ENHANCEMENT OF EEG SIGNALS CLASSIFICATION BY LINEAR DISCRIMINANT ANALYSIS FOR BRAIN COMPUTER INTERFACE

BY

MOHAMMAD NUR ALAM

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Kulliyyah of Engineering
International Islamic University Malaysia

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ABSTRACT

Motor imagery (MI) based electroencephalogram (EEG) signals classification is under research for the last few decades to develop a robust and user-friendly brain-computer interface (BCI) system without compromising its simplicity and efficiency. The number of channel selections is still the most challenging task to extract features and classify them for MI movement detection. Hence, an advanced but required simple computation with minimal channels selection, Linear Discriminant Analysis (LDA) based algorithm has been developed. BCI competition IV dataset-I has been utilized in this research that was collected by the renowned BCI group from the Berlin Institute of Technology. Initially, the signal is preprocessed in a few steps by applying a sliding window and utilizing a finite impulse response (FIR) filter to obtain a cutoff frequency ranging from 8-30 Hz. The power spectral density (PSD) technique has been adopted to extract the power spectrum of μ and β features over frequency components. A common spatial pattern (CSP) filter is also applied to optimize feature extraction and feature selection from the signal. Then, classification has been done in two stages, training, and evaluation phase. Comparatively lower classification error has been recorded by the LDA classifier for left and right-hand MI classification. The classification accuracy is measured at 91.14% and 81.4% in the training and evaluation phase respectively. Cohen's kappa coefficient is calculated at 0.822 in the training phase and 0.629 in the evaluation phase which proves the research's viability. Therefore, to aid persons such as with spinal cord injuries, the suggested approach can be applied to real BCI devices.

DR. MUHAMMAD IBN IBRAHIMY
Professor
Department of Electrical and Computer Engineering
Kulliyyah of Engineering
International Islamic University Malaysia

خلاصة البحث

يخضع تصنيف إشارات مخطط كهربية الدماغ (EEG) المستند إلى الحركة التخيلية (MI) للبحث على مدى العقود القليلة الماضية لتطوير نظام قوي وسهل الاستخدام لواجهة الدماغ والحاسوب (BCI) دون المساس ببساطته وكفاءته. لا يزال عدد تحديدات القنوات يمثل المهمة الأكثر صعوبة لاستخراج الميزات وتصنيفها لاكتشاف حركة MI. ومن ثم، فقد تم تطوير خوارزمية تعتمد على التحليل الخطي التمييزي (LDA)، وهي متقدمة، ولكنها تتطلب حسابًا بسيطًا مع تحديد الحد الأدنى من القنوات. تم استخدام مجموعة البيانات IV لمسابقة BCI في هذا البحث الذي تم جمعه من قبل مجموعة BCI الشهيرة من جامعة برلين للتكنولوجيا. في البداية، تمت معالجة الإشارة مسبقًا في خطوات قليلة عن طريق تطبيق نافذة منزلقة واستخدام مرشح استجابة نبضة محدودة (FIR) للحصول على تردد قطع يتراوح من 8 إلى 32 هرتز. تم اعتماد تقنية الكثافة الطيفية للقدرة (PSD) لاستخراج طيف القدرة للميزات وعبر مكونات التردد. يتم أيضًا تطبيق مرشح النمط المكاني المشترك (CSP) لتحسين استخراج الميزات واختيار الميزة من الإشارة. بعد ذلك، تم التصنيف على مرحلتين، مرحلة التدريب والتقييم. تم تسجيل خطأ تصنيف أقل نسبيًا بواسطة مصنف LDA لتصنيف MI الأيسر والأيمن. تم قياس دقة التصنيف عند 91.14٪ و81.4٪ في مرحلتي التدريب والتقييم على التوالي. تم حساب معامل كابا لكوهين عند 0.822 في مرحلة التدريب و0.629 في مرحلة التقييم مما يثبت جدوى البحث. لذلك، لمساعدة الأشخاص مثل إصابات الحبل الشوكي، يمكن تطبيق النهج المقترح في أجهزة BCI الحقيقية.

APPROVAL PAGE

I certify that I have supervised and read this study and that in my opinion; it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Master of Science (Electronics Engineering).

....
Muhammad Ibn Ibrahimy
Supervisor

....
S.M.A Motakabber
Co-Supervisor

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Master of Science (Electronics Engineering).

....
Othman Omran Khalifa
Internal Examiner

....
Faridah Abd Rahman
Internal Examiner

This dissertation was submitted to the Department of Electrical and Computer Engineering and is accepted as a fulfillment of the requirement for the degree of Master of Science (Electronics Engineering).

