

STUDY OF NON-INVASIVE COGNITIVE  
TASKS AND FEATURE EXTRACTION  
TECHNIQUES FOR BRAIN-COMPUTER  
INTERFACE (BCI) APPLICATIONS

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## **SUPERVISOR'S DECLARATION**

We hereby declare that We have checked this thesis and, in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.

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## **STUDENT'S DECLARATION**

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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EXTRACTION TECHNIQUES FOR BRAIN-COMPUTER INTERFACE (BCI)  
APPLICATIONS.

MAMUNUR RASHID

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## ABSTRAK

Antara muka otak-komputer (BCI) menyediakan alternatif penting bagi orang kurang upaya yang membolehkan mereka berkomunikasi antara pemikiran individu dan menggunakan alat bantu yang berbeza. Teknologi BCI pada dasarnya terdiri daripada pemerolehan data, pra-pemprosesan, pengekstrakan ciri, klasifikasi dan perintah peranti. Walaupun pencapaian penting dan hebat telah diperolehi dalam setiap komponen BCI, bidang BCI masih merupakan bidang penyelidikan yang masih baru dan masih banyak yang perlu dilakukan untuk menjadikan BCI menjadi teknologi yang bermanfaat. Untuk menjadikan teknologi ini lebih berkesan, kajian tugas kognitif menggunakan ciri EEG dan kerangka klasifikasi telah diselidiki. Di sini, terdapat empat eksperimen berbeza yang telah dilakukan untuk menentukan penyelesaian maksima bagi masalah-masalah di dalam bidang teknologi ini. Dalam eksperimen pertama, tiga tugas kognitif iaitu penyelesaian matematik cepat, permainan santai dan bermain telah disiasat. Ciri-ciri tersebut telah diekstrak menggunakan kepadatan spektrum daya (PSD), entropi log-tenaga, dan sentroid spektrum dan ciri yang diekstrak telah diklasifikasikan melalui mesin vektor sokongan (SVM), jiran terdekat-K (K-NN), dan diskriminasi linear analisis (LDA). Dalam eksperimen ini, ketepatan klasifikasi terbaik untuk set data dari saluran tunggal peranti EEG dan dari lima saluran peranti EEG masing-masing adalah 86% dan 91.66% telah diperolehi dengan menggunakan pendekatan PSD-SVM. Ekspresi wajah berdasarkan kenyanitan mata iaitu kenyanitan mata kiri, kenyanitan mata kanan dan tidak ada kedipan mata telah dikaji melalui teknik cepat transformasi Fourier (FFT) dan ciri julat sampel dan kemudian ciri-ciri yang diekstrak telah diklasifikasikan menggunakan SVM, K-NN, dan LDA. Ketepatan terbaik (98.6%) telah dicapai dengan pendekatan berasaskan julat-SVM. Ekspresi wajah berdasarkan mata berkelip telah diselidiki menggunakan metodologi yang sama dengan kajian ekspresi wajah berdasarkan kenyanitan mata. Selain itu, pendekatan pengesanan puncak PSD juga telah digunakan untuk menghitung jumlah kedipan mata. Ketepatan optimum 99% telah dicapai dengan menggunakan pendekatan pengesanan puncak PSD. Selain itu, pergerakan tangan citra motor dua kelas telah diklasifikasikan menggunakan SVM, K-NN, dan LDA di mana ciri tersebut telah diekstrak melalui PSD, centroid spektrum dan transformasi gelombang berterusan (CWT). Ketepatan optimum 74.7% telah dicapai dengan menggunakan pendekatan PSD-SVM. Akhirnya, dua prototaip arahan peranti telah direka untuk menterjemahkan output pengkelasan klasifikasi. Satu prototaip dapat menterjemahkan empat jenis tugas kognitif dari segi 5 Watt empat mentol berwarna yang berbeza, manakala, prototaip lain dapat mengendalikan motor DC yang menggunakan tugas kognitif. Kajian ini telah menggambarkan penerapan setiap komponen BCI untuk memudahkan penggunaan alat bantu gelombang otak. Akhirnya, tesis ini berakhir dengan meramal arah masa depan mengenai isu-isu semasa teknologi BCI dan petunjuk ini dapat meningkatkan kebergunaan untuk pelaksanaan aplikasi komersial bukan sahaja untuk orang kurang upaya tetapi juga untuk sebilangan besar pengguna yang sihat.

