



BRAIN MACHINE INTERFACE CONTROLLED ROBOT CHAIR

by

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TABLE OF CONTENTS

Acknowledgements	i
Table of Contents	iii
List of Tables	x
List of Figures	xi
List of Abbreviations	xiii
List of Symbols	xv
Abstract (BM)	xvi
Abstract (English)	xvii
1. INTRODUCTION	1
1.1. Introduction	1
1.2. Goal of a BMI system	2
1.3. Brain Machine Interface Design	3
1.4. Thesis Objectives	4
1.5. Brain Machine Interface Controlled Robot Chair- Scope of Thesis	7
2. BRAIN MACHINE INTERFACE TECHNIQUES AND NEUROPHYSIOLOGICAL BACKGROUND	11
2.1. Introduction	11
2.2. Disorders of the Motor Nervous System	12
2.2.1. Amyotrophic Lateral Sclerosis	13
2.2.2. Multiple Sclerosis	13
2.2.3. Stroke	13
2.2.4. Parkinson's Disease	14
2.2.5. Paralysis	14
2.3. Several Techniques to Achieve a BMI	15
2.3.1. Measurement Techniques	17
2.3.2. Subject or Machine Training	19
2.3.3. Synchronous and Asynchronous Systems	20
2.4. BMI State of Art	21
2.4.1. Invasive Methods	22
2.4.2. The Wadsworth BCI	22
2.4.3. The Thought Translation Device	22
2.4.4. The Graz BCI	23
2.4.5. The Martigny BCI	23

2.4.6.	The Berlin Brain Computer Interface	24
2.4.7.	Current trends in BMI based Wheelchair for Rehabilitation of the Disabled	25
2.5.	Neurophysiological Background	27
2.5.1.	Event Related Potentials	27
2.5.2.	Motor Imagery or unstimulated brain signals	30
2.5.3.	Oscillatory Features	31
2.6.	Real versus Imaginary Movements	34
2.7.	Preprocessing	35
2.7.1.	Temporal Filters	36
2.7.2.	Spatial Filters	36
2.7.3.	Independent Component Analysis and Blind Source Separation	37
2.7.4.	Common Spatial Pattern	38
2.8.	Feature Extraction	39
2.8.1.	Fourier Transform	39
2.8.2.	Wavelets	39
2.8.3.	Template Matching	40
2.8.4.	Kalman Filter	41
2.8.5.	Spike Detection	41
2.8.6.	Autoregressive Models	41
2.8.7.	Band Pass Filtering	42
2.8.8.	Laplacian Filter	42
2.8.9.	EEG Amplitudes	43
2.8.10.	Asymmetry Ratios and Differences	43
2.8.11.	Time-Space based Feature Extraction Methods	44
2.9.	Classification	45
2.9.1.	Properties of Classifiers	45
2.9.2.	Linear classifiers	46
2.9.2.1.	Linear Discriminant Analysis	46
2.9.2.2.	Support Vector Machine	47
2.9.3.	Hidden Markov Models	48
2.9.4.	Nearest Neighbour classifiers	49
2.9.4.1.	k-Nearest Neighbours	49
2.9.4.2.	Mahalanobis Distance	49
2.9.5.	Neural Network based Classifiers	50
2.10.	Summary	51

3. EEG SIGNAL ACQUISITION AND PREPROCESSING	53
3.1. Introduction	53
3.2. The EEG Signal	54
3.3. EEG Recording Techniques	54
3.3.1. International 10-20 Electrode Placement System	55
3.4. Motor Imagery Task Data Set	57
3.5. Motor imagery Recording Equipment	58
3.6. Motor Imagery Experimental Paradigm	58
3.6.1. Synchronous BMI Paradigm	59
3.7. EEG Motor Imagery Signal Acquisition	60
3.7.1. The Brain Regions Responsible for Movement	61
3.7.2. Signal Recording	64
3.8. EEG Preprocessing Techniques	67
3.8.1. Artefacts in BMI Systems	67
3.9. Preprocessing Techniques Proposed for Signal Segmentation and Denoising EEG Recording	69
3.9.1. Segmentation	69
3.9.2. Temporal filtering using Custom Filters	70
3.9.3. Spectral Analysis of the Denoised Motor Imagery Signal	71
3.10. Summary	74
4. FEATURE EXTRACTION ALGORITHMS FOR FOUR-CLASS BMI	75
4.1. Introduction	75
4.2. Band Power of EEG Rhythms	76
4.3. Modified Principal Component Analysis on Segmented Signals	77
4.4. Band power of Mu, Beta Rhythms using custom filters	79
4.5. Parseval Energy Spectral Density Features	80
4.6. Modified Eigen Vector Features	83
4.7. Summary	84
5. CLASSIFICATION ALGORITHMS FOR SYNCHRONOUS BMI USING NEURAL NETWORKS	85
5.1. Introduction	85
5.1.1. BMI Feature Properties	86

