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GENERIC PATTERN RECOGNITION MODELS BASED ON EEG–MI BRAIN COMPUTER INTERFACES FOR WHEELCHAIR STEERING CONTROL



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ZIADOON TAREQ ABDULWAHHAB AL-QAYSI

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DEGREE OF DOCTOR OF PHILOSOPHY**

**FACULTY OF ART, COMPUTING AND CREATIVE INDUSTRIES
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ABSTRACT

The purpose of this study was to develop generic pattern recognition models (GPRMs) based on two-class EEG–MI brain-computer interfaces for wheelchair steering control. Initially, a preprocessing procedure was performed to remove unwanted signals and to identify the optimal duration of MI feature components. Then, feature extraction based on five statistical features, namely min, max, mean, median, and standard deviation were utilized for extracting the MI feature components in three signal domains, namely time, frequency, and time-frequency domains. Seven classification algorithms, namely LDA, SVM, KNN, ANN, NB, DT, and LR were selected and tested to find the best algorithms that could be used for the development of hybrid classifiers. Two datasets were used, namely the BCI Competition dataset (which belonged to Graz University) and the Emotive EPOC dataset (which was collected in this study), with the former being utilized in the development, evaluation, and validation of the GPRM models and the latter being used for validation only. The research findings showed that GPRM models based on the LR classifier were highly accurate in the time and time-frequency domains in the range of 4 and 6 seconds and 4 and 7 seconds, respectively. In addition, GPRM models based on the MLP-LR classifier were highly accurate in the frequency domain in the range of 4 and 6 seconds. Furthermore, the validation of such models using the Emotive EPOC dataset showed that the LR-based GPRM model attained high classification accuracies of 90.2% and 85.7% in the time domain and time-frequency domain, respectively. The MLP-LR-based GPRM models achieved a classification accuracy of 84.2% in the frequency domain. In conclusion, the main findings showed that GPRMs were highly adaptable when deployed in the real-time application of the EEG-MI-based wheelchair steering control system. The implication of this study is that generic pattern recognition models based on EEG-MI Brain-Computer interfaces can be utilized to improve the effectiveness of wheelchair steering control.





MODEL-MODEL PENGECEMAN CORAK GENERIK BERASASKAN ANTARA MUKA OTAK MANUSIA-KOMPUTER UNTUK KAWALAN PENGEMUDIAN KERUSI RODA

ABSTRAK

Tujuan kajian ini adalah untuk membangunkan model pengecaman corak generik (GPRM) berasaskan antara muka otak manusia-komputer (BCI) berdasarkan EEG-MI untuk kawalan pengemudian kerusi roda. Mula-mula, prosedur pra-pemprosesan dijalankan untuk menyingkirkan isyarat yang tidak diinginkan dan untuk mengenal pasti tempoh optimum bagi komponen-komponen ciri MI. Kemudian, penyarian sifat berdasarkan lima sifat statistik, iaitu minima, maksima, min, median, dan sisihan piawai digunakan untuk mengekstrak komponen-komponen ciri MI ke dalam tiga domain isyarat, iaitu domain masa, domain frekuensi, dan domain masa-frekuensi. Tujuh algoritma pengelasan, iaitu LDA, SVM, KNN, ANN, NB, DT, dan LR dipilih dan diuji untuk menentukan algoritma-algoritma yang terbaik yang boleh digunakan untuk membangunkan pengelas hybrid. Dua set data digunakan, iaitu set data *Competition BCI* (yang dipunyai oleh Universiti Graz) dan set data *Emotive EPOC* (yang dikumpulkan dalam kajian ini). Set data pertama digunakan untuk pembangunan, penilaian, dan pengesahan GPRM, sementara set data kedua digunakan hanya untuk pengesahan. Dapatan kajian menunjukkan model GPRM berasaskan pengelas LR adalah sangat berkesan dalam domain masa dan domain masa-frekuensi bagi julat masa antara 4 dan 6 saat dan julat masa antara 4 dan 7 saat, masing-masing. Tambahan pula, model GPRM berasaskan pengelas MLP-LR adalah sangat berkesan dalam domain frekuensi bagi julat masa antara 4 dan 6 saat. Di samping itu, pengesahan model berdasarkan set data *Emotive EPOC* menunjukkan model GPRM berasaskan pengelas LR memperoleh peratusan ketepatan pengelasan setinggi 90.2% dan 85.7% dalam domain masa dan domain masa-frekuensi, masing-masing. Model GPRM berasaskan pengelas MLP-LR memperoleh peratusan ketepatan pengelasan setinggi 84.2% dalam domain frekuensi. Sebagai kesimpulan, dapatan menunjukkan model GPRM adalah amat sesuai bila digunakan dalam sistem kawalan pengemudian kerusi roda berasaskan EEG-MI dalam masa nyata. Implikasi kajian ini adalah model-model pengecaman corak generik berasaskan antara muka otak manusia-komputer boleh digunakan untuk meningkatkan keberkesanan kawalan pengemudian kerusi roda.



