CLASSIFICATION OF EEG SIGNALS FOR HUMAN COMPUTER INTERFACE (HCI) APPLICATION

NOOR NADIAH BT MOHD AZALI

A project report submitted in partial
fulfillment of the requirement for the award of the
Master of Electrical Engineering

Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

JULY 2015

ABSTRACT

Brain Computer Interface (BCI) is one of the alternatives available in situation when all other typical interface such as joystick is not an option. This situation is generally true for users with severe motor impairment such as spinal injury who are unable to control wheelchair. In this research, method to classify EEG signals for controlling wheelchair for severe impairment users is proposed. The proposed system will be using a low cost consumer grade device, Neurosky Mindwave Mobile, to safely measured and acquired EEG data. Two types of model are proposed, the first one is based on visualizing colour model, and the other one is imagining doing motor task. Colours chosen are cyan, black, green and yellow as this colour are proven to generate high brain activity. For mental task, subjects are required to imagine doing motor task such as running, kicking, juggling, and signing a song. Data acquired will then go through simplest pre-processing stage to obtain signal contain enough information for classification. Classification implemented using linear classifier, Support Vector Machine as EEG brainwave is presumed to be linear. Results by trying different combination of task were analyzed to deduct the best way to classify direction which might work for controlling wheelchair.

ABSTRAK

Antara muka dengan menggunakan minda merupakan salah satu alternatif yang boleh digunakan sekiranya terdapat situasi dimana kesemua antara muka konvensional yang lain tidak dapat digunakan. Situasi ini biasanya terjadi kepada pengguna dengan kemerosotan fungsi motor yang teruk seperti kecederaan tulang belakang dan tidak lagi mampu mengawal kerusi roda. Didalam penyelidikan ini, kaedah untuk mengklasifikasikan isyarat EEG bagi mengawal kerusi roda dicadangkan. Sistem ini akan menggunakan peranti termurah dengan gred konsumer, Neurosky Mindwave Mobile untuk mengukur dan mendapatkan data EEG dengan selamat. Dua model berbeza dicadangkan, yang pertama akan melihat warna sebagai asas dan satu lagi dengan membayangkan seolah-oleh sedang melakukan perbuatan melibatkan kemahiran motor. Warna yang dipilih adalah biru muda, hitam, hijau dan kuning kerana warna-warna ini telah terbukti akan mengaktifkan aktivti minda. Bagi tugas menggunakan minda sepenuhnya, subjek perlu membayangkan seolah-oleh sedang melakukan kemahiran motor seperti berlari, menendang, menjugel, dan menyanyikan lagu. Data yang diperolehi seterusnya akan malalui pra-pemprosesan paling mudah bagi mendapatkan isyarat yang mengandungi cukup maklumat bagi tujuan pengkelasan. Pengelasan dilakukan dengan pengekelas linear, Support Vector Machine (SVM) kerana isyarat EEG secara amnya adalah linear. Keputusan dengan menggabungkan pelbagai kombinasi tugas dianalisa bagi mengenalpasti cara yang terbaik untuk membezakan arah yang mungkin boleh diguanakan bagi mengawal kerusi roda.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

HCI	-	Human Computer Interface
BCI	-	Brain Computer Interface
EEG	-	Electroencephalography
TGCD	-	ThinkGear Connection Driver
SVM	-	Support Vector Machine
EP	-	Evoked Potentials
ERP	-	Event Related Potentials
SMR	-	Sensorimotor Rhythm
ERD	-	Event-Related Desynchronization
ERS	-	Event-related synchronization
KNN	-	K-Nearest Neighbour
LDA	-	Linear Discriminant Analysis
DFT	-	Discrete Fourier Transfrorm
FFT	-	Fast Fourier Transform
GUI	-	Graphical User Interface
IDE	-	Integrated Development Environment

LIST OF A APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Research background

Human Computer Interface (HCIs) is common nowadays. Interfaces such as joystick are usually used to steer electric wheelchair. There is a huge demand, however, for HCI's that can be used in situations where this typical interface is not an option. Brain Computer Interfaces (BCI) is one of the alternatives available to cater this problem.

Input devices based on cues or actions generated from the head (e.g., facial, brain, gaze, tongue and bite) can be possible media for such users at all levels of injury [1].The use of brain waves is the best alternative for users with severe motor impairment (e.g. spinal cord injury) to control wheelchair since they are lack muscle control and in worst cases they are unable to control the movement of arms and legs. To do so, electroencephalography (EEG) signal patterns can be used to capture the different pattern of brain waves. The EEG signal need to be acquired, classified and grouped into different actions such as forward, reverse, right and left.