5.2	Neural Networks	87
5.2.1	Static Neural Networks	87
5.2.2	Dynamic Neural Networks	88
5.3	Static Feed Forward Neural Network	89
5.4	Dynamic Elman Recurrent Neural Networks	90
5.5	Steps in Designing Neural Network Models	92
5.5.1	Step 1: Data Set Preprocessing	92
5.5.2	Step 2: Training and Testing sets	92
5.5.3	Step 3: Neural Network Paradigms	93
5.5.3.1	Number of Hidden Layers	93
5.5.3.2	Number of Hidden Neurons	94
5.5.3.3	Number of Output Neurons	95
5.5.3.4	Transfer Functions	95
5.5.4	Step 4: Evaluation Criteria	95
5.5.5	Step 5: Neural Network Training	96
5.5.5.1	Number of Training Iterations	96
5.5.5.2	The Particle Swarm Optimization Training Algorithm	97
5.5.5.3	The Back Propagation Training Algorithm	99
5.6	Classifier Validation and Model Selection	102
5.7	Performance of a classifier	103
5.8	Summary	105
6.	SYNCHRONOUS BMI: A TASK RECOGNITION APPROACH	106
6.1.	Introduction	106
6.2.	Synchronous BMI	107
6.3.	An algorithm to design synchronous BMI	107
6.4.	Evaluation of Static Feed Forward Neural Networks	108
6.4.1.	SFFNN Design 1	108
6.4.2.	SFFNN Design 2	109
6.4.3.	SFFNN Design 3	111
6.5.	Dynamic Elman Recurrent Neural Networks	113
6.5.1	DERNN Design 1	114
6.5.2	DERNN Design 2	115
6.5.3	DERNN Design 3	117

6.5.4	DERNN Design 4	118
6.5.5	DERNN Design 5	120
6.6	Statistical analysis of the synchronous BMI models	121
6.6.1	Comparison of BMI Designs using the MI Task Data Set	121
6.6.2	Comparison of Performance of ERNN classifier with that of other Synchronous BMI using Motor Imagery	122
6.7	Analysis on Sub-band Frequency versus Classification Performance	123
6.7.1	Results: Significance of Different Frequency sub bands for Classification	124
6.7.2	Classification accuracy using Mu, Beta and Gamma bands	128
6.8	Analysis on EEG Signals to Determine appropriate signal length	128
6.8.1	Results Analysis and Discussion	129
6.9	Summary	130
7.	ASYNCHRONOUS BMI FOR A ROBOT CHAIR: DESIGN AND IMPLEMENTATION	132
7.1	Introduction	132
7.2	Asynchronous BMI design	133
7.2.1	Two-class Asynchronous BMI	134
7.2.2	Multi- class Asynchronous BMI	134
7.3	Modelling the ABMI	135
7.3.1	Overview	135
7.3.2	Feature extraction	136
7.3.3	Classification	136
7.3.4	Task Translation	136
7.4	Designing a Customized ABMI	137
7.4.1	Feature Extraction	138
7.4.2	Classification	138
7.4.3	Evaluation	138
7.4.4	Signal Translation: Maxone Algorithm	140
7.4.5	Single Trial EEG Evaluation for Customized ABMI	140
7.4.6	Generalization of the DERNN based Asynchronous BMI	141
7.4.7	Customized ABMI: Predictive Power Analysis	143
7.4.8	Evaluation of Customized ABMI using Bit Transfer Rate	144
7.4.9	Discussion	145
7.5	Designing the Generalized ABMI	146
7.5.1	Classification	146

