

**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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UNIVERSITI MALAYSIA PERLIS**

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TABLE OF CONTENTS

THESIS DECLARATION	i
ACKNOWLEDGMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	viii
LIST OF FIGURES	x
LIST OF ABBREVIATIONS	xv
LIST OF SYMBOLS	xviii
ABSTRAK	xix
ABSTRACT	xx
CHAPTER 1 : INTRODUCTION	1
1.1 Research Background	Error! Bookmark not defined.
1.2 Problem Statements	3
1.3 Research Objectives	4
1.4 Research Scopes	5
1.5 Thesis Organization	6
CHAPTER 2: OVERVIEW OF MENTAL STRESS RECOGNITION USING EEG SIGNAL	8
2.1 Introduction	8
2.2 Human Brain	11
2.2.1 Anatomy of brain and functions	12
2.2.2 Neurophysiology of Human Brain	13
2.2.3 Action Potentials	14
2.3 Electroencephalography (EEG)	16
2.4 Origin of Stress	20
2.4.1 The Shortcut Road Route	20

2.4.2	The High Road Route	21
2.5	Stress and Human Performance Effectiveness	21
2.6	An Overview of Previous Studies on Mental Stress Recognition System	22
2.6.1	Stress and their effect to body regulation system	23
2.6.2	Stress and type of mental stress elicitation protocol	24
2.6.3	Stress and their effects on EEG signals	25
2.6.4	EEG classification for Mental Stress	Error! Bookmark not defined.
2.6.5	Mental stress and their quantification method	27
2.7	Summary	28

CHAPTER 3: DEVELOPMENT ON MENTAL STRESS ELICITATION PROTOCOL

		33
3.1	Introduction	29
3.2	Related Works	32
3.3	Proposed Methodology	35
3.3.1	Experimental Set Up and Subjects Description	37
	3.3.1.1 Subject Description	37
	3.3.1.2 Depression Anxiety Stress Index (DASS)	38
	3.3.1.3 Electroencephalography Device	39
	3.3.1.4 Patient Monitoring System	41
3.3.2	Mental Stress based on MAT protocol	41
3.3.3	Feature Extraction Algorithm	43
3.3.4	Signal Processing and Analysis	45
	3.3.4.1 Preprocessing	46
	3.3.4.2 Normalization	48
	3.3.4.3 Feature Extraction Using Modified Covariance	48
	3.3.4.4 Feature Reduction Using Statistical Features	52
	3.3.4.5 Classification	53
3.3.5	Performance Evaluation Method	54
	3.3.5.1 Statistical Analysis Using Paired t-test	54
	3.3.5.2 K-fold cross validation Method	55
3.4	Experimental Data	57
3.5	Experimental Results and Discussions	58
3.5.1	Validation based on Physiological Signal Analysis	58
3.5.2	Validation Based on Alpha Brain Asymmetry Score	59
3.5.3	Validation Based on k-Nearest Neighbors (KNN) classifier	61
3.6	Summary	62

CHAPTER 4: DETERMINATION OF MENTAL STRESS FEATURES 64

4.1	Introduction	64
4.2	Related Works	65
4.2.1	Preprocessing	65
4.2.2	Feature Extraction	67
4.3	Methodology	69
4.3.1	Feature Extraction Algorithm	69
4.3.2	Preprocessing Method	70
4.3.3	Feature Extraction Method	72
4.3.3.1	Welch Method	74
4.3.3.2	Yule Walker Method	75
4.3.3.3	Burg AR Method	77
4.3.3.4	Akaike Information Criterion	80
4.3.3.5	Eigenvector Method ó Multiple Signal Classification	80
4.3.4	Statistical Features Extraction	82
4.3.5	Feature Selection Using Principal Component Analysis	83
4.3.6	Validation of Classification	84
4.3.7	Classification Performance	84
4.3.8	Analysis	87
4.3.8.1	Statistical Analysis ó ANOVA	87
4.3.8.2	Multilayer Perceptron Neural Network	89
4.4	Experimental Result and Discussions	93
4.4.1	The Selection of Salient Preprocessing Method	93
4.4.2	Performance Measures	94
4.4.3	The Selection of Salient Spectrum Estimator	96
4.4.3.1	Classification Accuracy using k-Nearest Neighbors (KNN)	101
4.4.3.2	Classification Accuracy using Multilayer Perceptron Neural Network	103
4.4.3.3	Result based on Statistical Analysis (ANOVA)	105
4.5	Case Study	106
4.5.1	Case I: Classification of Statistical Features and Features Selection	106
4.5.2	Case II: Classification of Various Stress Level	107
4.6	Summary	108

