Motor Imagery Task Classification Enhancement Using Raw Signal Energy Data Dimension Reduction Approaches

by

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LIST OF ABBREVIATIONS

ANN	*Artificial Neural Network*
ANOVA	*Analysis of Variance*
ADC	*Analog Digital Converter*
AAR	*Adaptive Autoregressive Model*
ALN	*Adaptive Logic Network*
Ap	*Approximate Entropy*
AR	*Autoregressive Model*
ARMA	*Autoregressive Moving Average Model*
ALS	*Amyotrophic Lateral Sclerosis*
BCA	*Box Counting Algorithm*
BCI	*Brain Computer Interface*
BE	*Backward Elimination*
BMI	*Brain Machine Interface*
BP	*Backpropagation*
BPSO	*Binary particle swarm optimization*
BQM	*Bayes Quadratic Model*
CC	*Cross Correlation*
CFMA	*Channel-Frequency Map Analysis*
CSP	*Common Spatial Filter*
CRSD	*Channel Reduction based on Standard Deviation*
CRCV	*Channel Reduction based on Coefficient of Variation*
DFFF	*Detrended Fluctuation Fractal Feature*
ECoG	*Electrocorticography*
EEG	*Electroencephalography*
ERD	*Event Related Desynchronization*
ERP	*Even Related Potential*
ERS	*Event Related Synchronization*
ENN	*Elman Neural Network*
FA	*Forward Addition*
FBCSP	*Filter Bank Common Spatial Pattern*
FFNN	*Feed Forward Neural Network*
FD	*Fractal Dimension*

GA	*Genetic Algorithm*
HS	*Harmony Search*
HFF	*Higuchi Fractal Feature*
HMM	*Hidden Markov Model*
ITR	*Information Transfer Rate*
KNN	*K-Nearest Neighbor*
LDA	*Linear Discriminate Analysis*
LDC	*Linear Discriminate Classifier*
LVQ	*Learning Vector Quantization*
MA	*Moving Average Model*
MEG	*Magnetoenchaphalography*
MI	*Motor Imagery*
MI-BCF	*Motor Imagery Box Counting Fractal Feature*
MI-DFA	*Motor Imagery Detrended Fluctuation Analysis*
MI-HFF	*Motor Imagery Higuchi Fractal Feature*
MI-SE	*Motor Imagery Spectral Energy*
MI-SENT	*Motor Imagery Spectral Entropy*
MI-SEENT	*Motor Imagery Spectral Energy Entropy*
MLP	*Multilayer Perceptron*
MVAR	*Multivariate Autoregressive Model*
P300	*P300 Evoked Potential*
PLV	*Phase Locking Value*
PSD	*Power Spectral Density*
QDC	*Quadratic Discriminate Classifier*
RBFNN	*Radial Basis Function Network*
RMS	*Root Mean Square*
SD	*Standard Deviation*
SE	*Spectral Energy*
SENT	*Spectral Entropy*
SEENT	*Spectral Energy Entropy*
SCP	*Slow Cortical Potential*
SFFS	*Sequential Floating Forward Selection*
SOM	*Self-Organizing Map*
SSVEP	*Steady State Visually Evoked Potential*

SVM	*Support Vector Machine*
TDFD	*Time Dependant Fractal Feature*
TTD	*Thought Translation Device*
VEP	*Visual Evoked Potential*
WMEM	*Wavelet-based Maximum Entropy on the Mean*

LIST OF SYMBOLS

Θ	*Significant level*
F	*Number of frame*
N	*Number of samples*
F_d	*Higuchi fractal dimension value*
L_m	*Curve length value*
L_k	*Average length value*
R_k	*Raw energy signal matrix*
D	*Standard deviation matrix*
MV	*Raw energy mean value matrix*
RS	*Coefficient variation matrix*

Penambahbaikan pengkelasan tugas bayangan motor menggunakan pendekatan pengurangan dimensi data tenaga isyarat mentah