....
Md. Rafiqul Islam
Head, Department of Electrical and Computer Engineering

This dissertation was submitted to the Kulliyyah of Engineering and is accepted as a fulfillment of the requirement for the degree of Master of Science (Electronics Engineering).

....
Sany Izan Ihsan
Dean, Kulliyyah of Engineering

DECLARATION

I hereby declare that this dissertation is the result of my own investigations, except otherwise stated. I also declare that has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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This dissertation is dedicated to my beloved parents for their endless love, support, and encouragement.

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Finally, I wish to express my heartfelt gratitude to my beloved family members, for their continuous support, motivation, and love throughout the study period.

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LIST OF ABBREVIATIONS

AC	Alternate Current
AgCl	Silver Chloride
ANN	Artificial Neural Network
AR	Auto Regression
ARTM	Adaptive Resonance Theory Mapping
BCI	Brain Computer Interface
BLRNN	Bayesian Logistic Regression Neural Network
BGN	Bayes Graphical Network
BSS	Blind Source Separation
CM	Confusion Matrix
DC	Direct Current
ECG	Electrocardiogram
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyogram
EOG	Electrooculography
ERD	Event-Related Desynchronization
FFT	Fast Fourier Transform
FIR-MLP	Finite-Duration Impulse Response Multilayer Perceptron
FIRNN	Finite Impulse Response Neural Network
FP	Frontal Pole
GRB	Gaussian Radial Basis
HMM	Hidden Markov Model
IOHMM	Input-Output HMM
KNN	k-Nearest Neighbors
LDA	Linear Discriminant Analysis
LVQ	Learning Vector Quantization
MDA	Mahalanobis Discriminant Analysis
MI	Motor Imagery
NaCl	Natrium Chloride
PeGNC	Probability estimating Guarded Neural Classifier
PSD	Power Spectral Density
QDA	Quadratic Discriminant Analysis
RBF	Radial Basis Function
SNR	Signal to Noise Ratio
SSVEP	Steady-State Visual-Evoked Potential
SVM	Support Vector Machine
TDNN	Time-Delay Neural Network
TSD	Time-varying Signed Distance

LIST OF SYMBOLS

α	Alpha rhythm for the brain signal
μ	Mu rhythm for the brain signal
β	Beta rhythm for the brain signal
γ	Gama rhythm for the brain signal
Hz	Frequency in hertz
μV	Micro Volt
C3	Central left electrode
Cz	Midline central electrode
C4	Central right electrode
k	Cohen’s Kappa Coefficient

CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

Communicating with people and interacting with technology are still the most common tasks for human beings to seek their self or other's advantages regularly. However, for some people, communication or interaction becomes impossible due to physical disorder caused by an accident, disease, or genetic problem, in which case they have lost their normal pathways for sensing and expressing their feelings, thoughts, or even the ability to move their limbs completely. This type of person is called a "locked-in" patient (Han et al., 2019). These kinds of patients are still able to send messages and command soundings using electroencephalographic (EEG) activity or other electrophysiological measurements of brain function. This is the method or system known as Brain-Computer Interface (BCI), which provides another non-muscular approach to transmitting and interacting among humans and machines.

A conventional BCI system enables direct communication between the brain and the computer. In the absence of neuromuscular pathways, signals produced by the brain are known as EEG signals. Interfacing with any medium of communication produces a unidirectional communicating channel. EEG is one of the non-invasive tools for analyzing human brain dynamics because it allows a direct measurement of cortical activity with millisecond temporal precision, which is unique among non-invasive approaches.

According to studies, a neuromuscular patient can adapt to the BCI systems by changing many characteristics of the EEG signal. An effective BCI system comprises three distinct operations: signal acquisition, feature extraction, and classification of the features extracted. Feature extraction and classification are the most challenging tasks because the reliability of an entire BCI system is determined by the success of the feature extraction and classification performed. However, the success and accuracy of the classification are dependent on the precision and significant feature extraction of the EEG data, which is achieved by increasing the signal power to the noise ratio, the amplitude of the signal. As a result, Welch's Power Spectral Density (PSD) feature extraction approach has been used in this study to enhance the signal-to-noise ratio (SNR) (Qin et al., 2019).

There are frequent Gaussian and linear signal processing techniques are being used for detecting and classifying MI-based EEG signals. However, by nature, the MI-based EEG signals are not extremely Gaussian, stationary, or linear dynamic. Furthermore, the recorded EEG signals are also containing various types of Electrooculogram (EOG) artifacts, so, the standard EEG signal has been utilized for future extraction and classification in this research. However, to reduce the EOG artifacts initially pre-processing of the signal has been done before feature extraction.