7.5.2 Evaluation	147
7.5.3 Single Trial EEG Evaluation for Generalized ABMI	148
7.5.4 Generalized ABMI: Predictive Power Analysis	149
7.5.5 Evaluation of Generalized ABMI using Bit Transfer Rate	150
7.5.6 Discussion	151
7.6 Assimilation of the ABMI on a Robot Chair	152
7.7 Robot Chair: Design and Implementation	154
7.7.1 Need for Automation in a Robot Chair	155
7.7.2 Collision Avoidance System	155
7.8 Shared control Algorithm	156
7.9 Summary	157
8 BMI CONTROLLED ROBOT CHAIR: A QUANTITATIVE AND QUALITATIVE STUDY IN INDOOR ENVIRONMENTS	158
8.1 Introduction	158
8.2 Real-time Asynchronous Experiment Design	159
8.2.1 Navigation Protocol 1	160
8.2.2 Navigation Protocol 2	162
8.2.3 Navigation Protocol 3	163
8.2.4 Navigation Protocol 4	164
8.3 Training Sessions	165
8.4 ABMI Indoor Experiment Results	165
8.4.1 Results of Protocol 1	166
8.4.2 Results of Protocol 2 and 3	168
8.4.3 Results of Protocol 4	172
8.5 Discussion	175
8.6 Exploring the Practical Use of ABMI in an Out- Of- Lab Environment	177
8.6.1 Experiments at Exposition 1	177
8.6.1.1 Tasks	177
8.6.1.2 Feature extraction and classification	178
8.6.1.3 The Experiment	178
8.6.2 Experiments at Exposition 2	179
8.6.2.1 Tasks	180
8.6.2.2 Feature extraction and classification	180
8.6.2.3 The Experiment	181
8.7 Summary	182

9 CONCLUSION	184
9.1 Designing a four-class control BMI using hand MI	184
9.2 Designing asynchronous (self-paced) BMI	186
9.3 Real-time BMI Robot Chair navigation in Indoor Environments.	186
9.4 Outlook	187
References	188
Author's References	205
Appendix A	209
Appendix B	210
Appendix C	211
Appendix D	212

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LIST OF TABLES

Table No.	Description	Page No.
6.1	MI Classification Results of BP SFFNN using PCA for a four-class BMI	109
6.2	MI Classification Results of BP SFFNN using Segmented and non-segmented band powers for a four-class BMI	110
6.3	MI Classification Results of BP SFFNN using Mu and Beta band power and Parseval features for a four-class BMI	113
6.4	Classification performance of the PSO DERNN with Band power features	115
6.5	Classification performance of the PSO DERNN with PCA features	115
6.6	Classification Performance of BP DERNN For the MI Data using PCA features	116
6.7	Classification Performance of BP DERNN for the MI Data using MEIG Features	118
6.8	Classification Performance of BP DERNN for the MI Data using Band Power and Parseval Features	119
6.9	Classification Performance of PSO DERNN for the MI Data using Band Power and Parseval Features	121
6.10	Comparison of the BMI designs using Motor Imagery	122
6.11	Comparison of the proposed four-class DERNN BMI and Other multiclass BMI in literature using MI	123
6.12	Classification Accuracy for Mu, Beta and Lower Gamma Frequency Bands	128
6.13	Classification Accuracy for Different EEG Signal Lengths	130
7.1	Classification Accuracy of the SFFNN and DERNN classifier for subject S9	139
7.2	Classification Accuracy for Single-Trial MI of Subject S9	141
7.4	Classification Results of Generalized ABMI using Data of 10 subjects	147
7.5	Single trial EEG Classification Results for Ten Subjects using SFFNN and DERNN	149
7.6	Comparison of the proposed four-class asynchronous DERNN BMI and other multiclass ABMI in literature using Motor Imagery	152
8.1	Performance of Subjects for the Trajectory of Protocol 1	166
8.2	Performance of Subjects for the Trajectory of Protocol 2 and 3 for one of the sessions	172