ABSTRAK

Antara muka komputer-otak (BCI) ditakrifkan sebagai mesin kawalan yang menggunakan isyarat otak. Aktiviti saraf motor otak boleh direkodkan dari kulit kepala manusia dengan menggunakan peralatan rakaman EEG dan ditukarkan menjadi perintah kawalan yang mewakili keperluan seseorang. Ia boleh digunakan untuk mengawal peranti seperti lengan prostetik, kayu ria atau kerusi roda, dan mungkin berguna untuk orang kurang upaya fizikal. Walau bagaimanapun, prestasi sistem sedemikian bergantung kepada kualiti isyarat yang direkodkan dan ciri-ciri yang diekstrakkan daripada isyarat tersebut. Kajian ini mencadangkan satu protokol baru untuk persediaan eksperimen, pendekatan pemilihan jalur frekuensi serta pendekatan pemilihan elektrod EEG untuk memperbaiki prestasi proses pengurangan dimensi data. Satu protokol baru telah dibangunkan untuk merekodkan isyarat otak EEG menggunakan 19 elektrod kulit kepala yang tidak invasif. Jalur frekuensi yang berkaitan dengan tindakan motor, iaitu alpha 1 (8-10 Hz), alpha 2 (11-12 Hz), beta 1 (13-15 Hz), beta 2 (16-18 Hz) dan beta 3 (19-25 Hz) disarikan menggunakan penapis isyarat yang sesuai. Sebuah antara muka komputer-otak (BCI) yang baru berdasarkan empat jenis tugas isyarat bayangan motor juga direkabentuk. Pengelasan tugas telah dilakukan menggunakan tiga ciri jenis spektral dan tiga ciri jenis fraktal dengan tiga jenis jaringan neural yang berbeza. Kaedah baru untuk meminimumkan bilangan jalur frekuensi dan bilangan elektrod EEG untuk pengelasan jenis tugas dicadangkan tanpa mengganggu ketepatan pengelasan. Prestasi model jaringan neural menggunakan ciri-ciri dari EEG elektrod terpilih yang terhad dibandingkan dengan prestasi menggunakan semua 19 EEG elektrod. Pendekatan yang dicadangkan menggunakan bilangan EEG elektrod yang terpilih dapat mencapai ketepatan minimum 90% di mana ianya bersamaan dengan kaedah sekarang tetapi dengan pengurangan masa pengiraan. Kaedah yang dicadangkan juga mempunyai kelebihan untuk mengenal pasti kawasan paling signifikan bagi elektrod EEG untuk pengelasan tugas bayangan motor. Hasil kajian menunjukkan bahawa kaedah pemilihan jalur frekuensi dan kaedah pengurangan elektrod EEG yang dicadangkan adalah pendekatan dimensi data yang berdaya maju dengan masa pengiraan yang dikurangkan untuk mengelaskan tugas bayangan motor bagi sistem bayangan motor BCI . Kerja penyelidikan ini akan mengurangkan beban pengiraan, dan seterusnya mengurangkan masa dalam sistem BCI. Ini membuka kemungkinan untuk penghijrahan berasaskan mikrokontroller untuk mobiliti yang lebih baik.

Motor Imagery Task Classification Enhancement using Raw Signal Energy Data Dimension Reduction Approaches

ABSTRACT

Brain Computer Interface (BCI) is defined as machines using the brain signals for its control. The motor neural activity of the brain can be recorded from the human scalp using EEG recording equipment and converted into control commands representing the needs of the person. These can be used for the control of devices such as a prosthetic arm, a joystick or a wheelchair and may be very useful for persons with physical disabilities. The performance of such system, however, depends heavily on the quality of the recorded signals and the subsequent features extracted from it. This research proposes a new protocol for experimental setup, frequency band as well as channel selection approach based on raw signal energy to improve data dimension reduction process. A new protocol for acquiring brain EEG signal using 19 non-invasive scalp electrodes were developed. The frequency bands related to the motor actions, namely alpha1 (8-10 Hz), alpha 2 (11-12 Hz), beta 1 (13-15 Hz), beta 2 (16-18 Hz) and beta 3 (19-25 Hz) were extracted using a customized filter. A novel four class brain computer interface (BCI) based on four tasks motor imagery signals was also designed. Classifications of the tasks using three spectral and fractal-based features with three different types of neural networks were performed. A novel method to minimize the number of frequency bands and EEG channels for the classification of tasks is proposed without sacrificing the classification accuracy. The performance of the neural network models with features from the selected channels were compared to that with all the 19 channels. The proposed approach with limited number of chosen channels were able to achieve a minimum average accuracy of 90% similar to that of the present methods but with reduced computational times. The proposed method also has the advantage of being able to identify the most discriminating regions for the EEG electrode channels for motor imagery tasks classification. The results show that the proposed frequency band selection and channel reduction method is a viable data dimension approach with reduced computational time to classify a motor imagery task for a motor imagery BCI system. This research work will reduce the computational load, and hence, time in BCI systems. This opens up the possibilities for the migration of pc-based to microcontroller-based implementations for better mobility.

CHAPTER 1 : INTRODUCTION

1.1 Research Background

The current development in technology has resulted in the revolution of how computer and information are being conveyed and utilised. The impact of these have influenced the scientific community and has resulted with many new inventions. The one area of interest which will be the focus of this thesis is known as Brain Computer Interface (BCI). BCI is a system that acts as link for the brain signal to communicate with computer system without going through a usual route of peripheral nerves and muscles (Jonathan et.al., 2002).

People with physical impairment may have a limited ability in performing their daily life activities and work. For example, individuals who suffer paralysis and have severe neuromuscular disorders such as quadriplegics and Amyotrophic Lateral Sclerosis (ALS). They may not be able to use their limbs to perform physical movements. Based on the survey by Motor Neurone Disease Association Australia (2014), nearly half million people worldwide are suffering from neuromuscular disorders and the number keeps increasing year by year. Due to this disorder, they have difficulty to manage their daily lives on their own.

Although their limbs are not functioning as normal people, their brains are functioning like normal people. The same signals as per normal people can be generated. Hence, their brain signals can be used in order to communicate or control a device that can help them to manage their daily routine. This factor has encouraged researchers to develop BCI systems to help the neuromuscular disorders community.