In this research, two classes left hand, and right hand or foot have been classified using Linear Discriminant Analysis (LDA) classification technique in both training and evaluation phases. Multichannel EEG signals especially, channels C3, CZ, and C4 have been utilized. Because these three channels are performed to record MI-based electrical activity from the motor cortex of the human brain. To achieve better classification accuracy, two correct features μ-band, and β-band between 8 to 30 Hz, are being extracted with the PSD feature extraction technique.

1.2 PROBLEM STATEMENT

There are some fundamental limitations to the MI-based BCI systems. Among them, one is the number of channels selection for EEG signal feature extraction is still challenging and another is the low classification accuracy. Multichannel EEG is mostly utilized in BCIs, where conducting EEG channel selection improves BCI efficiency by eliminating unnecessary or noisy channels and increases user comfort by using fewer channels. As a result, the highest classification accuracy can be obtained by eliminating noisy and unnecessary channels or by keeping the smallest number of channels while maintaining the classification accuracy attained by utilizing all channels. Besides that, the reliability and classification accuracy of a BCI system also can be increased with enhanced feature extraction and classification techniques.

1.3 RESEARCH OBJECTIVES

The following are the main objectives of this research:

i. To select motor imagery channels for extracting the features by PSD from EEG signals.

ii. To develop an LDA-based classification algorithm for an efficient brain-computer interface.

iii. To validate the performance accuracy of the classification algorithm using statistical methods.

1.4 RESEARCH METHODOLOGY

The goal of this research is to develop an LDA-based classification algorithm that improves classification accuracy to build a reliable BCI system that can efficiently identify motor imagery movements. Pre-processing, feature extraction, feature selection, and classification are the four key steps of this research.

In this research, dataset-1 (which contains 59 channels, two MI classes; left and right/foot) from Berlin Institute of Technology BCI competition IV has been utilized. Firstly, some features have been identified and retrieved from the denoised EEG signal. These features were provided to the classifier to obtain the best possible outcome. An input feature vector is created with the extracted features and targets before feeding it to the classifier. Welch’s Power Spectral Density (PSD) was utilized for estimating spectral density to extract μ and β features. Then, the extracted features were discriminated into two classes filtering by a common spatial pattern (CSP). After that, the classification has been performed with Linear Discriminant Analysis (LDA) in two different states namely: the training and evaluation phases. Trails were randomly selected to train the classifier named training data and then, the suggested algorithm was applied to the remaining trials, which were referred to as evaluation data. Finally, performance accuracy and standard statistical method Cohen's kappa coefficient were calculated to validate the proposed classification technique.

1.5 SCOPE OF RESEARCH

This research work covers the extensive study and performance measurement of feature extraction and classification techniques of motor imagery-based EEG signals for BCI. The prerecorded EEG signal uploaded by the Berlin Institute of Technology BCI competition IV dataset-I was used to verify the classification result in this research. Two motor imagery classes were selected from the three available movements for each subject: left hand, right hand, and foot movement.

1.6 DISSERTATION ORGANIZATION

This dissertation demonstrates prominent feature extraction and classification technique from EEG signals for a reliable brain-computer interface. The dissertation is organized as follows:

Chapter 1: The first section of this dissertation is an introduction, which briefly covers the BCI system, the problem statement, and the methods used to achieve the research's main objectives.

Chapter 2: In this chapter, the analytical and mathematical background of EEG signal processing is described including signal acquisition, pre-processing, feature extraction, and classification techniques for motor imagery movements detection.

Chapter 3: In chapter three, the proposed techniques such as time sliding window, FIR bandpass filtering, CSP filtering, feature extraction with PSD, and classification with LDA methods are described step by step. The classification outcome validation by measuring performance accuracy and Cohen's kappa coefficient is also included here.

Chapter 4: Result has been discussed in this chapter with graphical figures and data tables. A comparison of the obtained result with the benchmark paper is also included in this chapter.

Chapter 5: Finally, the research findings are summarized in chapter five. This chapter includes concluding remarks as well as future recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

A brain-computer interface (BCI) system establishes a direct connection between the human brain and external devices allowing the brain to control and interact with them. There are several movements such as moving the right hand or left hand or blinking the eyes, which may be simply understood using EEG and ECoG brain signals. Motor Rehabilitation System – is one of the main types of BCI systems. This sort of system uses the human mind to do a physical task, such as moving the left or right hand, and it can be readily interpreted using a BCI system and neuro rehabilitation ideas, and it is also known as motor imagery. This imaginative activity produces a unique pattern of brain function that can be used for communication, object control, and real-time navigation.