LIST OF FIGURES

Figure No.	Description	Page No.
1.1	Architecture of a Brain Machine Interface for Robot Chair Control	4
3.1	International 10 - 20 System of electrode placement profile view taken from a public domain source from (Brain master)	56
3.2	EEG recording system used in the BMI experiments	59
3.3	Functional Areas of the Brain (picture taken from public online source: Purves, Sadava & Orians)	62
3.4	The motor homunculus in primary motor cortex (picture taken from http://www.thetutoradvantage.com/images/homunculus)	63
3.5	Electrode positions for MI task data collection	65
3.6	Plot of the MI signal of subject S9, recorded during one of the 10 second trial for four MI tasks	66
3.8	Spectrogram of (a) raw signals and (b) filtered signals of subject S1 for four MI tasks	73
5.1	Architecture of a three layered SFFNN	90
5.2	Architecture of a three layered ERNN	91
6.1	Plot of Classification Accuracy versus Training Rounds for the SFFNN classifier using PCA features of Subjects S3 and S9	109
6.2	Plot of Classification Accuracy versus Training Rounds for the SFFNN Classifier using Band power (segmented) features of Subjects S3 and S9	111
6.3	Plot of Classification Accuracy versus Training Rounds for the SFFNN Classifier using Band power (segmented) features of Subjects S3 and S9	111
6.4	Plot of Classification Accuracy versus Training Rounds for the SFFNN classifier Using Mu & Beta Band power and Parseval ESD features of Subject S3	113
6.5	Plot of Classification Accuracy versus Training Rounds for BP DERNN using PCA of MI Data	117
6.6	Plot of Classification Accuracy versus Training Rounds for BP DERNN using MEIG Features with MI Data of two Subjects	118
6.7	Plot of Classification Accuracy versus Training Rounds for BP DERNN using Band Power and Parseval Features with MI Data of Subject S10	120
6.8	Average Classification Accuracy in percentage of a four-class BMI for ten sub bands for subject S9	125
6.9	Average Classification Accuracy in percentage of four-class BMI for ten sub bands for subject S3	125
6.10	Classification Accuracy in percentage versus training rounds for five [0.1 to 50 Hz] sub bands for subject S9	126
6.11	Classification Accuracy in percentage versus training rounds for five [51 to 100Hz] sub bands for subject S9	126

6.12	Classification Accuracy in percentage versus training rounds For five [0.1 to 50 Hz] sub bands for subject S3	127
6.13	Classification Accuracy in percentage versus training rounds for five [51 to 100 Hz] sub bands for subject S3	127
7.1	A schematic diagram of an Asynchronous BMI model	137
7.2	Training Rounds versus Classification accuracy Plot for SFFNN and DERNN of Trial 1 for subject S9.	139
7.3	Training Rounds versus Classification accuracy Plot of SFFNN (trial 1) and DERNN (trial 2) for Generalized ABMI	148
7.4	Flow Diagram of the ABMI Robot Chair	153
7.5	(a)The ABMI – Robot Chair Prototype (b) the shared controller Board to control the robot chair joystick	154
7.6	Ultrasonic Sensors used in the Collision Avoidance System	156
8.1	Subject seated on the ABMI Robot Chair	159
8.2	Specified Trajectories for Robot Chair Navigation of Protocol 1	161
8.3	Specified Trajectory for Robot Chair Navigation of Protocol 2	162
8.4	Specified Trajectory for Robot Chair Navigation of Protocol 3	163
8.5	Specified Trajectory for Navigation Protocol 4	164
8.6	Trajectory achieved for Navigation Protocol 2: (a) Subject S3 on Day 2 (b) Subject S3 on Day 3(trial 2)	170
8.7	Trajectory of Subject S9 on Day 3 for Navigation Protocol 2	170
8.8	Trajectory achieved for Protocol 3: (a) Subject S9 on Day 2; (b) Trajectory of Subject S9 on Day 3 for Navigation Protocol 3	171
8.9	Trajectory of Subject S3 on Day 3 for Navigation Protocol 3	171
8.10	Trajectory for one of the sessions for Protocol 4 on day 1, (a) Subject S9, (b) Subject S12 (c) Subject S3	173
8.11	Trajectory for one of the sessions for Protocol 4 on day 2 (a) Subject S5, (b) Subject S3 (c) Subject S12	174
8.12	Trajectory of Subject S9 for Protocol 4 on day 2, (a) Trail 1, (b) Trial 2	174
8.13	Trajectory for one of the sessions for Protocol 4 on day 3, (a)Subject S5, (b) Subject S12 (c) Subject S3	175
8.14	Exposition 1 environment	178
8.15	Subjects driving the ABMI Robot Chair at the first Expo in a crowded environment	179
8.16	Exposition 2 Environment	180
8.17	Subjects driving the ABMI Robot Chair at the second Expo	182