## ABSTRACT

A brain-computer interface (BCI) provides an important alternative for disabled people that enables the non-muscular communication pathway among individual thoughts and different assistive appliances. A BCI technology essentially consists of data acquisition, pre-processing, feature extraction, classification and device command. Indeed, despite the valuable and promising achievements already obtained in every component of BCI, the BCI field is still a relatively young research field and there is still much to do in order to make BCI become a mature technology. To mitigate the impediments concerning BCI, the study of cognitive task together with the EEG feature and classification framework have been investigated. There are four distinct experiments have been conducted to determine the optimum solution to those specific issues. In the first experiment, three cognitive tasks namely quick math solving, relaxed and playing games have been investigated. The features have been extracted using power spectral density (PSD), log-energy entropy, and spectral centroid and the extracted feature has been classified through the support vector machine (SVM), K-nearest neighbor (K-NN), and linear discriminant analysis (LDA). In this experiment, the best classification accuracy for single channel and five channel datasets were 86% and 91.66% respectively that have been obtained by the PSD-SVM approach. The wink based facial expressions namely left wink, right wink and no wink have been studied through fast Fourier transform (FFT) and sample range feature and then the extracted features have been classified using SVM, K-NN, and LDA. The best accuracy (98.6%) has been achieved by the sample range-SVM based approach. The eye blinking based facial expression has been investigated following the same methodology as the study of wink based facial expression. Moreover, the peak detection approach has also been employed to compute the number of blinks. The optimum accuracy of 99% has been achieved using the peak detection approach. Additionally, two-class motor imagery hand movement has been classified using SVM, K-NN, and LDA where the feature has been extracted through PSD, spectral centroid and continuous wavelet transform (CWT). The optimum 74.7% accuracy has been achieved by the PSD-SVM approach. Finally, two device command prototypes have been designed to translate the classifier output. One prototype can translate four types of cognitive tasks in terms of 5 watts four different colored bulbs, whereas, another prototype may able to control DC motor utilizing cognitive tasks. This study has delineated the implementation of every BCI component to facilitate the application of brainwave assisted assistive appliances. Finally, this thesis comes to the end by drawing the future direction regarding the current issues of BCI technology and these directions may significantly enhance usability for the implementation of commercial applications not only for the disabled but also for a significant number of healthy users.

## TABLE OF CONTENT

<b>DECLARATION</b>	
<b>TITLE PAGE</b>	
<b>ACKNOWLEDGEMENTS</b>	<b>ii</b>
<b>ABSTRAK</b>	<b>iii</b>
<b>ABSTRACT</b>	<b>iv</b>
<b>TABLE OF CONTENT</b>	<b>v</b>
<b>LIST OF TABLES</b>	<b>ix</b>
<b>LIST OF FIGURES</b>	<b>x</b>
<b>LIST OF SYMBOLS</b>	<b>xii</b>
<b>LIST OF ABBREVIATIONS</b>	<b>xiii</b>
<b>CHAPTER 1 INTRODUCTION</b>	<b>1</b>
1.1 Background	1
1.2 Problem Statement	2
1.3 Objectives	4
1.4 Scope of Study	4
<b>CHAPTER 2 LITERATURE REVIEW</b>	<b>7</b>
2.1 Introduction	7
2.2 Why Brain-Computer Interface (BCI)?	7
2.3 Concept of Brain-Computer Interface (BCI)	7
2.4 Dependent & Independent BCI	9
2.5 Synchronous BCI and Asynchronous BCI	10
2.6 Brain Activity Measurement	11
2.6.1 Invasive recording Paradigm	11



2.6.2	Non-invasive Recording Paradigm	14
2.7	The brain and its functions	20
2.7.2	EEG Control Signal	21
2.8	Evoked Potentials	22
2.8.1	Steady State Evoked Potentials (SSEP)	22
2.8.2	P300	23
2.8.3	Error-related potential (ErrP)	23
2.9	Spontaneous signals	24
2.9.1	Slow cortical potentials	24
2.9.2	Non-motor cognitive tasks	24
2.10	Motor Imagery	25
2.11	Movement-related cortical potential (MRCP)	25
2.12	Architecture of EEG Based BCI System	25
2.12.2	EEG Signal Acquisition	26
2.12.3	Signal Pre-processing	30
2.12.4	Feature Extraction	31
2.12.5	Classification	36
2.13	Performance Evaluation Metrics	42
2.14	BCI Applications	42
2.14.1	BCI Wheelchair Control	43
2.14.2	BCI Cursor Control	43
2.14.3	BCI Speller	44
2.14.4	BCI Biometrics	46
2.14.5	BCI Emotion Recognition	46
2.14.6	BCI Virtual Reality and Game	48
2.14.7	BCI Robotic Arm	49