CHAPTER 5: OPTIMIZATION OF BRAIN COMPUTER INTERFACE (BCMSI) FOR MULTI CHANNEL MEASUREMENT 110

5.1	Introduction	110
5.2	Related Works	111

5.2.1	Frequency Component Selection in EEG Based On Brain Computer Mental Stress Interface (BCMSI)	111
5.2.2	Channel Selection of EEG for Brain Computer Mental Stress Interface (BCMSI)	113
5.3	Methodology	115
5.3.1	Frequency band Localization Algorithm	115
5.3.2	Optimizing the Channel Selection in EEG Based On BCMSI and Its Algorithm	Error! Bookmark not defined.
5.4	Experimental Results and Discussion	117
5.4.1	Classification Results for the Frequency Band Localization	117
	5.4.1.1 K- Nearest Neighbors	118
	5.4.1.2 Statistical Analysis	121
5.4.2	Classification Results for the Channel Selection	122
	5.4.2.1 Classification Results for the Discarded Channel with Less Than 10% of the Maximum Value	123
	5.4.2.2 Classification Results for the Discarded Channel with Less Than 20% of the Maximum Value	128
	5.4.2.3 Classification Results for the Discarded Channel with Less Than 30% of the Maximum Value	133
5.5	Summary	138
CHAPTER 6: DEVELOPMENT OF STRESS INDEX		139
6.1	Introduction	139
6.2	Related Works	139
6.3	Proposed Methodology	141
6.4	Results and Discussion	144
	6.4.1 Classification Results for Established and Proposed Stress Asymmetry Score	144
	6.4.2 Derivation of Mental Stress Index Based on BCMSI	149
	6.4.2.1 Gender Differences in Response toward Stimuli	149
	6.4.2.2 Differences in Response to Stressor for Stress and Non Stress Subject	150
6.5	Limitations	152
6.6	Summary	153
CHAPTER 7: CONCLUSIONS AND FUTURE WORKS		154
7.1	Introduction	154
7.2	Achievements	154
7.3	Contribution to knowledge	156
7.4	Suggestions for further work	157

REFERENCES **159**

LIST OF PUBLICATION **168**

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LIST OF TABLES

NO	PAGE
Table 2.1: Classification of brain waves and mental conditions	17
Table 2.2: Electrode position in related to functional brain area	19
Table 3.1: Type of inducer that have been used to induce mental stress in previous studies	34
Table 3.2: DASS severity ratings	39
Table 3.3: Paired <i>t</i> -test results for different between pre and post experiments of blood pressure and heart beat	58
Table 3.4: Means of weighted average natural log alpha power EEG values by right and left quadrants during relaxation, low stress, medium stress and high stress	59
Table 3.5: Classification accuracies of statistical (energy and power) features using KNN classifier	61
Table 4.1: Previous works on evaluation of preprocessing method using different performance measures	72
Table 4.2: Confusion matrix formula for 4 x 4 matrixes of datasets	85
Table 4.3: Generated confusion matrix for mental stress classification	86
Table 4.4: Basic one way ANOVA table	87
Table 4.5: Network Training Parameters of MLPNN	91
Table 4.6: Mean value of performances measures of different preprocessing method over raw (before preprocessing) and preprocessed EEG signal (64 data per frame)	94

Table 4.7: Mean value of performances measures of different preprocessing method over raw (before preprocessing) and preprocessed EEG signal (128 data per frame)	95
Table 4.8: Mean value of performances measures of different preprocessing method over raw (before preprocessing) and preprocessed EEG signal (256 data per frame)	96
Table 4.9: The Welch PSD values from four classes of two EEG channels	99
Table 4.10: The Burg PSD values from four classes of two EEG channels (F3 and F4)	99
Table 4.11: The Yule Walker PSD values from four classes of two EEG channels	100
Table 4.12: The Modified Covariance PSD values from four classes of two channels (F3 and F4)	100
Table 4.13: The Multiple Signal Classification (MUSIC) PSD values from four classes of two EEG channels (F3 and F4)	101
Table 4.14: The values of the statistical parameters of the classifier	104
Table 4.15: Statistical Analysis results (ANOVA) for different five types of PSD estimator	105
Table 4.16: Classification of mental stress between two features set and four features set	107
Table 4.17: Classification of mental stress for 3 and 5 levels.	108
Table 5.1: Test of Homogeneity of Variances: (a) Delta (b) Theta (c) Alpha (d) Beta	122
Table 5.2: Mean absolute power for 19 channels	123
Table 5.3: The occurrence of the active channels among the subjects	124