LIST OF ABBREVIATIONS

ABMI	Asynchronous Brain Machine Interface
AAR	Adaptive Auto-Regressive
ALN	Adaptive Logic Network
ALS	Amyotrophic Lateral Sclerosis
ALSA	Amyotrophic Lateral Sclerosis Association
AOR	Artifacts Occurrence Rate
AR	Autoregressive Model
ARMA	Autoregressive-Moving-Average Model
BCI	Brain Computer Interface
BLRNN	Bayesian Logistic Regression Neural Network
BMI	Brain Machine Interface
BP	Back Propagation
CSP	Common Spatial Patterns
CWT	Continuous Wavelet Transforms
DERNN	Dynamic Elman Recurrent Neural Network
DFT	Discrete Fourier Transform
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	ElectroMyoGram
EOG	ElectroOculoGram
ERD	Event Related Desynchronization
ERP	Event Related Potential
ERS	Event Related Synchronization
ESD	Energy Spectral Density
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
FIRNN	Finite Impulse Response Neural Network
fMRI	Functional Magnetic Response Imaging
FN	False Negative
FP	False Positive
GDNN	Gamma Dynamic Neural Network
GMM	Gaussian Mixture Models
HMM	Hidden Markov Models
IC	Intentional-Control
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
kNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
LRP	Lateralised Readiness Potential

LVQ	Learning Vector Quantization
MA	Moving Average Model
MEG	Magnetoencephalography
MEIG	Modified Eigen Vector Features
MI	Motor Imagery
MND	Motor Neuron Disorders
MS	Multiple Sclerosis
MSE	Mean Square Error
NC	Non-Control
NIND	National Institute of Neurological Disorders and Stroke
NIR	Near Infrared
NIRS	Near Infrared Spectroscopy
NN	Neural Network
NREM	Nonrapid Eye Movements
P300	Potential Detected At 3000 Milliseconds
PCA	Principal Component Analysis
PD	Parkinson's Disease
PET	Positron Emission Topography
PMA	Pre-Motor Area
PMC	Primary Motor Cortex
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
REM	Rapid Eye Movements
RFLDA	Regularized Fisher's Linear Discriminant Analysis
RP	Readiness Potential
SCP	Slow Cortical Potentials
SCP	Slow Cortical Potential
SFFNN	Static Feed Forward Neural Network
SFFNN	Static Feed Forward Neural Network
SMA	Supplementary Motor Area
SSVEP	Steady-State Visual Evoked Potentials
STFT	Short Time Fourier Transform
SVD	Singular Value Decomposition
SVM	Support Vector Machines
TDNN	Time-Delay Neural Network
TN	True Negative
TP	True Positive
TTD	Thought Translation Device
TTD	Thought Translation Device
WHO	World Health Organization

LIST OF SYMBOLS

β	Beta
μ	Mu
μ_c	Mean of each class c
μV	Micro volt
Σ	$m \times n$ diagonal matrix
Ω	Frequency of a waveform
c	class
C	Central Lobe
C3	Central Lobe electrode position for left hand
C4	Central Lobe electrode position for right hand
cm	Centimeters
Cz	Central Lobe electrode position for legs
E_x	Total Energy of a finite continuous time signal
F	Frontal Lobe
Hz	Hertz
k	Gain Factor of a filter
K	Kernel function
M	$m \times n$ matrix
M_c	Covariance matrix of class c
mV	Milli volt
N	Data length
n	No. of mental activities (tasks)
O	Occipital Lobe
P	Parietal Lobe
p	poles
p_a	Mean recognition accuracy
T	Temporal Lobe
T_{act}	EEG signal action period
U	$m \times m$ unitary matrix
V	$n \times n$ unitary matrix
x	Feature vector
$X_a(j\Omega)$	Discrete Fourier Transform of $x_a(t)$
$x_a(t)$	Finite continuous time signal
z	zeros