2.14.8	BCI Environment Control	50
2.15	Potential Research Gap	51
2.16	Summary	53
<b>CHAPTER 3 METHODOLOGY</b>		<b>55</b>
3.1	Introduction	55
3.2	Complete Methodology of BCI Technology	55
3.3	Study of Cognitive Task for BCI Applications	56
3.3.1	Quick Math Solving, Relaxed and Playing Game	57
3.3.2	Wink based Facial Expression Recognition	62
3.3.3	Eye Blink based Facial Expression Recognition	65
3.3.4	Left-hand and Right-hand Motor Imagery Recognition	67
3.4	Feature Extraction and Classification	71
3.4.1	Filtering the Data	71
3.4.2	Feature Extraction Techniques	72
3.4.3	Classification Algorithms	75
3.4.4	Quick Math Solving, Relaxed and Playing Game: Data Analysis Framework	77
3.4.5	Data Analysis Framework for Wink based Facial Expression	79
3.4.6	Eye Blink based Facial Expression: Data Analysis Framework	81
3.4.7	Left-hand and Right-hand MI: Data Analysis Framework	85
3.5	Device command	87
3.6	Summary	88
<b>CHAPTER 4 RESULTS AND DISCUSSION</b>		<b>90</b>
4.1	Introduction	90
4.2	Outcomes from the Study of Cognitive Tasks	90

4.2.1	Quick Math Solving, Relaxed and Playing Game	90
4.2.2	Wink based Facial Expression: Left-Wink, Right-Wink and No Wink	93
4.2.3	Eye Blinking based Facial Expression: One Blink, Two Blink, Three Blink and No Blink	94
4.2.4	Left-Hand Right-Hand Motor Imagery Movement	95
4.3	Outcomes from the Study of Feature Extraction and Classification	96
4.3.1	Quick Math Solving, Relaxed and Playing Game Classification	96
4.3.2	Left-Wink, Right-Wink and No Wink Classification	103
4.3.3	One Blink, Two Blink, Three Blink and No Blink Classification	107
4.3.4	Left-Hand Right-Hand Motor Imagery Movement Classification	110
4.4	Prototype for Device Commands	113
4.4.1	Prototype for Switching the Bulb	113
4.4.2	Prototype for Controlling the DC motor	117
4.5	Summary	119
<b>CHAPTER 5 CONCLUSION</b>		<b>122</b>
5.1	Introduction	122
5.2	Summary	122
5.3	Contribution	124
5.4	Future Work	124
<b>REFERENCES</b>		<b>126</b>
<b>APPENDICES</b>		<b>153</b>
<b>APPENDIX A DATA ACQUISITION SET-UP</b>		<b>154</b>
<b>APPENDIX B LIST OF PUBLICATIONS</b>		<b>156</b>

## LIST OF TABLES

Table 2.1	Advantages and disadvantages of dependent and independent BCI	9
Table 2.2	Advantages and disadvantages of synchronous and asynchronous BCI	10
Table 2.3	Advantages and disadvantages of Invasive recording paradigm	12
Table 2.4	Advantages and disadvantages of Non-invasive recording paradigm	14
Table 2.5	EEG frequency band with properties	16
Table 2.6	Neuroimaging modalities with their characteristics	19
Table 2.7	Summary table of recent EEG devices.	29
Table 2.8	Widely used EEG features with references.	34
Table 2.9	Widely used classification algorithms with reference	40
Table 3.1	Cognitive tasks with brief description	57
Table 3.2	Details about subjects selection.	59
Table 3.3	Experiment details of data acquisition.	63
Table 3.4	Details about subjects and observations number for MI movement.	69
Table 3.5	Summary table in terms of Methodology of all cognitive tasks.	89
Table 4.1	Achieved classification accuracy with the single channel data.	98
Table 4.2	Achieved classification accuracy with five channel dataset.	100
Table 4.3	Performance comparison of related studies.	102
Table 4.4	Classification accuracy for wink based facial expression.	106
Table 4.5	Classification accuracy of motor imagery movement.	111
Table 4.6	Operation of device command prototype corresponding to the cognitive tasks	116
Table 4.7	Summary of all experiments in this research.	121