Table 5.4: Number of active channels within the identified regions per subject	125
Table 5.5: Correlation coefficients between the candidate channels in Region 2	125
Table 5.6: Correlation coefficients between the candidate channels in Region 3	126
Table 5.7: Classification accuracy of selected optimal channels	126
Table 5.8: The occurrence of the active channels among the subjects	128
Table 5.9: Number of active channels within the identified regions per subject	129
Table 5.10: Correlation coefficients between the candidate channels in Region 1	130
Table 5.11: Correlation coefficients between the candidate channels in Region 2	130
Table 5.12: Classification accuracy of selected optimal channels	131
Table 5.13: The occurrence of the active channels among the subjects	133
Table 5.14: Number of active channels within the identified regions per subject	134
Table 5.15: Correlation coefficients between the candidate channels in Region 1	135
Table 5.16: Correlation coefficients between the candidate channels in Region 2	135
Table 5.17: Classification accuracy of selected optimal channels	136

LIST OF FIGURES

NO.	PAGE
Figure 1.1: General Adaptation Syndrome (GAS)(Goldberg, 2012b)	Error!
Bookmark not defined.	
Figure 2.1: Anatomy of human brain (Saeid, 2007)	12
Figure 2.2: A simple structure of neuron (Saeid, 2007)	14
Figure 2.3: An example of action potential (Saeid., 2007)	15
Figure 2.4: Typical normal EEG signal	17
Figure 2.5: Labels for points according to 10-20 electrode placement system (Teplan, 2002)	20
Figure 2.6: Two different ways in respond to stress: A-The Shortcut and Route B- The High Road Route	21
Figure 2.7: The efficiency and the stress in human stress response (Reisman, 1997)	22
Figure 3.1: Overview of mental stress recognition system	31
Figure 3.2: Process flow of the validation of designed experimental protocol	36
Figure 3.3: Process flow of entire process for the mental stress elicitation protocol	37
Figure 3.4: Subjects fill in the form before undergoing the experiment	38
Figure 3.5: Position of 19 EEG electrodes according to the 10-20 International System	40
Figure 3.6: Experiment Set Up with Mindset 24 Topographic Neuromapping device and 2 desktops	40
Figure 3.7: Portable Patient Monitoring System	41
Figure 3.8: Process flow of mental stress protocol based on MAT	42

Figure 3.9: The process flow of the development mental stress elicitation protocol	44
Figure 3.10: Plots showing raw EEG signal and elliptic bandpass filtered EEG	47
Figure 3.11: Frequency response for designed 4 th order elliptic bandpass filter.	47
Figure 3.12: Estimation of data spectrum using AR model, p=15, p=20 and p=25	52
Figure 3.13: Partitioning design of the obtained feature vectors for the 10-fold cross validation method	56
Figure 3.14: Exemplary EEG signals for relaxation, easy stage, moderate stage and difficult stage taken from Subject 1.	57
Figure 3.15: Boxplot elucidates alpha brain Asymmetry Score for channel F3-F4 in four mental states; baseline (relaxation), Low stress, Medium stress and High stress	60
Figure 4.1: Block diagram depicts the selection of salient preprocessing method for BCMSI	71
Figure 4.2: Block diagram shows the process to determine the mental stress features	73
Figure 4.3: PSD plot of EEG signal using FFT with (a) Welch method (b) Burg AR method (c) Yule Walker AR method	79
Figure 4.4: Pattern of Multilayer Perceptron Neural Network (MLPNN)	92
Figure 4.5: The classification scheme for BCMSI	92
Figure 4.6: Power Spectrum (PS) of low stress obtained by Welch, Burg, Modified Covariance, MUSIC and Yule Walker method (Alpha wave, Channel F3).	97
Figure 4.7: Power Spectrum (PS) of moderate stress obtained by Welch, Burg, Modified Covariance, MUSIC and Yule Walker method (Alpha wave, Channel F3).	97