CONTENTS

	Page
DECLARATION OF ORIGINAL WORK	ii
DECLARATION OF THESIS	iii
ACKNOWLEDGMENT	iv
ABSTRACT	v
ABSTRAK	vi
CONTENTS	vii
LIST OF TABLES	xii
LIST OF FIGURES	xiv
LIST OF ABBREVIATIONS	xvi
LIST OF APPENDICES	xviii
CHAPTER 1 INTRODUCTION	1
1.1 Overview	1
1.2 Motivation of the Study	2
1.3 Research Problem	6
1.4 Research Objectives	11
1.5 Research Questions	12
1.6 Research Scope	13
1.7 Thesis Structure	15
CHAPTER 2 LITERATURE REVIEW	17
2.1 Introduction	17
2.2 Systematic Review Protocol	18
2.2.1 Information Resources	19
2.2.2 Selection of Studies	19
2.2.3 Search in Databases	20
2.2.4 Eligibility Criteria	20
2.2.5 Data Collection Process	22
2.2.6 Statistical Data Analysis	22



2.3	Taxonomy Analysis	23
2.3.1	Development of a Wheelchair Control System Based on BCI	25
2.3.2	The proposed Framework for a Wheelchair Control System based on BCI	30
2.3.3	Simulation of a Wheelchair Motion Control System based on BCI	32
2.3.4	Review of the Wheelchair Control System based on BCI	34
2.3.5	Analysis of BCI based Wheelchair Control System	35
2.4	Motivation of using EEG-based BCI	37
2.4.1	EEG based BCI in Human-Robot Interaction	40
2.4.2	EEG based BCI in EPW Control	43
2.4.3	SSVEP and P300 based EEG Signals	44
2.4.4	Wheelchair	46
2.4.5	Intelligent Wheelchair	47
2.5	Challenges of the use of BCI Techniques for EPW Control	48
2.5.1	Concerns on using P300 for EPW Control	51
2.5.2	Concerns on using SSVEP for EPW Control	53
2.5.3	Concerns on Hybrid BCI for EPW Control	53
2.5.4	Concerns on Classification Accuracy and System Response	54
2.5.5	Concerns on Navigation Safety and Reliability	55
2.6	Recommendations for Researchers and Developers	56
2.6.1	Concerns on EEG Devices	57
2.6.2	Concerns on Wheelchair Navigation	58
2.6.3	Concerns on using Hybrid BCI for EPW Control	58
2.6.4	Concerns on Samples	59
2.6.5	Recommendations for Health Federation and Authorities and Governments	60
2.7	Neural Oscillations	61
2.8	EEG-based Motor Imagery	62
2.9	Preparing Dataset	64
2.9.1	BCI Competition IV Dataset-IIb	70
2.10	Feature Extractions	72
2.10.1	Fast Fourier Transform	75



2.10.2 Discrete Wavelet Transform	76
2.11 Classification	79
2.12 Research Gap Analysis	84
2.13 Summary	90

CHAPTER 3 RESEARCH METHODOLOGY **93**

3.1 Introduction	93
3.2 Phase One: Systematic Review	95
3.3 Phase Two: Preparing Dataset	96
3.4 Phase Three: Preprocessing	98
3.4.1 EEG Signal Filtering	100
3.4.2 Segmentation of EEG-MI Signal	100
3.5 Phase Four: Feature Extraction and Classification	103
3.5.1 Feature Extraction	103
3.5.1.1 Time Domain	105
3.5.1.2 Frequency Domain	106
3.5.1.3 Time-frequency domain	109
3.5.2 Classification	113
3.5.3 Performance Evaluation	114
3.6 Phase 5: Validation	118
3.6.1 Validation using BCI Competition (Dataset I)	120
3.6.2 Validation using Emotive EPOC (Dataset II)	121
3.6.2.1 Data Collection Experimental Design	121
3.7 Devices and Software Tools	125
3.7.1 Emotive EPOC EEG Device:	125
3.7.2 Software Tools	127
3.8 Summary	128

CHAPTER 4 THE DEVELOPMENT AND EVALUATION OF AN EEG-MI GENERIC PATTERN RECOGNITION MODELS **130**

4.1 Introduction	130
4.2 Preparing the Generic Dataset	133
4.3 Preprocessing	134



4.3.1 EEG-MI Signal Filtering	135
4.3.2 EEG-MI Signal Segmentation	136
4.4 Experiment-1: GPRM using Single Classifier in Time, Frequency, and Time-Frequency Domain	137
4.4.1 Development of EEG-MI GPRM and Experimental Findings in the Time Domain	139
4.4.2 Development of EEG-MI GPRM and Experimental Findings in the Frequency Domain	141
4.4.3 Development of EEG-MI GPRM and Experimental Findings in the Time-Frequency Domain	145
4.5 Experiment-2: GPRM using a Hybrid Classifier in the Time, Frequency, and Time-Frequency Domain	148
4.5.1 Development of EEG-MI GPRM and Experimental Findings in the Time Domain	149
4.5.2 Development of EEG-MI GPRM and Experimental Findings in the Frequency Domain	150
4.5.3 Development of EEG-MI GPRM and Experimental Findings in the Time-Frequency Domain	151
4.6 Experiment-3: The Evaluation of Single and Hybrid Classifiers in the Time, Frequency, and Time-Frequency Domains	153
4.6.1 Evaluation Result in the Time Domain	155
4.6.2 Evaluation Result in the Frequency Domain	157
4.6.3 Evaluation Result in the Time-Frequency Domain	160
4.7 Summary	165

CHAPTER 5 THE VALIDATION OF GENERIC PATTERN RECOGNITION MODELS 169

5.1 Introduction	169
5.2 Preparing the EEG-MI Dataset	172
5.2.1 BCI Competition IV Dataset IIb	172
5.2.2 Emotive EPOC EEG-MI Dataset	173
5.3 Preprocessing	177
5.4 Experiment-1: The Validation of GPRM based on Generic Dataset in the Time, Frequency, and Time-Frequency Domains	178