Study on BCI have been explored by researchers for more than 20 years. The number of publications on BCI is increasing rapidly. By refer the number of publications as indicator, research on BCI can be considered as inspiring research area. The amount of researchers who had done study about BCI also become greater from year to year (Shih et al, 2012). Even though study about BCI become greater from year to year, there are still great possibilities in this research field. A lot of enrichment in variety aspects of BCI performance can be studied such as the BCI control skill in order to produce reliable and stable brain activity pattern and to come out better EEG signal processing algorithm (Lotte et al., 2015).

This thesis proposes a novel asynchronous motor imagery (MI) data collection protocol. The effectiveness of the data collection protocol was analysed using different features and neural network models.

This thesis also proposes a method to improve the effectiveness of discriminating the motor imagery tasks and the approach to represent real environment in which the system may be implemented through:

- A band selection method in order to reduce the data dimensionality.

- Channel reduction methods based on high order statistical parameters to reduce the feature dimension in order to enhance the classification performance.

1.2 Problem Statement

Research on BCI using Electroencephalography (EEG) signal have been explored by many researchers in recent years. However, EEG signal processing is a very challenging task. The EEG signal itself is complex and easily influenced by either internal and external disturbances. Also, there are no standard procedures for developing a BCI based on EEG signals. There are advantage and disadvantage from variety of perspective for each of the developed BCI system.

In addition to that, even though BCI based on EEG signals have been explored by many researchers, there are still outstanding issues that need to be addressed. Focus should be given to the key factors that play important role in the development of a BCI system in order to enhance its performance. These include:

- Development of the experimental protocols to acquire and record the EEG signals of the brain.
- Determination of the significant area of brain regions that relate to motor imagery signal.
- Proposals for feature extraction methods.
- The classification method in order to discriminate various types of brain tasks.

- EEG channel reduction and band selection method.

1.3 Research Objectives

The goal of this research is to develop a BCI system for recognizing hand movements from brainwaves stimulated by Motor Imagery (MI) tasks. The objectives are as follows:

- To design a new experimental protocol for MI hand movements from EEG signals.
- To implement feature extraction methods based on spectral and fractal approach.
- To develop new EEG channel and band reduction methods.

1.4 Scope of Thesis

This research work concentrated on the implementation of channel selection and band selection technique to enhance the performance of a BCI system using brain wave signals stimulated by MI tasks in a more realistic operating environment. The following describes the scope of this thesis:

- The use of 'Mindset-24' with 19 differential input channels on ten normal subjects
- Develop a new experimental protocol for MI BCI system with four (4) different hand movement-based MI tasks
- The use of feature extraction methods based on fractal (Box Counting Algorithm (BCA), Higuchi Fractal Feature (HFF), Detrended Fluctuation Fractal Feature (DFFF)) and spectral (Spectral Energy (SE), Spectral Entropy (SENT), Spectral Energy Entropy (SEENT)) to analyse the EEG MI data.
- The use of non-linear classification (Feed Forward Neural Network (FFNN), Radial Basis Function Network (RBFNN) and Elman Neural Network (ENN)) for the classification of different MI tasks.
- The evaluation of the performance for all the features methods by comparing their classification accuracy, sensitivity and specificity. The features that give the best performance identified.
- The relevant channels and frequency bands are identified in the collected EEG signals; in order to reduce the number of input features and to enhance the classification performance. Two channel reduction methods were proposed in this research. Using the feature set that gives the best classification accuracy from spectral and fractal feature extraction method, both methods were validated using three non-linear classification namely FFNN, RBFNN and ENN.

1.5 Thesis Contribution

The contributions through this research are:

- A novel asynchronous experimental protocol to acquire a brain signal using motor imagery as a predefined task was developed. The proposed system has the capability to discriminate MI based on hand movement tasks without depending on cue signals.
- Six feature extraction algorithms namely Motor Imagery Spectral Energy (MI-SE), Motor Imagery Spectral Entropy (MI-SENT), Motor Imagery Spectral Energy Entropy (MI-SEENT), Motor Imagery Box Counting Algorithm (MI-BCA), Motor Imagery Higuchi Fractal Feature (MI-HFF) and Motor Imagery Detrended Fluctuation Fractal Feature (MI-DFFF) were analysed to test the performance of the proposed BCI methods. All these feature extraction methods were modelled and tested using FFNN, ENN and RBFNN model.
- The application of Band Reduction Method to choose the essential frequency band combination by selecting the significant frequency band that leads to the reduction of the number of input features and enhance classification performance.
- The proposal of Channel reduction methods namely Channel Reduction based on Standard Deviation (CRSD) of raw energy signal and Channel Reduction based on Coefficient of Variation (CRCV) in raw energy signal to enhance the classification performance by selecting significant channel and discard a channel that may give irrelevant information. Both

the proposed algorithms were validated using three classifiers, namely FFNN, ENN and RBFNN.

1.6 Structure of Thesis

The thesis is organized in five chapters. Chapter 1 introduces the research and discusses the existing methods of various BCI systems. This chapter also discusses the objectives, scope and provides an overview of the thesis.

Chapter 2 comprehensively presents a literature review on a basic concept of the EEG signals and comprehensive review of its applications. This chapter also provides a review of existing BCI research works, including the channel and feature selection techniques.