## LIST OF FIGURES

Figure 2.1	Classification of BCI systems in terms of dependability, recording methods and mode of operation.	8
Figure 2.2	EEG, ECoG, and intracortical recording system	13
Figure 2.3	Human brain (a) different lobe of brain, (b) different lobe with their functionalities	20
Figure 2.4	General architecture of a brain-computer interface	26
Figure 2.5	Standardized electrode placement schemes	28
Figure 3.1	Complete methodology of BCI technology.	56
Figure 3.2	Complete flow diagram of data collection system for quick math solving, playing game and relaxed.	58
Figure 3.3	Electrode positioning system	60
Figure 3.4	Neurosky Mindwave set-up for EEG data collection.	60
Figure 3.5	Emotiv Insight set-up EEG data collection.	61
Figure 3.6	EEG stimulation protocol	61
Figure 3.7	Complete flow chart of data collection system for wink based facial expression.	62
Figure 3.8	Experimental design for data collection through Emotiv Insight.	64
Figure 3.9	Data acquisition protocol for wink based facial expression.	65
Figure 3.10	Complete flow diagram of data acquisition architecture for eye blinking based facial expression.	66
Figure 3.11	Data acquisition protocol for eye blinking facial expression.	67
Figure 3.12	The complete methodology of data acquisition system for motor imagery activity.	68
Figure 3.13	Equipment set-up for BioRadio.	70
Figure 3.14	Data acquisition protocol for motor imagery data collection.	70
Figure 3.15	Flow chart of the determination of filter coefficient.	71
Figure 3.16	Complete data analysis framework for quick math solving, relaxed and playing game.	78
Figure 3.17	Testing framework of trained model.	79
Figure 3.18	Data analysis framework for wink based facial expression classification.	80
Figure 3.19	Testing process of wink based trained model.	81
Figure 3.20	Complete data analysis framework for eye blinking based facial expression classification.	82
Figure 3.21	Testing process of eye blinking based trained model.	83

Figure 3.22	Architecture of peak detection for eye blink counting.	84
Figure 3.23	Complete data analysis framework for motor imagery activity classification.	85
Figure 3.24	Testing process for motor imagery based trained model.	86
Figure 3.25	Architecture of device command prototype.	87
Figure 4.1	Raw EEG data in time and frequency domain.	91
Figure 4.2	EEG alpha and beta band in time domain.	92
Figure 4.3	EEG alpha and beta band in frequency domain.	92
Figure 4.4	Raw data plotting of three cognitive tasks.	93
Figure 4.5	Raw data plotting of left wink, right wink and no wink.	94
Figure 4.6	Raw data plotting of one blink, two blink, three blink and no blink.	95
Figure 4.7	Raw data plotting of motor imagery hand movement.	95
Figure 4.8	Confusion matrix of all trained model from the single channel data.	97
Figure 4.9	Confusion matrix of all trained model with five channel dataset.	99
Figure 4.10	All classifiers with FFT (a) Confusion matrix (b) True positive rate (TPR) and false negative rate (FNR)	104
Figure 4.11	All classifier with sample range (a) Confusion matrix (b) True positive rate (TPR) and false negative rate (FNR)	105
Figure 4.12	Confusion matrix for Blink classification using SVM, K-NN and LDA	107
Figure 4.13	Peak detection process	108
Figure 4.14	Confusion matrix of Blink detection process.	109
Figure 4.15	Confusion matrix of different models for MI data classification.	111
Figure 4.16	Flow chart of the translational protocol.	114
Figure 4.17	Proteas simulation device command prototype.	115
Figure 4.18	Prototype of device command for BCI applications	116
Figure 4.19	Flow chart of translational Protocol for DC motor Control.	117
Figure 4.20	Complete connection diagram of DC motor controlling system.	118
Figure 4.21	Complete hardware set-up for DC motor controlling system	119
Figure 4.22	DC Motor Attached to Wheels.	119