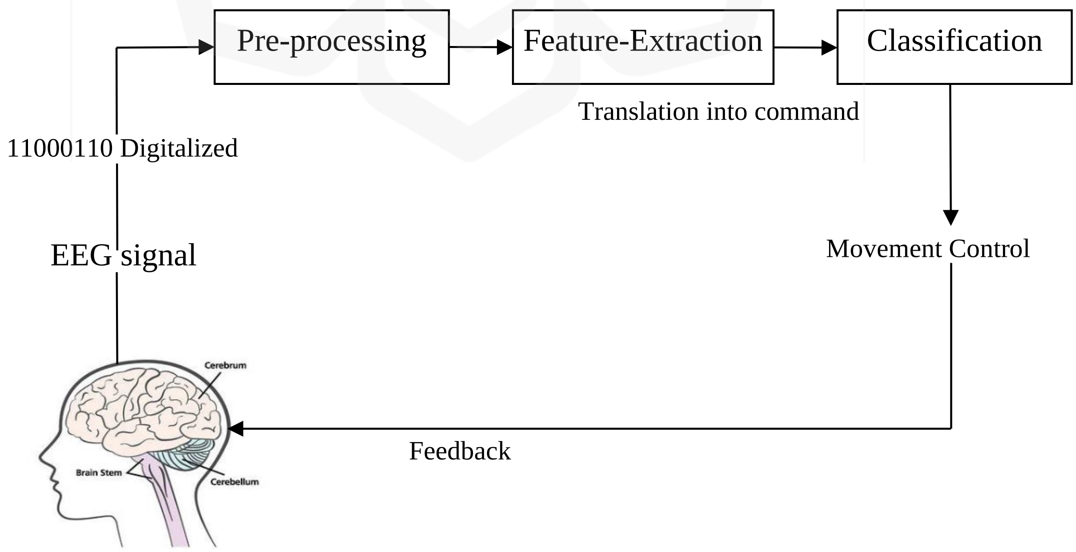

Figure 2.1: The basic concept model of a BCI system

Various studies have been carried out over the last few years to develop a novel and promising strategy to build an MI-based BCI system that can be used to improve motor rehabilitation in a variety of applications. The basic design of a rehabilitation BCI system is illustrated in Figure 2.1. The system includes three main sequential processes called pre-processing which includes denoising the raw signal, feature extraction, and classification of the features extracted to detect motor imagery classes to control external devices. The external devices are controlled by the instructions from the feature translation algorithm, which provides features such as character selection, cursor movement, robotic arm movement, and so on. The device's functionality gives the user feedback to end the control loop. The device's feedback allows the user to adjust their brain signals in maintaining optimal device performance. For better understanding, all these processes including types of brain signal, acquisition technique, and their intensity are explained below based on the literature review of published articles.

2.2 BIOSIGNALS

Biosignal is a signal that can be detected and monitored by any biological entity. Biosignals have traditionally been used to relate to bioelectric signals. The nervous system produces bioelectric signals. Bioelectric signals come in a variety of forms. They are EEG (Electroencephalogram), EMG (Electromyogram), ECG (Electrocardiogram) and EOG (Electrooculogram). When compared to optical systems, EOG aided devices are far more realistic and helpful for people with spinal cord injuries (Kaur, 2021). These systems also have a lot of promise for controlling the mouse indicator. The learning complexity and calibration procedure are the key downsides of these systems. Hence, researchers are still providing their full effort in developing the system. The use of an EEG signal to observe brain activity from the human scalp is a noninvasive method (Millán et al., 2004). However, because the noninvasive approach has a limited spatial resolution and SNR, the signal obtained displays multiple activities of a large number of cortical neurons. Furthermore, invasive brain surveillance reveals the unique activity of the cortical. These biosignals must pass through the human skull and pericardial muscle to contact the shell electrodes. The amplitude of EEG waves is in the 5-300 μV range. As a result, bio-potential amplifiers must be designed in such a way that they induce extremely high amplification (Taberner and Barreto, 1997). The EEG signal can be easily contaminated by the EMG signal due to muscle activity in the neck or head. Moreover, when people are cerebral paralyzed, it may be a huge nuisance.

The most common EEG artifacts are eye blinking and neck movements. Many BCI researchers have attempted to remove EEG artifacts to the best of their abilities. There have been a lot of neurobiological questions and ambiguities about EEG artifacts up to now. Proper works are ongoing to solve these obscures, and a wide range of training is required to have practical work with the brain and computer interfacing-related operations.