Chapter 3 describes the development of novel protocols for acquiring an EEG MI signal. It also deals with the complete procedure and experimental methodology involved in the data acquisition process. This chapter also provides the concepts of pre-processing. In this chapter the feature extraction formulation is explained. In general, there are six feature extraction methods employed in this thesis, namely MI-SE, MI-SENT, MI-SEENT, MI-BCA, MI-HFF and MI-DFFF. The chapter also deals discusses about the choice of classifiers and reasons for choosing the artificial neural network (ANN). This chapter also presents the concepts of FFNN, ENN and RBFNN together with their architectural design, training and testing methods of the neural network, and learning algorithms. The proposed frequency band reduction method and two channel reduction methods (CRSD and CRCV) performed in this research are also presented in this chapter. The concept of the proposed method is based on high order statistical parameter.

Chapter 4 presents and discusses the results of the developed FFNN, ENN and RBFNN models. The classification results of feature extraction methods i.e., spectral-based features and fractal-based features are also elaborated. The results of the frequency band reduction as well as the channel reduction method are also discussed in this chapter.

Chapter 5 concludes the work of this research and highlight the key research points and problems faced. It also suggests future research directions.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

This chapter provides a review on BCI-based research works and type of EEG signals. The discussion and review on various categories of data dimension reduction through EEG channel selection and frequency band selection are also presented in this chapter. The summary of the literature review sums up this chapter.

2.2 Brain Computer Interface (BCI)

The BCI system elements are made up of five sequential steps, namely brain signal measurement, pre-processing, feature extraction, classification and the control interface (Nicolas-Alonso & Gomez-Gil, 2012). A BCI system is used to discover and identify the brain signals. The brain signals indicate the subject's desire of doing a particular movement. The BCI system then converts this signal in real time into commands that can be understood by the output device. In order to achieve this process, five sequential steps mentioned above need to be followed.

In the brain signal measurement step, the brain signal is obtained via various types of recording equipment such as electroencephalography (EEG), magnetoenchaphalography (MEG) and near infrared spectroscopy.

In the pre-processing step, the recorded brain signal is enhanced by removing the noise and artefacts via a filtering process. The discriminative and relevant information values known as 'features' are then discovered from the upgraded brain signal. More specifically, this process is known as feature extraction step.

In the classification step, a class is allocated to the features that had been extracted from the upgraded brain signal. The class is allocated such as it represents the type of a mental state that the user undergoes. This step is also known as 'feature translation'.

In the final step of BCI systems, once the mental state is identified, the classified signal is encoded into a significant command in order to control a target device such as a wheelchair, a prosthetic arm or a robotic arm (Nicolas-Alonso & Gomez-Gil, 2012, Mason & Birch, 2003). Figure 2.1 shows the architecture of a BCI system.

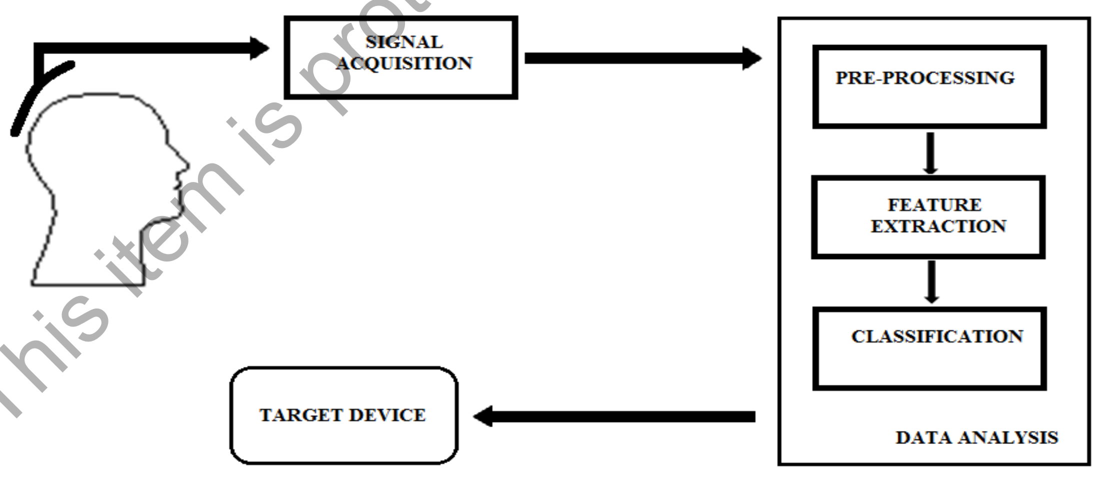

Figure 2.1 : BCI Systems Elements

One of the important elements of BCI system is to quantify the brain signal activity and convert it into a form that represents the electrical control signal. The electrical control signal is then used to control any target device. However, the brain signal needs to be measured and recorded before it can be quantified. In general, there are two approaches for measuring brain signals, namely invasive and non-invasive methods.

The BCI used to acquire a brain signal via implanted electrodes is known as invasive BCI. The process of inserting the implanted electrode into the skull required very high cost. Medical expert is also needed because it is a very high risk process and need to go through a surgical procedure (Haselager et al., 2009).