MESIN OTAK ANTARA MUKA MENGAWAL KERUSI ROBOT

ABSTRAK

Mesin Otak Antara Muka Mengawal Kerusi Robot: Mesin otak antara muka adalah sebuah alat hubungan otak manusia secara langsung untuk alat-alat seperti komputer, kerusi roda dan lengan palsu. Antara muka tersebut menyediakan satu saluran digit untuk komunikasi dan kawalan dalam ketiadaan saluran-saluran biologi dan oleh itu membantu dalam pemulihan mobiliti dan individu-individu hilang upaya bercakap. Dalam tesis ini, sebuah novel empat-kelas mesin otak antara muka direka bentuk untuk sebuah kerusi robot menggunakan jaringan saraf. Mudah dan protokol-protokol novel untuk memperolehi isyarat otak EEG daripada dua elektrod kulit kepala tidak invasif dibentangkan. Empat kerja berdasarkan imejan penggerak oleh pergerakan tangan kiri dan kanan adalah dicadangkan untuk mengawal arah bagi kerusi robot. Satu algoritma novel untuk pemerolehan isyarat-isyarat imejan penggerak menggunakan pergerakan tangan adalah dicadangkan. Prapemprosesan algoritma mudah diperkenalkan untuk membuang hinggar daripada isyarat-isyarat mentah. Jalur-jalur frekuensi Mu, beta dan Gamma yang berkaitan dengan tindakan-tindakan penggerak adalah disari menggunakan penapis yang ditempa. Ciri-ciri baru berdasarkan bahagian-bahagian masa dan frekuensi isyarat-isyarat EEG adalah dicadangkan dan diuji dengan pengelasan. Pengelasan isyarat-isyarat imejan empat tangan penggerak dibentangkan menggunakan jaringan saraf statik dan dinamik. Algoritma berasaskan pengoptimum kumpulan zarah dicadangkan bagi melatih jaringan saraf. Gabungan cadangan ciri-ciri dan pengelasan statik dan dinamik dianalisis. Isyarat-isyarat dihimpun dari 10 subjek terlatih untuk digunakan dalam menganalisis reka bentuk BMI segerak dan tak segerak. Satu maxone algoritma untuk penterjemahan bagi isyarat-isyarat imejan penggerak tangan kepada pergerakan kerusi robot dibentangkan. Sebuah kerusi robot prototaip direka dan diantaramukan dengan tak segerak maju BMI. Ciri-ciri keselamatan disepadukan melalui satu sistem pengelasan pelanggaran untuk meningkatkan prestasi bagi kerusi robot. BMI mengawal kayu ria bagi kerusi robot menggunakan satu algoritma kawalan kongsi. Eksperimen-eksperimen masa-nyata adalah juga dipersembahkan menggunakan 10 terlatih dan 5 tak terlatih subjek untuk mensahihkan kebolehgunaan bagi mesin otak antara muka. Eksperimen-eksperimen dijalankan pada dua penjelasan (luar dari persekitaran makmal) dengan 25 subjek tak terlatih bagi menilai kemungkinannya dalam persekitaran kehidupan sebenar.



BRAIN MACHINE INTERFACE CONTROLLED ROBOT CHAIR

ABSTRACT

Brain Machine Interface Controlled Robot Chair: Brain Machine Interface is a device that links the human brain directly to devices such as computer, wheelchairs and prosthetic arms. Such interfaces provide a digital channel for communication and control in the absence of the biological channels and thus help in the rehabilitation of mobility and speech impaired individuals. In this thesis, a novel four-class brain machine interface (BMI) is designed for a robot chair using neural networks. Simple and novel protocols for acquiring brain EEG signals from two non-invasive scalp electrodes are presented. Four tasks based on motor imagery of left and right hand movements are proposed to control the directions of the robot chair. A novel algorithm for acquisition of motor imagery signals using only hand movements is proposed. Simple preprocessing algorithms are presented to remove noise from the raw signals. Mu, Beta and Gamma frequency bands related to the motor actions are extracted using customised filters. New features based on time and frequency components of the EEG signals are proposed and tested with classifiers. Classification of the four hand motor imagery signals is presented using static and dynamic neural networks. A particle swarm optimization based algorithm is proposed to train the neural networks. Combinations of the features proposed and the static and dynamic classifiers are analysed. Signals collected from 10 trained subjects are used in the analysis of synchronous and asynchronous BMI designs. A max-one algorithm for translation of the hand motor imagery signals into robot chair movements is presented. A prototype robot chair is designed and interfaced with the developed asynchronous BMI. Safety features are integrated through a collision avoidance system to enhance the performance of the robot chair. The BMI controls the joystick of the robot chair using a shared control algorithm. Real-time experiments are also presented using 10 trained and 5 untrained subjects to validate the applicability of the brain machine interface. Experiments were carried out at two expositions (out-of-lab environments) with 25 untrained subjects to assess its feasibility in real life environments.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Controlling objects or machines by thought is a dream which is currently moving from science fiction to science and technology. The prospect of humans interfacing the mechanical world through brain-coupled devices and thereby controlling everyday machines through the process of mere thought is certainly appealing. The technology that can make this to happen is known as a Brain Machine Interface (BMI). Hans Berger in 1929 through his experiments on human Electroencephalography (EEG) introduced the idea that brain activity could be decoded and used as a communication channel. EEG is a technique which makes it possible to measure, on the scalp, micro currents that reflect the brain activity.