5.4.1 Validation and Findings in the Time Domain	180
5.4.2 Validation and Findings in the Frequency Domain	181
5.4.3 Validation and Findings in Time-Frequency Domain	184
5.5 Experiment-2: Validation of the GPRM using BCI Competition Single-Subject Dataset	186
5.5.1 Validation and Findings in the Time Domain	187
5.5.2 Validation and Findings in the Frequency Domain	189
5.5.3 Validation and Findings in the Time-Frequency Domain	192
5.6 Experiment-3: Validation of the GPRM using the Emotive EPOC Dataset	195
5.6.1 Validation and Findings in the Time Domain	197
5.6.2 Validation and Finding in the Frequency Domain	199
5.6.3 Validation and Finding in Time-Frequency Domain	201
5.7 Summary	206
CHAPTER 6 RESEARCH SUMMARY	209
6.1 Introduction	209
6.2 Comparative Analysis of the Findings for the Current Study and Previous Studies	210
6.3 Research Outcomes	221
6.3.1 Systematic review	221
6.3.2 Preparing Generic Dataset	223
6.3.3 Segmentation of EEG-MI Signal in Multiple Signal Domain	225
6.3.4 Developing and Validating Feature Extraction Technique in Three Signal Domains	226
6.3.5 Developing and Validating Single and Hybrid Classifiers in Multiple-Signal Domain	229
6.3.6 Validation by Recording EEG data using Emotive EPOC EEG Device	231
6.4 Recommendations for Future Work	232
REFERENCES	235
LIST OF PUBLICATIONS	250
APPENDICES	251

**LIST OF TABLES**

Table No.	Page
2.1 Study of BCI Competition Datasets	67
2.2 Mostly used Machine Learning in EEG Based Wheelchair Control	79
2.3 Studies Based on Two Classes of EEG-MI Signal for Wheelchair Control	88
3.1 Emotive EPOC EEG Device Technical Specifications	126
4.1 Classification Accuracies of GPRM Using Single Classifier in the Time Domain with Different Time Segments	140
4.2 Classification Accuracies of GPRM Using Single Classifier in the Frequency Domain with Different Time Segments	144
4.3 Classification Accuracies Of GPRM Using Single Classifier in the Time-Frequency Domain with Different Time Segments	147
4.4 Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on a Single-Subject Dataset in the Time Domain	157
4.5 Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on a Single-Subject Dataset in the Frequency Domain	159
4.6 Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on a Single-Subject Dataset in the Time-Frequency Domain	162
4.7 Summary of Classification Accuracies of GPRM using Single and Hybrid Classifiers based on a Single-Subject Dataset in all Signal Domains	163



4.8	Proposed GPRM Based Single and Hybrid Classifier in Three Signal Domains	164
5.1	Demographic Information of the Healthy Volunteers	175
5.2	Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on a Single-Subjects Validation Dataset in the Time Domain	188
5.3	Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on a Single-Subjects Validation Dataset in the Frequency Domain	191
5.4	Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on a Single-Subjects Validation Dataset in the Time-Frequency Domain	193
5.5	Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on an Emotive EPOC Single-Subject Dataset in the Time Domain	198
5.6	Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on an Emotive EPOC Single-Subject Dataset in the Frequency Domain	200
5.7	Classification Accuracies of GPRM Using Single and Hybrid Classifiers Based on an Emotive EPOC Single-Subject Dataset in the Time-Frequency Domain	202
5.8	Summary of Classification Accuracies of GPRM Validation using Single and Hybrid Classifiers	204
5.9	Proposed Methods and Techniques for the Procedures of the GPRM	205
6.1	Summary of the Comparative Analysis	218

**LIST OF FIGURES**

Figure No.		Page
1.1	Architecture of Brain-Controlled Wheelchair Adapted from (Faria, Reis, & Lau, 2012a)	3
1.2	Research Problem Configuration	10
1.3	The Scope of Study	14
2.1	Articles Collections Protocol	21
2.2	Taxonomy of Wheelchair Control Based on EEG Signals	23
2.3	Number of Articles by Databases and Objectives	24
2.4	EEG-Based SSVEP Command for Wheelchair Control Adapted from (Müller, Bastos-Filho, & Sarcinelli-Filho, 2011)	25
2.5	Wheelchair with Mounted Arms Adapted from (Achic, Montero, Penaloza, & Cuellar, 2016)	29
2.6	Wheelchair Integrated with a Smart Environment Adapted from (Tello Et Al., 2015)	30
2.7	3D Wheelchair Simulator Adapted from (Gentiletti Et Al., 2009)	32
2.8	Articles Based on EEG Signal Analysis	36
2.9	Emotive Wireless EEG Device Adapted from (Naijian, Xiangdong, Yantao, Xinglai, & Hui, 2016)	39
2.10	HRI Adapted from (Perrin, Chavarriaga, Colas, Siegwart, & Millán, 2010)	41





2.11	BCI Works Conducted Based on EEG Device Type	57
2.12	Sample Participants in the EEG Experiments	59
2.13	Number of Studies Supported by Grants Distributed by Countries	60
2.14	Timing Scheme without Feedback	71
2.15	Timing Scheme with Smiley Feedback	71
2.16	Wavelet Decomposition Levels Adapted from (Al-Fahoum & Al-Fraihat, 2014)	78
2.17	Research Gap Analysis	89
3.1	Research Methodology Process	94
3.2	Systematic Review Process	95
3.3	Mapping Continuous Signal to Trials	98
3.4	Preprocessing Steps of EEG-MI Signal	99
3.5	EEG Signal Segmentation Groups	102
3.6	EEG-MI Signal Feature Extraction Domain	104
3.7	Time Domain-Based Statistical Feature Extraction	106
3.8	Frequency Domain-Based Statistical Feature Extraction	108
3.9	Statistical Feature Extraction in the Time-Frequency Domain	111