In 2004, researchers from Cyberkinetics research company successfully acquired a human brain signal using implanted electrodes. They applied the signal and developed a BCI to control a computer cursor and TV operation (Brower, 2005). In 2013, researchers from the University of Pittsburgh have developed a BCI system based on electrocorticography (ECoG). They implanted high density 32-electrodes in an individual with spinal cord injury and acquired brain signal from the sensorimotor cortex region. The individual was then able to control the movement of character on computer screen (Wang et al., 2013).

The approach that does not require surgical process is known as non-invasive BCI. In the non-invasive BCI, the electrodes are placed over the scalp externally without the need of any surgical procedure. Non-invasive method is more preferred because it does not involve to any high-risk operation. Various types of recording equipment such as Electroencephalography (EEG), Magnetenchaphalography (MEG) and near infrared spectroscopy are considered as non-invasive methods.

The majority developed BCI systems for rehabilitation use non-invasive method to acquire brain signal activity (Gongora et al., 2013). Most of the researchers obtained the brain signal activity using the EEG recording device. EEG is widely used because it requires minimal cost and it is classified as low risk equipment. Furthermore, EEG provide most of the information about the brain activity (Ramadan & Vasilakos, 2017).

2.3 Electhroencephalography (EEG)

Electroencephalography (EEG) signal is also known as an electrophysiological or electro biological signal. The signal is actually a measurement of brain activity and it is acquired by employing a scalp or implanted electrodes on cognitive brain region. Richard Caton was the first individual who discovered the existence of electrical currents in the brain. The English Physician has observed the electrical activity in the exposed brains of rabbits and monkeys (Teplan, 2002, Ravelli et al., 1976).

In 1924, Hans Berger, a German scientist has discovered a method to record the brain signals. He used an ordinary radio equipment to amplify and measure the electrical signal in his experiment (Teplan, 2002). Analysis and observations made by Hans is more focused on changes in brain signals when an individual is in different conditions such as sleep, lack of oxygen and anaesthesia. EEG wave diagrams alterations and its interrelation over the brain diseases such as in epilepsy and seizure were also analysed. From all analysis and observation made by Hans, he has made a conclusion that a brain activity changes in a consistent and recognizable pattern when the general status of the subject changes from relaxation to alertness. The successes achieved by these two scientists have motivated many researchers to conduct studies of brain signals in a variety of applications.

EEG signals are extensively used in biomedical application areas such as patient monitoring system, neurological disorder diagnosis, various abnormalities detection in human body and other clinical application (Alonso et al., 2015, Palaniappan, 2005, Teplan, 2002, Farwell & Donchin, 1991).

Based on the studies related to the EEG signal, the idea of using brain signals as a medium to control the machine has attracted the attention of many researchers. Back in the 1970's, the initiative of using a brain signal in developing a BCI system has been investigated. A variety of EEG signals were used in order for communication based BCI system comes into existence.

2.4 EEG Control Signals

Past researchers utilized various types of EEG control signal to develop a BCI system. These signals are such as Visual Evoked Potential (VEP), Slow Cortical Potential (SCP), P300 evoked potential and sensorimotor rhythm activity. Those can act as a bridge to communicate between human and the control device.

The systematic research activities related to EEG-based BCI has been done in the early 1970's (Vidal, 1973). Initially, early studies on EEG-based BCI were intended to find out and evaluate the possibilities of brain signal in order to control neuroprosthetic devices. These could be used to help individuals suffering from brain related problems such as impaired vision, hearing impairment and restricted movement of body limbs. Individuals with last stage amyotrophic lateral sclerosis could also potentially benefit from this (Shih et al., 2012).

During late 1970's and throughout the 80's, not many studies related to BCI were conducted due to limited computer capabilities. However, in early 1990's, researches related to BCI started to increase again. Then, the research works related to BCI were growing at an extremely rapid rate starting in the year 2000 onwards. This can be seen by looking at the number of peer-reviewed publications in this field from year 2002 as shown in Figure 2.2.

In the late 80's, Farwell & Donchin (1988) demonstrated how a human subject spelt a word onto the computer screen using the brain's P300 signal. It is reported that Wolpaw and his team demonstrated how a human was capable of controlling a movement of cursor on computer screen in one dimensional using sensorimotor rhythm signal from EEG (Wolpaw et al., 1991).

