Signals

ABSTRACT

Nowadays, stress is one of the major issues where too much stress may lead to depression, fatigue and insomnia. Stress can be divided into two types called Eustress and Distress. Eustress or positive stress refers to the positive stress which helps to improve the performance of an individual. In contrast, Distress or negative stress can devastate a person by creating depression and damage the quality of life. It is essential to comprehend and to figure out the state of current stress in numerical index. The development of a reliable data acquisition protocol is a crucial part to elicit mental stress in different level of stress. In this study, some modification on the existing Mental Arithmetic Task (MAT) has been made to ensure the designed protocol is capable to induce the different intensity of stress such as low, moderate and high. The dynamical excitation protocol and time pressure concept are proposed in this work. There are three validation methods have been used, namely, K Nearest Neighbor (KNN), Alpha Brain Asymmetry and statistical analysis (Paired T-test). As a result of this study, it was found that the proposed experimental protocol is comparable as the verification has been made with the following: (i) The t-test result based on physiological changes during pre and post experiment were found to be statistically significant ($p < 0.01$) (ii) The mean value of Alpha Brain Asymmetry are comparable and have a potential to discriminate between levels and (iii) the classification accuracy of 84% confirmed that the proposed protocol have potential in classifying the mental stress level. Besides that, the preprocessing technique applying elliptic filters with 256 data per frame is the most suitable technique. Five types of spectral estimator (Welch, Burg, Yule Walker, Modified Covariance and Multiple Signal Classification) based feature extraction is performed on the normalized signals. The extracted features are cross validated using 10-fold cross validation and classified using KNN and have been proved using statistical analysis (ANOVA). The maximum mean classification rate of 86.75% is achieved using Modified Covariance feature derived from alpha waves using KNN. Besides that, this study found that F3 and F4 are the most informative electrodes with the classification rate of 93.50%. Last but not least, a new algorithm has been proposed based on the more established index, Alpha Asymmetry Score (AAS), as a reference. Modifications have been made in term of the frequency band as a variable in the stress index. The classification accuracy of the proposed Stress Asymmetry Score (SAS) is approximately 96% which is 10% higher than AAS. The development of the stress index promises new era of stress brain related research for future people's benefit.

CHAPTER 1

INTRODUCTION

In a modern society, it is impossible to live without stress. Stress is the emotional and physical strain caused by human body response to pressure from the outside world. Stress is the response to stressor. Every people experienced different stressor daily in their life. Stressor can be physiologic (surgery, injection, disease, exercise, and trauma); environmental (prolonged heat, cold, chemical, radiation and noise); or psychological (threat, intense competition, prolonged conflicts, fear and unpredictability) (Sawyer & Escayg, 2010; Van de Kar LD *et.al*, 1991). For example, in working environment, stress may be triggered when people need to meet the deadlines to complete the task and overloading of task given by the employer. Moreover, in personal view, the issues which are related to family relationship, financing problem, death of family members and bad health status tend to excite the stress. If chronic, stress can have serious consequences, and is a leading risk factors for heart diseases, diabetes, asthma and depression.

Human body is designed to cope with stress and react to it. Stress can become positive and negative side to human health. Stress can be positive by keeping us alert and ready to avoid danger whereas stress becomes negative when a person faces continuous challenges without relief or relaxation between challenges. As a result, the person becomes overworked and stress related tension builds.

World Health Organization (WHO) has reported that 43% of all adults suffer adverse health effects from stress. Stress can play a part in problems such as headaches, high blood pressure, heart problems, diabetes, asthma, arthritis, depression and anxiety.

On the other hand, untreated stress reactions may caused the lifetime prevalence of an emotional disorder is more than 50% (Goldberg, 2012a). Physiological responses serve the role as objective indicators of stress as well as a link between stress and health outcomes. Several studies have reported the correlation between physiological changes and stress. (Hayashi, 2006; Tanaka *et.al.* 2012).

Severe and chronic stress can have a destructive effect on the human body including brain function (Lewis *et.al* 2007). Brain is the major part in human body that has an ability to control and maintain the body regulation by releasing or blocking brain chemical and hormones in blood. In human body, Autonomic Nervous System (ANS) is divided into two types called Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS). SNS is taken place when our body in "fight and flight" condition. In contradictedly, PNS stabilizes the body system when the body readies for relaxation. In adjusting the stabilization process by SNS and PNS, it will affect the body regulation such as respiration, digestion, immunization and etc.

The brain's response to stress are varies in term of the amount of brain signal been released, oxygen demand in brain cell and etc. These stress response can be monitored through the scientific techniques such as Electroencephalography (EEG), Magnetic Resonance Imaging (MRI), functional Magnetic Resonance Imaging (fMRI) and etc. The aforementioned scientific technique gives us a better understanding of how the brain interacts to the external situation and what role of human brain plays whilst an individual is performing a number of tasks in their routine life. EEG is the most used technique to capture brain signals due to its excellent temporal resolution, non invasiveness, usability and low set up costs (Teplan, 2002).

Recently, EEG is becoming increasingly important in the diagnosis and treatment of brain related disease, neurological disease and other abnormalities. The signal