3.10	Discrete Wavelet Transform Decomposition Levels	112
3.11	Classification Methods	113
3.12	Cross Validation Data Partitioning Procedure	116
3.13	Process Involved in the GPRM Development	117
3.14	Validation Process of the GPRM	119
3.15	Emotive EPOC EEG Setup	122
3.16	Electrodes Setup Using the International 10-20 System	123
3.17	Emotive EPOC EEG Device	126
4.1	Development Procedure of the GPRM	131
4.2	EEG Signal Filtering	135
4.3	Classification Accuracies Based on Time Segments in the Time Domain	139
4.4	Classification Accuracies Based on the Time Segments in the Frequency Domain	142
4.5	Classification Accuracies Based on the Time Segments in the Time- Frequency Domain	146
5.1	GPRM Validation Procedure	171
5.2	Emotive EPOC EEG Contact Quality	177
5.3	Emotive EPOC EEG Signal Filtering	178





LIST OF ABBREVIATIONS

AAR	Adaptive Auto-Regressive
ALS	Amyotrophic Lateral Sclerosis
B.F	Band-Pass Filter
BCI	Brain-computer Computer Interface
DT	Decision Tree
DWT	Discrete Wavelet Transform
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
EPW	Electrical Powered Wheelchair
FFT	Fast Fourier Transform
fMRI	Functional MRI
FPGA	Field Programmable Gate Array
GPRM	Generic Pattern Recognition Model
GPRMs	Generic Pattern Recognition Models
HRI	Human Robot Interaction
IoT	Internet of Thing
ITR	Information Transfer Rate
KNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
LR	Logistic Regression
Max	Maximum





MI	Motor Imagery
Min	Minimum
MLP	Multi-Layer Perceptron
MRI	Magnetic Resonance Imaging
NB	Naive Base
PCA	Principal Component Analysis
PSD	Power Spectral Density
S1	Subject One
S2	Subject Two
S3	Subject Three
S4	Subject Four
S5	Subject Five
S6	Subject Six
S7	Subject Seven
S8	Subject Eight
S9	Subject Nine
SNR	Signal to Noise Ratio
SSVEP	Steady-State Visually Evoked Potential
STD	Standard Deviation
SVM	Support Vector Machines





LIST OF APPENDICES

- A Emotive EPOC Safety Test Certificate
- B Ethical Approval and Medical Doctor Letter
- C Machine Learning Parameters
- D Emotive EPOC EEG Device Manual





CHAPTER 1

INTRODUCTION



1.1 Overview

This chapter gives an overview of the research which comprises the research problem, research gap, research objectives, motivation, background of the study, scope of the study, and thesis structure.

Section 1.2 describes the research motivation, while Section 1.3 presents the research problem as well as the research gap. Research questions and research objectives are clarified in Section 1.4 and Section 1.5, respectively. Section 1.6 follows with the scope of the study highlighting the boundary of the research. Finally, Section 1.7 summarizes the structure of the thesis





1.2 Motivation of the Study

Clearly, mobility is one of the challenges faced by stroke survivors. For example, a wheelchair can assist patients to become partially independent in performing certain daily activities (Caesarendra et al., 2015; J. Li et al., 2013). At present, the need for wheelchairs has increased for paralyzed patients and elderly people (Tomari, Hassan, Zakaria, & Ngadengon, 2015). However, for physically challenged individuals, the use of a push wheelchair is not ideal as it does not provide the needed comfort and maneuverability. Therefore, electric-powered wheelchairs (EPWs) were invented to conserve the physical energy of users and provide them with increased maneuverability (Jayabhavani, Raajan, & Rubini, 2013; Mirza et al., 2015). Also, many patients with spinal cord injuries and neuromuscular disorders mainly rely on electrical powered wheelchairs (EPWs) to gain mobility (Shinde & George, 2016).



Universal statistical data indicate that roughly 650 million people, who are approximately 10% of the global population, suffer from a motor disability, with nearly 7% in need of an electrical wheelchair (Lamti, Gorce, Ben Khelifa, & Alimi, 2016). Also, according to the Department of Social Welfare statistical data, there has been an exponential increase in the number of paralyzed patients in Malaysia. (Swee, You, & Kiang, 2016). Therefore, to accommodate such mobility-impaired persons, numerous cutting-edge techniques and functionalities have been developed over the years (Rabhi, Mrabet, & Fnaiech, 2018). For example, advanced research in the field of biomedical engineering (Xie & Li, 2015) and robotic technologies (Widyotriatmo & Andronicus, 2015) has delivered a new generation of wheelchairs called brain-controlled wheelchairs (BCWs), such as in (Turnip, Suhendra, & WS, 2015a).



Figure 1.1 shows the system architecture of the brain-controlled wheelchair (BCW). Specifically, the BCW is deemed to be the appropriate equipment for completely paralyzed patients with a healthy brain to navigate their environment (Budiharto, Gunawan, Parmonangan, & Santoso; Ramli, Arof, Ibrahim, Mokhtar, & Idris, 2015). As highlighted in the literature, BCW has been designed with different wheelchair platforms, such as normal BCW as in (Kim, Carlson, & Lee, 2013a) or BCW with robotic manipulator (Naijian, Xiangdong, Yantao, Xinglai, & Hui, 2016a) or BCW integrated with a smart environment (Tello et al., 2015).