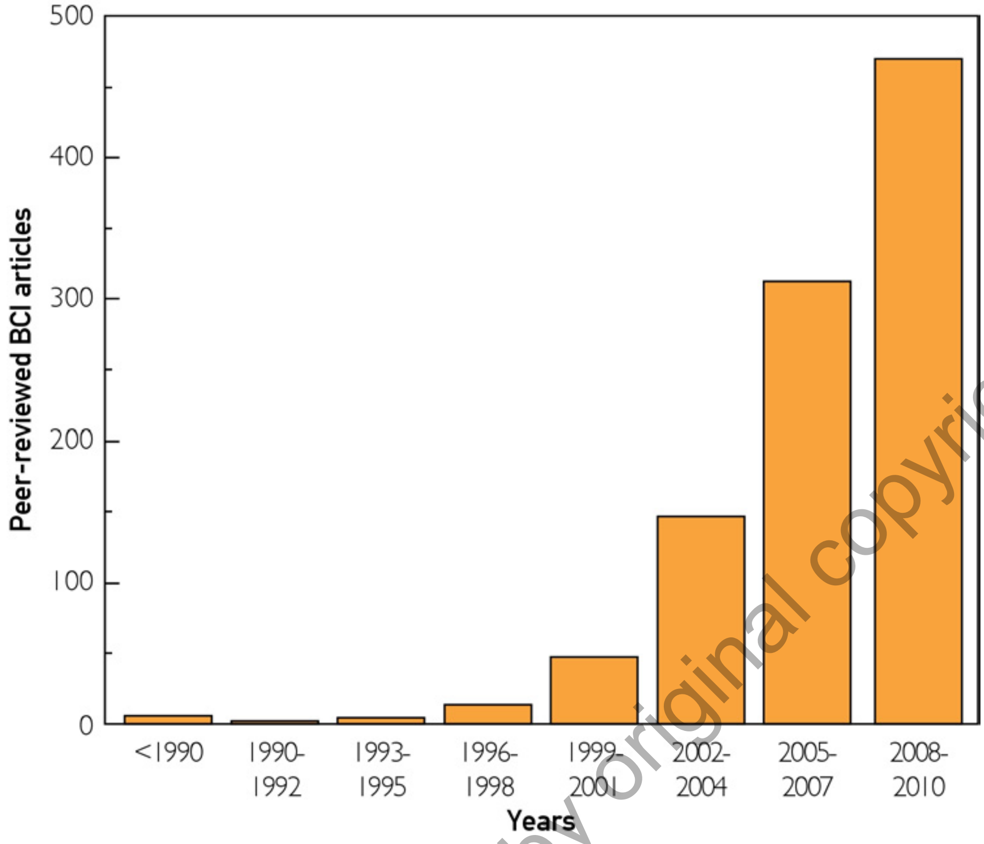

Figure 2.2 : BCI articles in the peer-reviewed scientific literature (Shih et al., 2012)

For the past two decades, various BCI systems have been developed using different types of EEG signals such as VEP, SCP, P300 evoked potential and sensorimotor activity (Bashashati et al., 2007, Vaughan, 2003, Wolpaw et al., 2000)

Slow Cortical Potential (SCP) is the measurement of the visual, auditory and sensory activity using the EEG signal recorded from the human scalp. SCP signals is one of the EEG signal types recorded from the human scalp using EEG measurement systems. SCP signals had been utilised by previous researchers in order to develop a BMI system. SCP signals exist in the very low frequency range, between 1-2Hz (Hinterberger et al., 2004).

Initially, SCP was used to control the movement of an object on a computer screen. This allows the user or an individual to be able to choose any letter or computer character without the use of a mouse or a keyboard (Hinterberger et al., 2003). SCP signals have also been used as a communication medium for paralyzed persons. A communication system known as Thought Translation Device (TTD) was developed based on the SCP signal from paralyzed peoples (Birbaumer & Cohen, 2007).

P300 Evoked Potential is one of the evoked potential components. It is produced when an individual response to external stimulus, for example auditory, visual or somatosensory stimuli. P300 Evoked Potential signal is generated in the parietal cortex region and normally has the positive peaks about 300 milliseconds (Cipresso et al., 2012, Sellers & Donchin, 2006, Guan et al., 2004). P300 signals arise while the subject visualises a 6X6 matrix of letters, numbers or symbols or commands with row/column flashing effect (Sellers, Kübler, & Donchin, 2006).

P300 Evoked Potential signal was used in an intelligent BMI system to communicate using one word (Farwell & Donchin, 1988). The signal also been used to analyse the consequence to human when they are growing old. This analysis had been done through the auditory P300 (P3 or oddball paradigm) event brain potential (Zenker & Barajas, 1999). The P300 Evoked Potential signal has also been used as navigation medium to control movement of a wheelchair (Bi, Fan, & Liu, 2013). A wheelchair navigation system based on P300 Evoked Potential signal wave had been developed by Rebsamen et al. where the system can avoid the obstacle and collision (Rebsamen et al., 2010).

VEP is one of the classes of evoked potentials. VEP is produced when an individual visualizes any external or internal stimulus. The visually evoked potentials are obtained by means of visualization stimulus (Tai, Blain, & Chau, 2008, Tanaka, Matsunaga, & Wang, 2005, Cheng, Gao, & Xu, 2002, Sutter, 1992). VEP signal occur when people are gazing or visualizing symbols and pictures.

In 1992, Sutter (1992) came out with a new method to produce a VEP signal. He mapped various types of symbol on an 8-by-8 checker board and displayed them on the video screen. The VEP signal that emerges during the task done by the subject was then used to control the keyboard. The VEP signal produced while the subject selects the symbol on the screen through eye gazed interaction.

Lee et al. (2006) introduced a new experiment paradigm to acquire a VEP signal by presented 5 x 5 matrices on the LCD screen to the subject. The subject was stimulated through the LCD screen by flashing stimulation and the matrix was performed either as a digit, character or symbol.