A promising class of applications of BMI are those concerning assistive devices for people with serious motor impairments. The classical interfaces, that disabled people commonly use to control or manipulate an assistive device, typically require the patient to have adequate control over one or more physical components of his or her body. Typically that would be one of the limbs: an arm, hand or finger. Bioprosthetic systems that are directly controlled through brain signals on the other hand could provide for a more natural extension of human capabilities. Especially in the case where the patient is completely paralysed, this technology may provide the only possible way for the patient to gain control over basic aspects of their daily life.

Amongst these the ability to control the personal mobility is generally considered as an important one. The reduction in mobility that many people experience, due to various impairments or simply due to the effects of ageing, often has a profound impact on the

person's independence, social activity and self esteem. For many people suffering from a diverse range of impairments, the primary device that could provide for that mobility is the electrical wheelchair. It is worth noting however, that in case of locked-in patients their highest priority is not mobility. Still, learning to drive complex devices such as a wheelchair will also lead to better communication and domotic tools. BMIs are also becoming more popular in the gaming and virtual reality sector for normal users. This thesis focuses on the development of a BMI system to control a robot chair as an assistive device for the mobility impaired people.

1.2 Goal of a BMI System

BMI research goes back to the early 1970s. At that time Jacques Vidal designed a brain-computer interface by a computer-based system that produced detailed information on brain functions and built the first brain computer interfaces based on visual evoked potentials (Vidal, 1973). During the last decade the definition and the goal of a BMI has been refined and specialized. Definition of a BMI given by Wolpaw (Wolpaw et al, 2002) states that 'a BMI is a system for controlling a device (e.g., wheelchair, neuroprosthesis or computer) by human intentions without using activity of muscles or peripheral nerves'. Previous systems were mainly developed for patients suffering from several disabilities, especially for ALS and spinal cord injuries.

When the cognitive abilities are still intact a BMI might be the last opportunity for them to communicate with other people. A BMI could also help patients like amputees to lead a more comfortable life. Recently, many groups have suggested using a BMI system for healthy people as a further communication path for gaming or in real life. However, the functionality of a BMI is so far very limited as current BMI systems are not convenient for workplace applications. Nevertheless, recent results have given reasons to hope that the system can be improved to be useful for healthy users too (Washington University, 2006).

1.3 Brain Machine Interface Design

The BMI for a robot chair is designed in two phases, (1) an offline training phase which calibrates the system and (2) an online phase which uses the BMI to recognize mental states and translates them into commands for the robot chair. An online BMI follows a closed-loop process, usually comprising of six steps: brain activity measurement, pre-processing, feature extraction, classification, translation into a command and feedback (Mason & Birch, 2003). These are briefly explained as:

- (a) **Brain activity measurement:** This step consists of using various types of sensors in order to obtain signals reflecting the user's brain activity. This thesis focuses on EEG motor imagery as the measurement technology.
- (b) **Pre-processing:** This step is used to denoise the input data in order to enhance the relevant information embedded in the signals.
- (c) **Feature Extraction:** Feature extraction aims at describing the signals by a few relevant values called 'features'.
- (d) **Classification:** The classification step assigns a class to a set of features extracted from the signals. This class corresponds to the kind of mental state identified. This step can also be denoted as 'feature translation' (Mason & Birch, 2003).
- (e) **Translation into a Command:** Once the mental state is identified, a command is associated to this mental state in order to control a given machine such as a robot, a wheelchair or a prosthetic device (Kubler, Mushahwar, Hochberg & Donoghue, 2006).
- (f) **Feedback:** Finally, this step provides the user with a feedback about the identified mental state. This aims at helping the user controlling his brain activity and as such the BMI. The overall objective is to increase the user's performances.

The architecture of a BMI to control a robot chair is schematised in Figure 1.1; it should be noted that before operating such a BMI, considerable calibration work is necessary; this work is generally done offline and aims at calibrating the classification algorithm.