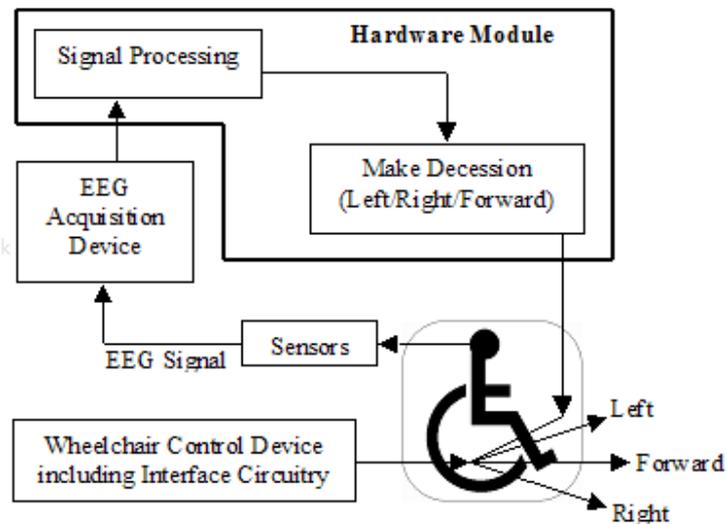


Figure 1.1. Architecture of Brain-Controlled Wheelchair adapted from (Faria, Reis, & Lau, 2012a).

In fact, several types of BCI exist, depending on the recording technique of the physiological signals, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), near-infrared spectroscopy (NIRS), and Magnetoencephalography (MEG) (Nicolas-Alonso & Gomez-Gil, 2012).



Among such physiological signals, EEG has been widely used because of its adequate temporal resolution, portability, and relatively low cost (Fernández-Rodríguez, Velasco-Álvarez, & Ron-Angevin, 2016).

To date, there have been many attempts to design brain-computer interfaces (BCIs) for wheelchair control based on steady-state visual evoked potential (SSVEP), event-related desynchronization/synchronization (ERD/ERS) during motor imagery (MI) tasks, P300 evoked potential, and some hybrid signals (J. Li et al., 2014). However, the effectiveness of using P300 has several limitations, particularly for patients suffering from a neurological illness, ALS (Kodi, Kumar, Kodali, & Pasha, 2013). Similarly, EEG-based SSVEP relies on certain motor movement control, which is ineffective for patients with severe motor disabilities (Bastos, Muller, Benevides, & Sarcinelli-Filho, 2011; Fernández-Rodríguez et al., 2016; S. M. T. Müller, Bastos-Filho, & Sarcinelli-Filho, 2011; Puanhvuan & Wongsawat, 2012; Widyotriatmo & Andronicus, 2015).

Another weakness of these schemes is that the user has to continuously focus on the mission when the process is synchronous (Inaki Iturrate, Antelis, & Minguez, 2009). As such, users may become exhausted or suffer from sore eyes if exposed to a visual stimulus for a long time. Therefore, such type of brain signals is unsuitable and ineffective for wheelchair control, as people with disability can easily become exhausted (Chai, Ling, Hunter, & Nguyen, 2012a; Chai, Ling, Hunter, Tran, & Nguyen, 2014; Kim, Suk, & Lee, 2016; Puanhvuan & Wongsawat, 2012)





Currently, motor imagery (MI) is one of the most common methods used in BCI-based EEG control systems (Hema, Paulraj, Yaacob, Adom, & Nagarajan, 2009; Kaneswaran, Arshak, Burke, & Condron, 2010). Recently, MI-based EEG signals have been used in various types of applications such as sports, psychology, neuroscience, rehabilitation technology as well as wheelchair control (Jiang, Tham, Yeo, Wang, & Jiang, 2014; J. Li et al., 2014).

In general, MI pattern recognition systems involve raw MI EEG signal preprocessing, feature extraction, and pattern classification (Liu, Zhang, Duan, Zhou, & Meng, 2017). In particular, segmentation is a significant preprocessing step in the signal analysis, and its performance plays a vital role in the efficiency of the subsequent steps such as feature extraction and classification (Azami & Escudero, 2015). Feature extraction is another critical step in MI pattern recognition. Common EEG features include those in the time domain, frequency domain, time-frequency domain, and spatial domain (Liu et al., 2017). Technically, a feature represents a distinguishing property, a recognizable measurement, and a functional component obtained from a section of a pattern. Extracted features are meant to minimize the loss of relevant information embedded in the signal. This is necessary to reduce the complexity of implementation, to reduce the cost of information processing, and to eliminate the need to compress information (Al-Fahoum & Al-Fraihat, 2014).

Generally, EEG signals are represented in high dimensional feature space, making such signal very difficult to interpret. In this regard, machine learning methods are helpful for interpreting high dimensional feature sets and analyzing the characteristics of brain patterns (Bhuvaneswari & Kumar, 2013).





In fact, many classification algorithms have been developed to distinguish brain activity states during different mental tasks (Belkacem, Hirose, Yoshimura, Shin, & Koike, 2014). Machine learning algorithms that have appeared in the literature of BCW are as follows: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Naive-Base (NB), Decision Tree (DT), and Logistic Regression (LR).

1.3 Research Problem

Admittedly, people with disability and the elderly will find steering and driving a wheelchair with electrical and mechanical schemes challenging. Therefore, various technologies to assist people with disability have been recently proposed (Mirza et al., 2015), one of which is Brain-Controlled Wheelchair (BCW) that has been considered to be an appropriate device for completely paralyzed patients with a healthy brain to navigate their environment (Budiharto et al.; Ramli et al., 2015).

Up to the present, there have been many attempts to design Brain-Computer Interfaces (BCIs) for wheelchair control based on Steady State Visual Evoked Potential (SSVEP), Event-Related Desynchronization/Synchronization (ERD/ERS) for MI tasks, P300 evoked potential, and some hybrid signals (J. Li et al., 2014). However, P300 has several limitations, particularly for patients suffering from neurological illnesses such as ALS (Kodi et al., 2013).