VEP signal was also utilized in the development of BMI in biometric studies. In the biometric field, BMI was developed to recognize human identity. A picture set by Snodgrass & Vanderwart (1980) which consists of black and white line was used to emerge a VEP signal. The VEP EEG signals were successfully acquired through this method (Palaniappan & Mandic, 2007). The VEP signal, which was obtained through this idea were then utilized to develop the BMI system to recognize human identity (Wang et al., 2008).

Steady State Visually Evoked Potential (SSVEP) is another one of the classes of visually evoked potential. SSVEP are produced when an individual visualize a flickering light, single graphic stimuli or phase reversing check board pattern (Zhu et al., 2010, Lee et al., 2010, Cecotti, 2010, Wang et al., 2008).

SSVEP was also utilized by previous researchers to develop a BCI system. A flight simulator based on a BCI system was developed by previous researchers using SSVEP. Two different methods of acquiring SSVEP signals were introduced by the researchers. The first method is through a white fluorescent tube of luminance. The tube was used as a stimulate medium to get a SSVEP signal at a frequency of 13.25Hz. The second method is by using virtual knobs and blinking colour LED with letter or words appeared on the computer screen at different rates. The subjects were required to gaze at the knobs and the SSVEP was recorded (Wolpaw et al., 2002, Middendorf et al., 2000).

Lalor et al. (2005) had come out a BCI system that can be used to control a 3D game in real time. The BCI system is based on the SSVEP signal. The SSVEP signal is induced while the person gave a response to the checkerboard patterns. A mobile object controller using SSVEP also have been proposed by Diez et al. (2011) by using asynchronous interface paradigm. In 2013, they enhanced their BCI system with higher frequency stimuli (Diez et al., 2013).

Sensorimotor rhythms signal or also known as Event Related Potential (ERP) is one of the EEG signal types used for BCI development. The sensorimotor signal is triggered from real limb movements such as realism movement of hands, leg or tongue. The sensorimotor signal also can be triggered from the imagination of limb movement, such as imagination of hand, legs and tongue movements (motor imagery tasks). Sensorimotor rhythms can be measured from the motor cortical areas of human scalp (Krepki et al., 2007).

Group research from Graz University found that primary sensory or motor activity response normally occurred at alpha rhythm (8–12 Hz) and beta rhythms (18–26 Hz). The result is according to their BCI based on two-state classification using Motor Imagery tasks (Pfurtscheller & Neuper, 2001, Neuper et al., 2009, Pfurtscheller et al., 1997).

The BCI based on primary sensory or motor activity response has been developed since 1980's. One of the main purpose of the BCI is to help the patients with motor disabilities by means of medical devices such as wheelchairs and prosthetic devices (Carra & Balbinot, 2013, Hema et al., 2009, Wolpaw et al., 2002, McFarland et al., 2000, Pfurtscheller & Neuper, 1997).

By using sensorimotor rhythms as a signal for BCI, the interface can be easily controlled by the user intends. In addition, the user can easily modulate sensorimotor rhythms through their own intention through continuous training time (Wright et al., 2011). Some researchers have proved that BCI based on sensorimotor rhythms can give a better classification and information transfer rate result by applying a right signal processing algorithms (Vaughan et al., 2006, Kübler et al., 2005).

Among all of those types of EEG signals, sensorimotor rhythms can provide a flexible control condition in terms of degree of freedom. Sensorimotor rhythms are the uninterrupted oscillation behaviour occurs in the brain and they can be detected at frequencies between 8Hz to 30Hz in sensorimotor cortex of the human brain. The oscillation occurs continuously during brain in rest condition. It can be observed in both healthy and disabled person that suffer from neuromuscular injuries, stroke or spinal cord injury (He et al., 2015).

It is observed that as a person is planning or executing a movement, the oscillation of brain rhythms in the sensorimotor cortex area will deal with two conditions. First, the decrease of the amplitude in the frequency component which is known as event-related desynchronization (ERD) or secondly, an increase of amplitude in the frequency component which known as event-related synchronization (ERS) (Pfurtscheller & Lopes, 1999). This finding indirectly leads the ability to discriminate various types of limb movement through motor imagery and so on can be applied in BCI development (Anderson, 2007).

Overall, it can be concluded from the above review, the EEG brain control signals can be used to develop a system to control devices such as prosthetic limbs and wheelchairs in order to enable the disabled person to facilitate their daily lives. Since the proposed system is to contribute to the application of BCI rehabilitation, motor imagery of hand movements is more suitable and practicable.

2.5 Motor Imagery-based BCI

Motor imagery can be defined as the process to carry out pretended movement of arm or other parts of human body. The concept of pretended movement of arm can be defined such as preparation for movement, passive observations of action, and mental operations of sensorimotor representations (Jeannerod, 1994).

Decety and Grèzes (1999) defined a motor imagery as a progressive process to represent a motor act or body movement which is occurred internally within a working memory of the brain. The motor act is practiced internally within a working memory without translate it through any body movement.

The concept of motor imagery is suitable in formulating the development of BCI system for rehabilitation applications. Study shows that motor imagery and execution of motor movement have similar characteristics. This is because both of them are operating in same brain link (O'Shea & Moran, 2017).