Figure 4.8: Power Spectrum (PS) of high stress obtained by Welch, Burg, Modified Covariance, MUSIC and Yule Walker method (Alpha wave, Channel F3).	98
Figure 4.9: Percentage of accuracy for 5 types of PSD estimator using KNN classifier	102
Figure 4.10: Classifier performance for KNN using Modified Covariance	103
Figure 5.1: Process flow of the frequency-channel optimization method for EEG signal classification	115
Figure 5.2: Process flow in determination of frequency band for BCMSI	116
Figure 5.3: Process flow of the EEG channel selection Error! Bookmark not defined.	
Figure 5.4: Percentage accuracy of each sub band frequency by different PSD estimator using KNN classifier for Low stress level	118
Figure 5.5: Percentage accuracy of each sub band frequency by different PSD estimator using KNN classifier for Moderate stress level	120
Figure 5.6: Percentage accuracy of each sub band frequency by different PSD estimator using KNN classifier for High stress level	120
Figure 5.7: Classifier performance for KNN (Modified Covariance + Alpha Wave)	121
Figure 5.8: Identified region over the scalp for the discarded channel with less than 10% of the maximum value	124
Figure 5.9: Classifier performance for KNN for different number of channels	126
Figure 5.10: Computational time for different number of channels	127
Figure 5.11: Identified region over the scalp for the discarded channel with less than 20% of the maximum value	129

Figure 5.12: Classifier performance for KNN (different number of channels)	131
Figure 5.13: Computational time for different number of channels	132
Figure 5.14: Identified region over the scalp for the discarded channel with less than 30% of the maximum value	134
Figure 5.15: Classifier performance for KNN for different number of channels	136
Figure 5.16: Computational time for different number of channels	136
Figure 6.1: The number of subject in stress and non stress with respect to the gender	142
Figure 6.2: Diagram in developing mental stress index	142
Figure 6.3: Classification Performance of Established (AAS) and Proposed Stress Asymmetry Score (SAS)	145
Figure 6.4: Classification accuracy of different k -fold ($k=2, 4, 6, 8, 10$) for low level	146
Figure 6.5: Classification accuracy of different k -fold ($k=2, 4, 6, 8, 10$) for moderate level	147
Figure 6.6: Classification accuracy of different k -fold ($k=2, 4, 6, 8, 10$) for high level	147
Figure 6.7: Stress Index Graph with respect to gender	149
Figure 6.8: Stress Index Graph with respect to subject's condition	151

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 contradictly, 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

processing and classification of the brain signal is crucial part for contributing to a better understanding of cognitive process. The main rationale from signal analysis is to separate EEG segments and to estimate the mental state of a subject related to a severity of stress while performing tasks. Huge amount of data are generated by EEG signals and highly complex of interpretation for discriminating EEG signal is time consuming, high cost, error prone, and missing a lot of reliable information. Thus, developing automated system for EEGs is vital to ensure the proper evaluation.

This work focuses on the development of neurometric acute stress based on EEG signals. This study proposes the Mental Stress Induction Protocol based on dynamical excitation via Mental Arithmetic Task (MAT) and algorithm for features extraction and neurometric index based on EEG signals in BCI developments. These proposed methods can distinguish the intensity of the mental stress through EEG signals and provide valuable information about the brain behaviour. The findings from this study will be useful for psychologist, especially to identify the severity of the stress correctly and efficiently using typical patterns of EEG signals.

1.1 Problem Statements

According to the Ministry of Health Malaysia prevalence of mental patients and mental health problems among adults is 10.7%, which was 1.5 times the rate of women is higher prevalence than men. The prevalence of mental illness and mental health problems among the elderly was 26 %, while among children and teenagers is 15.5 %. Alarming statistic on the involvement among children and teenagers in mental disease problem gives hint to responsible organization that some actions should be taken to avoid this problem from rapidly increased (Malaysia Ministry of Health, 2011).

Currently, in Malaysia, there are only 233 Malaysian psychiatrists for a population of nearly 30 million. The ratio is 0.8 specialists per 100,000 population (Malaysia