Similarly, EEG-based SSVEP has some drawbacks in that it relies on a certain motor movement control, which is ineffective for patients with severe motor disabilities (Bastos et al., 2011; Fernández-Rodríguez et al., 2016; S. M. T. Müller et al., 2011; Puanhvuan & Wongsawat, 2012; Widyotriatmo & Andronicus, 2015). Another weakness of these schemes is that users have to continuously focus on a mission when the process is synchronous (Inaki Iturrate et al., 2009). Naturally, they may become exhausted or suffer from sore eyes after exposing to visual stimuli for a long time. Therefore, such type of brain signals is unsuitable and ineffective for wheelchair control, especially for people with disability who can easily become exhausted (Chai et al., 2012a; Chai et al., 2014; K.-T. Kim et al., 2016; Puanhvuan & Wongsawat, 2012).

At present, MI is one of the most common methods used in BCI-based EEG control systems (Hema et al., 2009; Kaneshwaran et al., 2010). For example, EEG-based MI signals have been used in various types of applications, such as sports, psychology, neuroscience, rehabilitation technology as well as wheelchair control (Jiang et al., 2014; J. Li et al., 2014). In general, MI pattern recognition systems involve raw MI EEG signal preprocessing, feature extraction, and pattern classification (Liu et al., 2017). These pattern recognition processes are essential in EEG-MI based system design because these processes have a significant effect on system performance.

In particular, the presence of errors can cause the initiation of a wrong command that can lead to dangerous situations (Abiyev, Akkaya, Aytac, Günsel, & Çağman, 2016). In a complex and real environment, driving a wheelchair safely is essential for people with disability because of the requirement for sending commands on time (Carlson, Leeb, Chavarriaga, & Millán, 2012).





Therefore, the safety criterion in designing a wheelchair system for people with physical impairment must be given more importance (Jayabhavani et al., 2013). Hence, reliable navigation control systems are required for wheelchair users to comfortably and freely navigate around with a high degree of safety (Kaufmann, Herweg, & Kübler, 2014).

For example, in an unsafe or unfamiliar condition, a wheelchair control system needs to be sensitive in checking the accuracy of extracted commands from the EEG-MI based system for placing the user in a safe zone (Widyotriatmo & Andronicus, 2015). Otherwise, the EEG-MI based system can pose a threat to the user or to nearby people because of the unwanted navigation controls of the wheelchair resulting from the use of wrong commands, unfamiliarity with the machine interface, and misinterpretation of user's gestures by the machine (Shinde & George, 2016).

Therefore, in designing a wheelchair for stroke survivors, for example, the accuracy of the classification in distinguishing mental tasks such as the thinking process of the user in deciding to move forward, backward, to the right, and to the left, has to be taken into account (Amarasinghe, Wijayasekara, & Manic, 2014). However, to attain a high classification accuracy is challenging for a BCI-based system because of the complexity of brain signals (Parmonangan, Santoso, Budiharto, & Gunawan, 2016).

In addition, individual differences in EEG signals can also affect the stability of a control system, given that such signals are not ideally stable (Min Li, Zhang, Zhang, & Hu, 2013). Furthermore, the EEG based system has the disadvantage of having higher sensitivity to noises, including ocular, muscular, and electromagnetic noises.





Nonetheless, the noise problem can be reduced and the classification accuracy can be improved by using better computational intelligent methods for both feature extraction and classification algorithms to extract high dimensional EEG features (Chai et al., 2012a). The use of high-quality EEG devices is prohibitively expensive (Abiyev et al., 2016). Moreover, the financial cost and the reliability of BCI-based wheelchair control systems have been called into question given the less favorable results of the numerous models of smart wheelchairs that have been developed using high-tech assistive solutions, which have yet to be marketed (Naijian, Xiangdong, Yantao, Xinglai, & Hui, 2016b; Taher, Amor, & Jallouli, 2016).

In addition, recent applications in the field of EEG-based BCI systems have other limitations such as the lack of complex configuration during EEG measurement that uses a large number of electrodes, the amount of time used for the arrangement and setup of electrodes (Andronicus, Harjanto, & Widyotriatmo, 2015; Kaysa & Widyotriatmo, 2013), and their bulkiness and lack of maturity (Taher, Amor, & Jallouli, 2015). As a result to that, many studies using different techniques and methods of preprocessing, feature extraction, and classification in recognizing EEG patterns of EEG-MI based wheelchair control commands have been found in the literature; however, studies focusing on the best method or technique in distinguishing EEG-MI commands to be deployed in a wheelchair control system are seriously lacking. This revelation is not surprising given the challenges in designing and developing a motor imagery-based brain computer interface (BCI) with powerful pattern recognition and strong generalization capability (Zhang et al., 2018). Figure 1.2 highlights the research problem configuration, challenges, and issues discussed in this Chapter.