Motor Imagery based BCI has been applied in many area of application by previous researchers. Different kinds of motor intention from brain can be detected through different tasks of motor imagery. This allows a device to be controlled by human using brain signal. Research on motor imagery has been conducted since 1980's (Epstein, 1980). A reported study has mentioned that Wolpaw research group has developed a BCI system to control a cursor which is based on sensorimotor EEG rhythm (Jonathan Wolpaw et al., 1991).

Pfurtscheller et al., (1997) from Graz research group has proven that imagination of limb movement can be discriminated using EEG signal which is known as motor imagery. In that experiment, three subjects were asked to imagine either right- or left-hand movement depending on a visual cue stimulus (arrow form) and the corresponding

EEG signal were recorded. The EEG was recorded bipolarly from left and right central and parietal regions. For each subject, different frequency components in the alpha and beta band were found which provided best discrimination between left and right hand movement imagination.

Later in 1998 the same researchers constructed the first BCI using motor imagery EEG signal to control cursor movement on computer screen (Pfurtscheller et al., 1998). The system was also known as the Graz BCI. Two electrodes C3 and C4 were used in this system. Power spectrum in different range of frequency bands was used as features. Signal was recorded from one female subject 25 years of age. The subject was required to start imagining left- or right-hand movement in response to the visual cue which presented on a computer monitor. The error rate obtained varied between 5.8% and 32.8%.

Studies related to BCI based on motor imagery have grown rapidly. Researchers have developed variety of experiment paradigm for motor imagery BCI in various way based on the type and number of motor imagery task in order to detect variety kinds of motor intentions from human subject. A 2-class motor imagery BCI have been investigated by Obermaier et al. (2001) to classify two types of motor imagery task, namely movement of left hand and right hand motor imagery. The BCI to discriminate between left hand and right motor imagery also been investigated by Chen et al. (2014). Apart from investigating the movement of left and right hand as a task, a discrimination between left and right foot also been investigated by researcher in 2-class BCI (Bhaduri et al., 2016).

The EEG signal based on multiclass motor imagery task also widely been adopted in BCI. By imagining left hand, right hand, tounge or feet movement, a multidimensional BCI using motor imagery can be realized. For example, a 3-class motor imagery BCI have been investigated by Scherer et al. (2004). They successfully discriminated three different motor imagery task namely right hand, left hand and foot movement. A three dimensional virtual keyboard controlled using brain signal were then proposed by them. A three-class motor imagery BCI also been proposed by McFarland et al. (2010). They successfully developed a three-dimensional cursor control using motor imagery signal.

Apart from the study of upper limb imagery, its combination with tounge imagery have also been widely used in the development of motor imagery BCI. For example, Hamedi et al. (2014) proposed 3-class motor imagery BCI. Brain signal was recorded from ten healthy subjects (right-handed, aged 25-34 years) through three channels, namely C3, C4 and Cz. In this work, noncue-based recording paradigm was proposed. The subjects were asked to continuously imagine the movements of left hand, right hand, and tongue in three separate runs. A positive result is obtained where the proposed system is yielded up to 89% classification rate.

Amanpour & Erfanian (2013) developed a BCI system to discriminate motor imagery movement of hand grasping, opening, and reaching. Five healthy subjects were involved in this study. EEG signal were recorded from positions F3, F4, Fz, C3, C4, Cz, P3, P4 and Pz according the Internasional 10-20 system. The subjects started the experiment by imagining hand grasping, hand opening, or hand reaching based on the visual cue which were shown on the monitor of the computer. The performance of classifying different two mental tasks was reported. It was observed that the mean classification accuracies were 75.7%, 78.9%, and 78.2% respectively for grasping/opening, reaching/grasping, and reaching/opening imageries.

Besides three-class BCI, a four-class motor imagery has also been adopted by previous researchers. For example, Obermaier et al. (2001) developed a motor imagery based BCI which were able to discriminate four different motor imagery tasks. 10 healthy subjects between 25-34 years of age were involved in this research. Signals were measured from C3, C4 and Cz electrodes. The classification accuracy achieved was up to 84%.

Majority of past literatures report indicated that the studies of motor imagery BCI mostly occur in quiet, small and shielded room where the environment is artificially regulated. Hence the subjects involves in the experiments can focus deeply in order to perform respective imagery task (Enomae et al., 2017, Lu, Jiang, & Liu, 2017, Shedeed & Issa, 2016, Mizuguchi et al., 2015, Chen et al., 2014, Taylor et al., 2014, Li & Zhang, 2012, Arvaneh et al., 2011, Howida AbdelFattah Shedeed, 2011, Barbosa et al., 2010).

Literatures also reported that the majority of the existing motor imagery based BCI systems used traditional signs of direction as the cue stimuli before the subject start to imagine a movement task. This includes a graphical symbol such as arrow form and other types of directional sign. For example, Jiralerspong et al. (2014) developed a 2-class BCI system to control a electronic device through human intention using brain signal. In this study, three subjects were asked to imagine tasks related to movements of up and down. Once the visual cue (arrow form) appeared on the monitor of the computer, the subject will start to imagine any movement intention that related to the up and down