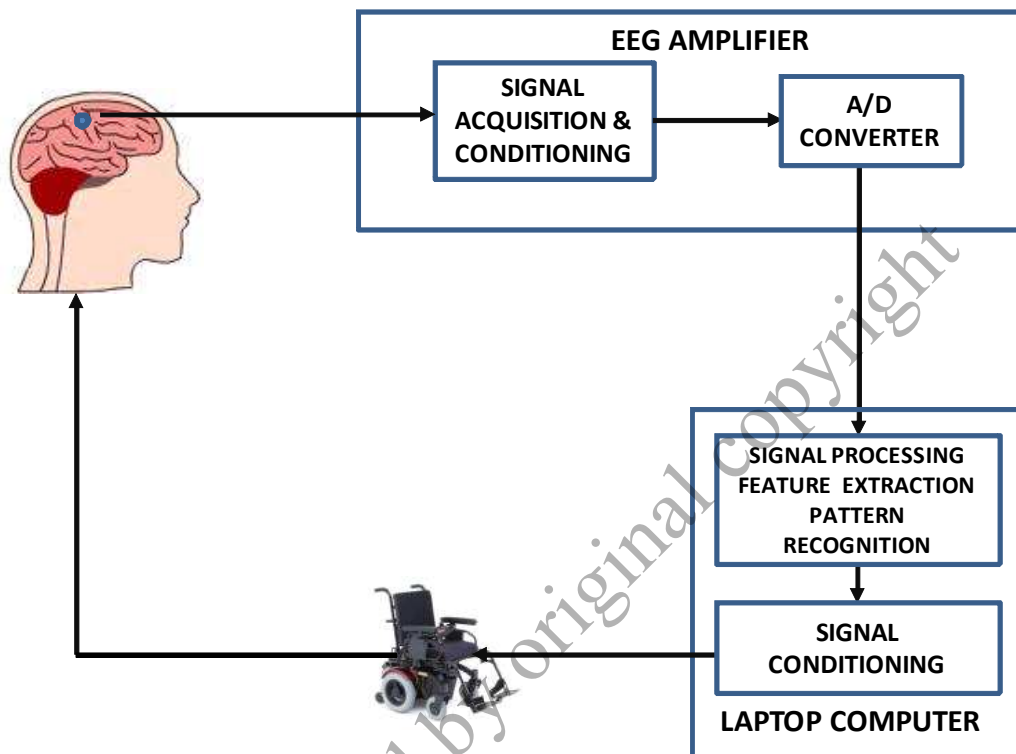


Figure 1.1
Architecture of a Brain Machine Interface for Robot Chair Control.

In order to do so, a training data set must have been recorded previously from the user. Since EEG signals are highly subject-specific, the BMI systems must be calibrated and adapted to each user. This training data set contains EEG signals recorded, when the subject performs each mental task of interest several times according to given instructions. The recorded EEG signals are then used as mental state samples in order to find the best calibration parameters for the user.

1.4 Thesis Objectives

The work presented in this thesis belongs to the framework of BMI research. More precisely, it focuses on the study of EEG signal processing and classification techniques in order to design and use BMI for controlling and navigating a robot chair. Despite the valuable and promising achievements already obtained in the literature to

interface the brain and computers (BCI), brain machine interfacing is still a relatively young research field and there is still much to do in order to make BMI become a mature technology. Among the numerous possible improvements, three main points are addressed in this thesis; that is, designing a four-class control BMI using hand Motor Imagery (MI); designing an asynchronous BMI to control a robot chair and real-time robot chair navigation studies in indoor environments using the four-class BMI. The BMI community has highlighted these points as being important and necessary research topics for the further development of BMI technology for real life situations (Wolpaw, Birbaumer, McFarland, Pfurtscheller & Vaughan, 2002; Millán, Renkens, Mourino & Gerstner, 2004; Leeb et al, 2007). The aspects of the three improvements are illustrated as below:

(i) Designing a four-class control BMI using hand MI

Most current BMI systems focus on left hand, right hand, feet, cheek and tongue movements to design a four-class BMI which require more electrodes to record these signals. Designing a four-class BMI using only hand movements with only two electrodes reduces the processing time and thus increases the transfer rate of the BMI for real-time control of a robot chair. A practical four-class BMI for a robot chair can be achieved through effective acquisition protocols and good classification accuracy.

a. Designing protocols using only hand motor imagery for a four-class BMI: The number of classes used is generally very small for BMI. Most current control BMI propose only 2 classes (two kinds of mental states) using hand MI. Designing algorithms that can efficiently recognize a larger number of mental states would enable the subject to use more commands and thus benefit from a higher information transfer rate (Kronegg, Chanel, Voloshynovskiy & Pun 2007; Dornhege, Blankertz, Curio & Muller, 2004). However, to really increase the information transfer rate, the classifier