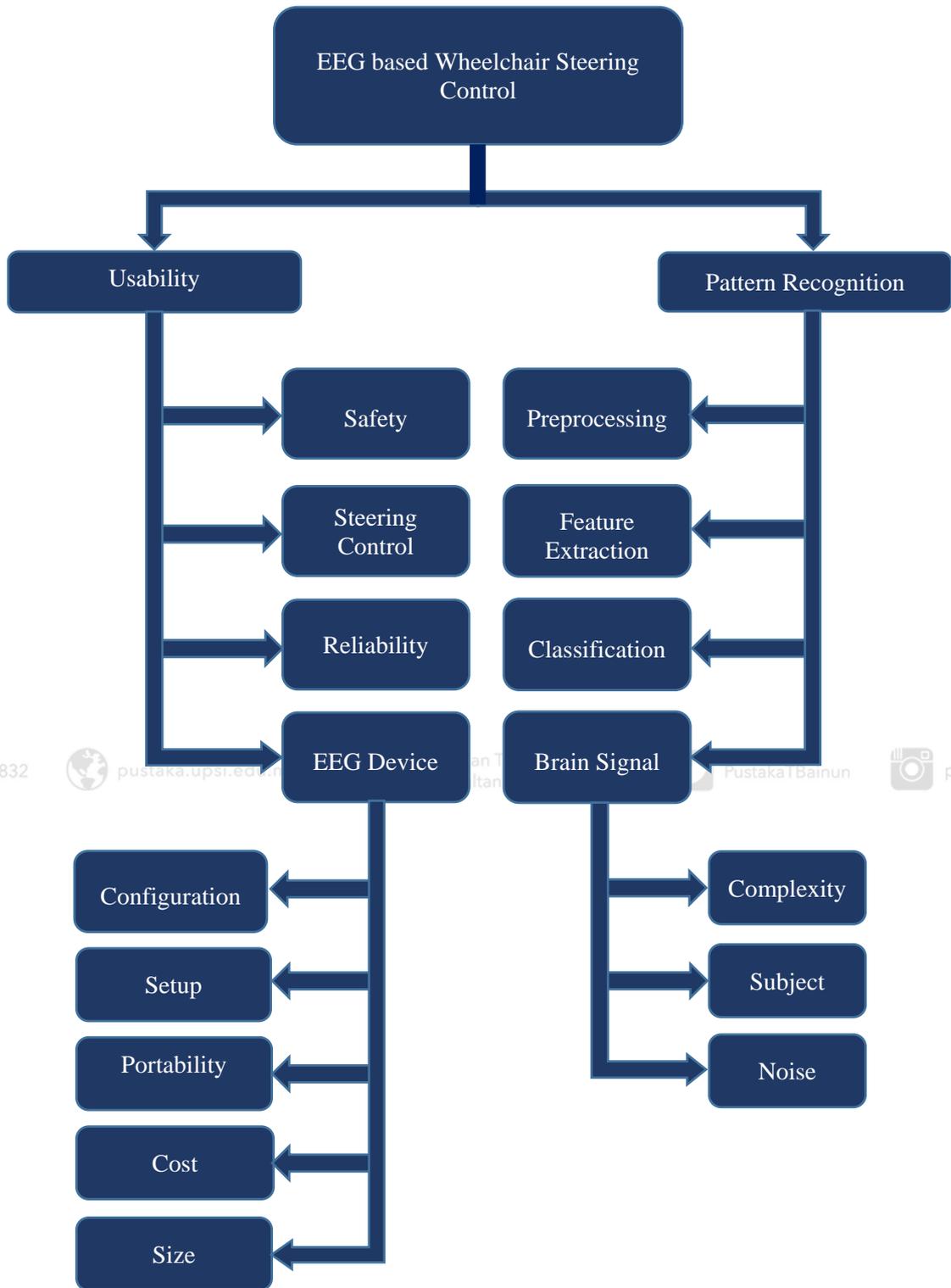


Figure 1.2. Research Problem Configuration



1.4 Research Objectives

The main objective of this research is to develop a generic pattern recognition models (GPRMs) for two-class EEG-MI signal wheelchair commands. To achieve the main objective, several sub-objectives were identified as follows:

1. To develop a generic preprocessing procedure of EEG motor-imagery signal in terms of generic dataset construction, signal filtering, and segmentation.
2. To develop a feature extraction technique based on statistical methods in multiple-signal domains.
3. To develop and evaluate a GPRM of two-class EEG motor-imagery signal wheelchair control commands in three signal domains using single classifiers and hybrid classifiers.
4. To validate the developed GPRM in multiple-signal domains using EEG-MI BCI competition dataset and Emotive EPOC EEG-MI dataset.





1.5 Research Questions

Four research questions were formulated to guide the design and focus of the study as follows:

Q1. What are the preprocessing techniques that can be used to find the generic time segment of EEG-MI feature components?

Q2. What is the most appropriate feature-extraction technique to extract signal features in multiple signal domains?

Q3. What are the most appropriate pattern recognition models that can be used in the multi-signal domain to decode the EEG-MI brain signals for a couple of wheelchair commands that can be used for multi-subjects?

Q4. What is the most appropriate approach to ensure that the developed models can be used for multi-subjects and deployed on several EEG-based BCI platforms?





1.6 Research Scope

The scope of this research was limited to addressing the following issues: wheelchair platform, brain sensors, brain signal, the number of commands, study type, and a signal domain. With regard to the wheelchair platform, a standard wheelchair platform was selected without any other extensions, such as a robotic arm, and without integrating the wheelchair system with smart environmental control. However, for brain sensors for reading brain signals to be translated as a control command to the wheelchair platform, the EEG device was selected in this study. Out of several types of brain signals to be used for controlling the wheelchair, such as MI, P300, SSVEP, and SSSEP, MI was selected as a control signal.



For the number of commands to control the movements of the wheelchair using the MI signal, this study focused on the steering control of the wheelchair in two main directions, namely the right and left direction, entailing the use of two commands. The study type to be conducted to MI-based wheelchair control system involved analysis, development, simulation, and framework. In particular, this study focused on developing a GPRM for analyzing brain signals and examining their impacts on system performance using laboratory data and off-line data collected from a simulated environment. Furthermore, coherent work was selected for analyzing the MI signal-based wheelchair control system. As such, this study was carried out in three signal domains, namely time, frequency, and time-frequency domain as summarized in Figure 1.3.