## LIST OF SYMBOLS

$\delta$	Delta
$\theta$	Theta
$\alpha$	Alpha
$\beta$	Beta
$\Gamma$	Gamma
$\mu\text{V}$	Micro-Volt
Hz	Hertz
F	Frontal lobe
P	Parietal lobe
T	Temporal lobe
O	Occipital lobe
$p(x)$	Probability distribution function
$c_t$	Cell state
$h_t$	Hidden state
$f_t$	Forget gate
$i_t$	Input gate
$g_t$	Cell candidate
$O_t$	Output gate

## LIST OF ABBREVIATIONS

AEP	Auditory evoked potential
AUC	Area under the Curve
ALS	Amyotrophic lateral sclerosis
AP	Action potential
AR	Autoregressive model
AFA	Amplitude frequency analysis
AIMF	Analytic intrinsic mode functions
BCI	Brain–Computer Interface
BP	Band Power
BMI	Brain–Machine Interface
BOLD	Blood oxygenation level dependent
BSS	Blind source separation
CLIS	Completely locked-in state
CAR	Common average referencing
CNS	Central nervous system
CSP	Common spatial patterns
CNN	Convolutional neural networks
CBP	Checkerboard paradigm
CSSSP	Common sparse spatio-spectral patterns
CWT	Continuous wavelet transforms
CCA	Canonical Correlation Analysis
DBI	Direct brain interface
DBN	Deep belief networks
DFT	Discrete Fourier transform
DTW	Dynamic time warping
DWT	Discrete wavelet transforms
DM	Density matrix
ErrP	Error-related potential
ECG	Electrocardiogram, Electrocardiography
ECoG	Electrocorticogram, Electrocardiography
EEG	Electroencephalogram, Electroencephalography



EMG	Electromyogram, Electromyography
EMD	Empirical mode decomposition
EOG	Electrooculogram
EP	Evoked potential
EPSP	Excitatory postsynaptic potential
ERD	Event-related desynchronization
ERP	Event-related potential
ERS	Event-related synchronization
FES	Functional electrical stimulation
FN	False negative
FNR	False negative rate
FP	False positive
fMRI	Functional magnetic resonance imaging
fNIR	Functional near infrared
FFT	Fast Fourier Transformation
GAN	Generative adversarial network
GDI	Gini Diversity Index
HCI	Human–computer interface
IFSECN	International Federation of Societies for Electroencephalography and Clinical Neurophysiology
ICA	Independent component analysis
IPSP	Inhibitory postsynaptic potential
ITR	Information transfer rate
K-NN	K-nearest neighbor
LDA	Linear discriminant analysis
LFP	Local field potential
LogEE	Log Energy Entropy
LIS	Locked-in state
MEG	Magnetoencephalogram, magentoencephalography
MEP	Movement-evoked potential
MRCP	Movement-related cortical potential
MI	Motor imagery
MND	Motor neuron disease

MRI	Magnetic resonance imaging
NMD	Nonlinear mode decomposition
MSD	Multi-scale Shape Description
NIRS	Near-infrared spectroscopy
NN	Neural Network
PCA	Principal component analysis
PSD	Power spectral density
PET	Positron emission tomography
PSF	Phase space feature
ROC	Receiver Operating Characteristic
RCP	Row column paradigm
RSVP	Rapid serial visual presentation
RBM	Restricted Boltzmann machines
RNN	Recurrent neural networks
SuBAR	Surrogate-based artifact removal
SCP	Slow cortical potential
SMA	Supplementary motor area
SMR	Sensorimotor rhythm
SOBI	Second-order blind identification
SNR	Signal-to-noise ratio
SVM	Support vector machine
SSVEP	Steady-state visual-evoked potential
SSAEP	Steady-state auditory evoked potential
SSSEP	Steady-state somatosensory evoked potential
SWCS	Sliding window cropping strategy
SAE	Stacked autoencoder
TP	True positive
TPR	True positive rate
TN	True negative
VEP	Visual evoked potential
VR	Virtual reality
WHO	World health organization
WT	Wavelet Transforms

WPA	Wavelet packet analysis
WPS	Wavelet Packet Statistics
WPES	Wavelet Packet Energy Statistics

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