2.3 MOTOR CORTEX OF THE BRAIN

The brain is the most vital organ of the nervous system (Mamun et al., 2015) because it regulates almost every system of the body. The motor cortex is a region of the brain that controls voluntary movements. Figure 2.2 depicts the motor cortical region. Small electrical probes stimulated regions of the motor cortex in brain surgery patients causing them to move. Nowadays, researchers have become able to figure out the motor cortex very accurately. The muscles of the mouth and face are controlled by the lower parts of the motor cortex. Legs and feet are controlled by parts of the motor cortex at the top of the brain.

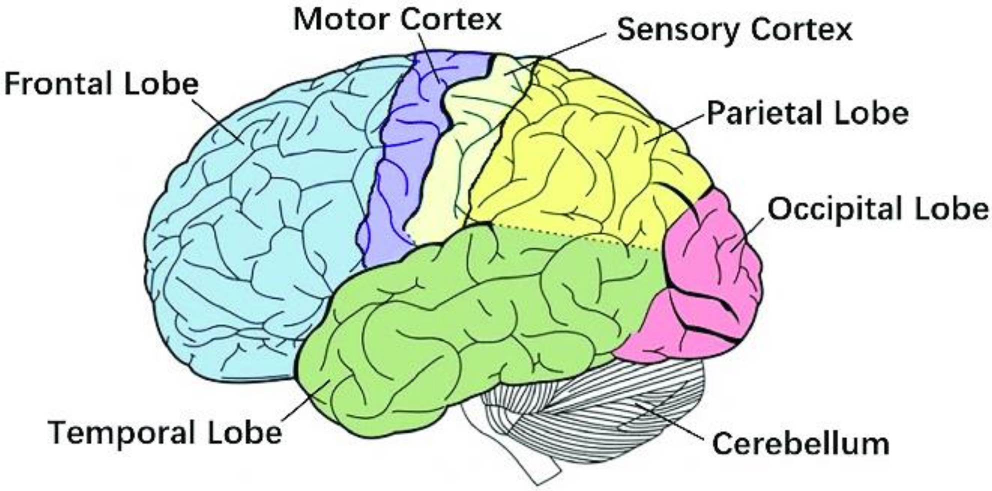

Figure 2.2: Motor cortex of the human brain (Liu et al., 2019).

2.4 EEG SIGNAL ACQUISITION

There is a possibility of experiencing several artifacts during the EEG signal recording from the human brain. For this reason, EEG detection has become crucial. To record the EEG, it needs to have a very clear idea regarding EEG electrodes, EEG montage, noise sources, and ways of electrode placement to record the best possible electrical activity for further processing of the acquired signal. Therefore, all of these terms are briefly explained below.

2.4.1 EEG Electrodes

EEG electrodes play important role in the acquisition of EEG signals. Metal discs such as stainless steel, gold, tin, or silver are usually bound by a silver chloride (AgCl) shell that surrounds the scalp at particular points. The metal electrode acquires an EEG signal. As the signal amplitude is very low, it is difficult to extract the EEG signal from the composite signal. Then synchronized signals are stored for processing. Summing up the activities of neurons is very necessary to detect the EEG signal because its amplitude range is very low. Whenever those samples are summed up then it seems clear to recognize whether it is a signal or a noise. However, the moment in time of their activity is decisive. To get the larger signal, it needs to combine the neuron activity in a synchronized way.

2.4.2 EEG Montages

The placement of electrodes is widely known as a montage. Bipolar or referential montage can acquire the EEG signal. In the bipolar montage, there are two electrodes in each channel: one electrode acts as the reference electrode. For all the channels, a common electrode is called reference montage.

Each channel in a reference montage (Motamedi-Fakhr et al., 2014) indicates the difference between a specific electrode and a reference electrode. This electrode is not in the same place as the "recording" electrodes, thus there is no standard position for it. Because they do not enhance the signal in one hemisphere over the other. Therefore, midline locations are often utilized. Another common term is "connected ears," which refers to a physical or mathematical average of electrodes connected to either the earlobes or the mastoids.

2.4.3 EEG Artifacts

Noise or artifact is the major issue in signal transferring or recording. The artifact detection and reduction are very crucial in EEG recording. In general, there are two major types of artifacts namely subject-related and technical artifacts. Movements of the subject, sweating, eye blinking, ECG effects, etc. are subject-related artifacts. 50 to 60 Hz artifacts, electrode paste, movement of the cable, etc. are the technical artifacts