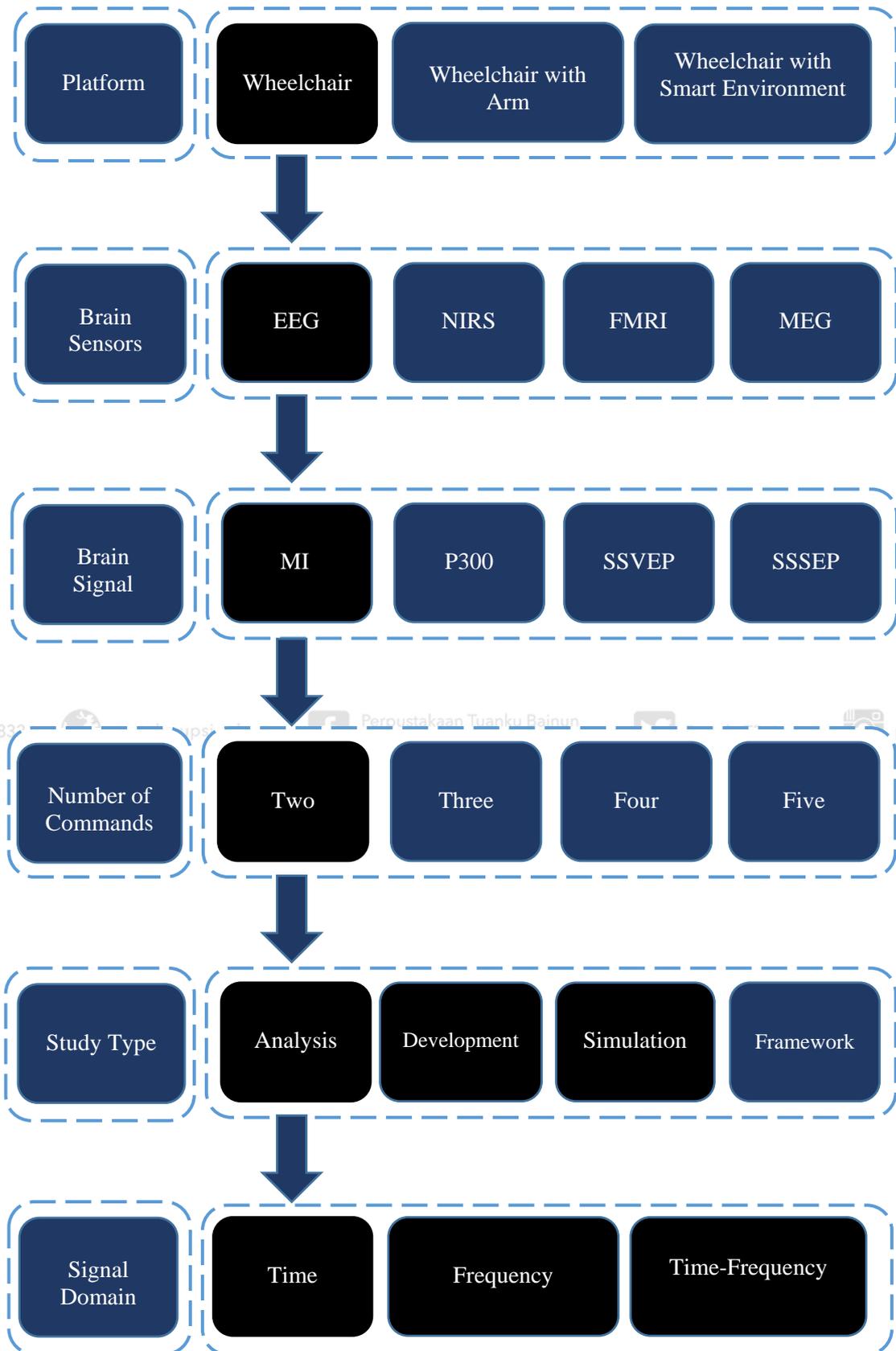


Figure 1.3. The Scope of Study



1.7 Thesis Structure

To assist reading, this thesis is organized based on six Chapters as follows:

Chapter One: This Chapter provides an overview of the workflow of the research regarding the research problem, research gap, research objectives, the motivation and background of the study, the scope of the study, and thesis structure.

Chapter Two: This Chapter details a critical, in-depth review of the current literature pertaining to the field of wheelchair control based on a brain-computer interface using EEG. In particular, a systematic review approach was followed in collecting and analyzing relevant research articles, in identifying prevailing challenges in this area of research, in building a taxonomy for the selected articles, and in analyzing the research gap.



Chapter Three: This Chapter explains the research methodology process of this study consisting of five phases that were sequentially carried out in solving the research problem. The first phase describes the systematic review process, starting from collecting the research articles and ending with identifying the research gap. The second phase and third phase describe the first objective pertaining to preparing the dataset and to the preprocessing of the EEG-MI signal. The fourth phase describes the second and the third objectives for the process of feature extraction and the classification of the GPRM respectively. The final phase describes the fourth objective concerning the validation of the GPRM by using two datasets, namely BCI competition dataset and Emotive EPOC dataset.





Chapter Four: This Chapter discusses the experimental results that helped guide the development of a GPRM for the EEG-MI signal consisting of two classes. Three experiments were conducted in each signal domain. Experiment 1 was performed with the aim of finding a GPRM for the EEG-MI signal consisting of two classes with the use of a single classifier. Experiment 2 was carried out to find a GPRM for the EEG-MI signal using a hybrid classifier. Experiment 3 was conducted to evaluate the GPRM based on single and hybrid classifiers using the individual subjects' dataset.

Chapter Five: This Chapter discusses the validation of the performance of the GPRM for the EEG-MI signal. Specifically, three experiments were conducted to validate the GPRM using single and hybrid classifiers. The first experiment involved the validation of the GPRM using the second generic dataset. The second experiment dealt with the validation of the GPRM using a single subject's dataset. Principally, the first and second experiment conducted using BCI Competition dataset IV-2b/validation part. The third experiment involved the validation of the GPRM using the Emotive EPOC dataset.

Chapter Six: This Chapter provides a summary of the conclusion of this study, research outcome, research finding, future work, and recommended solutions for future research.

