



AIN SHAMS UNIVERSITY

FACULTY OF ENGINEERING

MECHATRONICS ENGINEERING

***Hand Prosthetic Controlled System Based on  
Signal Pattern Recognition of  
Electroencephalography***

A Thesis submitted in partial fulfillment of the requirements of the

***M.Sc. in Mechanical Engineering***

By

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B.Sc., Mechanical Engineering, Mechatronics Engineering Department

Helwan University, 2010

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Cairo – (2017)



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# Statement

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This thesis is submitted as a partial fulfillment of M.Sc. degree in Mechanical engineering, Faculty of Engineering, Ain Shams University.

The author carried out the work included in this thesis and no part of it has been submitted for a degree or qualification at any other scientific entity.

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# Abstract

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Electroencephalography (EEG) motor imagery (MI)-based Brain Computer Interface (BCI) systems have been recently employed to enhance the quality of life of disabled people. However, to naturally trigger particular applications (i.e. upper limb prostheses), independent BCIs appeal further paradigms to involve realistic motor imagery tasks. On the other hand, most of the EEG recording systems are clinical so that they cannot be integrated with such real time BCI mobility. In terms of machine learning, this work is intended to investigate into a realistic and intuitive motor imagery-based BCI for right hand using Consumer-graded EEG acquisition devices. The present study proposes an approach to classify imagined hand gesture tasks, including the water glass gesture and the index pointer gesture of the right hand using OPENBCI as a consumer-grade EEG acquisition device. For three subjects, the data recorded by OPENBCI were sampled with a sampling rate of 250 Hz. The Minimum Redundancy Maximum Relevance (MRMR) technique was implemented as a feature selection method along with the Support Vector Machine (SVM) algorithm for classification. By obtaining a maximum classification accuracy of 91.7%, the results shown the feasibility of such Brain Computer Interface systems to detect different motor imagery tasks for the right hand. Consequently, upper limb prostheses could be manipulated using the intended motor imagery tasks.

**Key words:** Brain Computer Interface (BCI), Feature Selection, OPENBCI, MRMR, ERD.

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# List of Abbreviations

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<b>AR</b>	Auto <b>R</b> egressive
<b>BP</b>	<b>B</b> and <b>P</b> ower
<b>DBN</b>	<b>D</b> ynamic <b>B</b> ayesian <b>N</b> etwork
<b>LDA</b>	<b>L</b> inear <b>D</b> iscriminant <b>A</b> nalysis
<b>MD</b>	<b>M</b> ahalanobis <b>D</b> istance
<b>MI</b>	<b>M</b> otor Imagery
<b>MRMR</b>	<b>M</b> inimum <b>R</b> edundancy <b>M</b> aximum <b>R</b> elevance
<b>PCA</b>	<b>P</b> rinciple <b>C</b> omponent <b>A</b> nalysis
<b>PSD</b>	<b>P</b> ower <b>S</b> pectral <b>D</b> ensity
<b>SVM</b>	<b>S</b> upport <b>V</b> ector <b>M</b> achines
<b>TFR</b>	<b>T</b> ime- <b>F</b> requency <b>R</b> epresentation

# Chapter 1: Introduction

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## 1.1. Motivation

It was estimated that there are nearly 10 million amputees all over the world. Among the world population of amputees, there are 3 million population who have upper limb amputation [1]. Thanks to the recently astonishing advances of the interaction between human and computers, multidisciplinary paradigms have been revealed to improve the quality of upper limb amputee's life. Among those paradigms, Brain Computer Interfaces are novel technologies that are devoted to assist the people with severe disabilities. Nowadays, BCIs are widely utilized in different paradigms such as rehabilitation, mental spellers, motor restoration, clinical diagnoses and mental gaming.

Among the last two decades, investigations have been diversely conducted exploiting the non-invasiveness property of Electroencephalography (EEG) signals. These studies have shown promising outcomes for helping people with different cases of disability. However, BCIs experience outstanding issues as the complexity of the disability increases.

Upper limb amputations are considered one of the most severe disabilities, due to the intervention of the arm in most of the daily life activities. Moreover, upper limbs perform in such flexible and dexterous pathways. Therefore, relative BCIs appeal further paradigms to, approximately, retrieve the functions of the amputated upper limb. In other words, diverse investigations of BCIs should be developed to trigger prosthetics by adopting the following aspects:

- BCIs should be based on recognizing realistic, voluntary and intuitive motor imagery tasks.
- Real-time BCIs should be accomplished by means of real-time computational performance.
- BCIs are not generalized yet, as the EEG waveforms are known of the non-stationarity and the low spatial resolution.