Electrical impulses from the nerves in the head can be recorded by using electroencephalography (EEG). "Electro" refers to the electrical impulses, "Encephalo" refers to the head, and "gram" refers to the printed record. Currently the most common used of EEG is to diagnose a number of conditions, including epilepsy, sleep disorders, and brain tumors. However the scopes are now broadening with new technology introduced and the necessary equipment are now become available with minimal cost. Thus, it is now possible to utilize the brainwave as one of the HCIs.

1.2 Problem statement

Standard joystick provided for electric wheelchair is unable to accommodate users with severe impairments. According to Simpson [2] the disabilities may due to several reasons such as cerebral palsy or cognitive impairment. Patient cannot use a power wheelchair because they lack of requisite motor skills and strength. Fehr, Langbein and Skaar [3] concluded that "individuals indicate with severe disabilities which compromise respiratory drive and/or limit the dexterity of the head and hands have few options for steering a power wheelchair".

1.3 Aim and objective

This project builds upon previous project - Enhancing Wheelchair Maneuverability for Severe Impairment Users [4]. Two modules were proposed in previous project in order to enhance wheelchair manoeuvrability. The first one was the alternative hybrid input interface to issue control easily and second one is semi-autonomous driving assistance to assist the user's mobility in difficult situation.

The project's aim is to expand the capabilities of the first one (alternative hybrid input interface) by introducing brainwave as hands-free interface (HFI). This method however will not be used to continuously control the wheelchair because the user needs high level of concentration and if it is used in full–time operation, user will find it tiring and not practical. Therefore, the signal from brainwave will be extracted and classified according to user's intended direction only such as forward, reverse, left and right. The rest will be taken care of by semi-autonomous driving assistance done in previous project.

The main aim of this system is to utilize the most economical means of extracting the brainwave so that it will be available as one of the HCI used to maneuver the wheelchair for severe impairment user. To achieve the aim of this research, the following objectives are formulated:

i. Capture frontal EEG activities by a single-channel mobile EEG system.
ii. Extract the raw EEG wave and record the data for further analysis.
iii. Classified the brainwave according to the user's intention to move the wheelchair.
iv. Evaluate the performance of the system by analyzing the accuracy of the classification system.

1.4 Scope of works

This research will only concentrate to:

i. Communicate wirelessly with NeuroSky Mindwave portable biosensor EEG via Bluetooth using ThinkGear Connection Driver (TGCD).
ii. Build Graphical User Interface for signal acquisition and data recording using Visual C#.
iii. Classification process will take place offline using SVM.
iv. Comparing result to achieved best combination for BCI implementation.

1.5 Outline of thesis

The contents of this Report are distributed by the following chapter:

i. Chapter 1: Introduction. The first chapter contemplates this introduction.
ii. Chapter 2: Literature Review. Comprehensive and published works by accredited scholars and researchers in BCI and wheelchair maneuverability will be reviewed in this chapter.
iii. Chapter 3: Methodology. This chapter will cover in detail about devices used to obtain the raw EEG, data gathering method, classification procedures and step taken to analyze system performance.
iv. Chapter 4: Result. The fourth chapter is devoted result obtained.
v. Chapter 5: Summary and recommendation for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Brain Activity Patterns

In 1929, Hans Berger discovers that electrical activity can be recorded by amplifying signal captured $(30 - 100\mu V)$ using electrodes placed on scalp. He named it as Electroencephalogram or EEG, procedures to measure the brain activity over time by placing electrodes at certain area of the brain. Since his discovery, the research area in brain activity evolved and can be further divided as discussed in this section.

Malmivuo, J. & Plonsey,R [5] classify the electrical activity that can be monitored in the brain into three group: spontaneous activity, evoked potentials and bioelectric events produced by single neurons.

i. Spontaneous activity – called EEG. Measured on the scalp and cycles through several different brainwave states (Beta, Alpha, Delta, Theta, Gamma) as further discussed in section 2.2.

ii. Evoked Potentials – these are component of EEG which response to a given stimulus such as electric, auditory, visual, etc. The signals usually are below the noise level. A train of stimuli and signal averaging are required to improve the signal-to-noise-ratio so that it can be distinguished and identified. Most of the time, Evoked Potential is also known as Event Related Potential. But there are time when this two should be properly distinguished as discussed in section 2.3.

iii. Bioelectric events produced by single neurons – the spiking rate of single neurons can be recorded by placing microelectrodes implanted in the brain.

There are two types of BCI system, invasive and non-invasive. Invasive system used to record bioelectric events produced by single neurons, while non-invasive system used to record EEG signals whether it comes from spontaneous activity or evoked potentials. To conclude, the BCI used related to the brain activity pattern can be summarized as Figure 2.1 below.

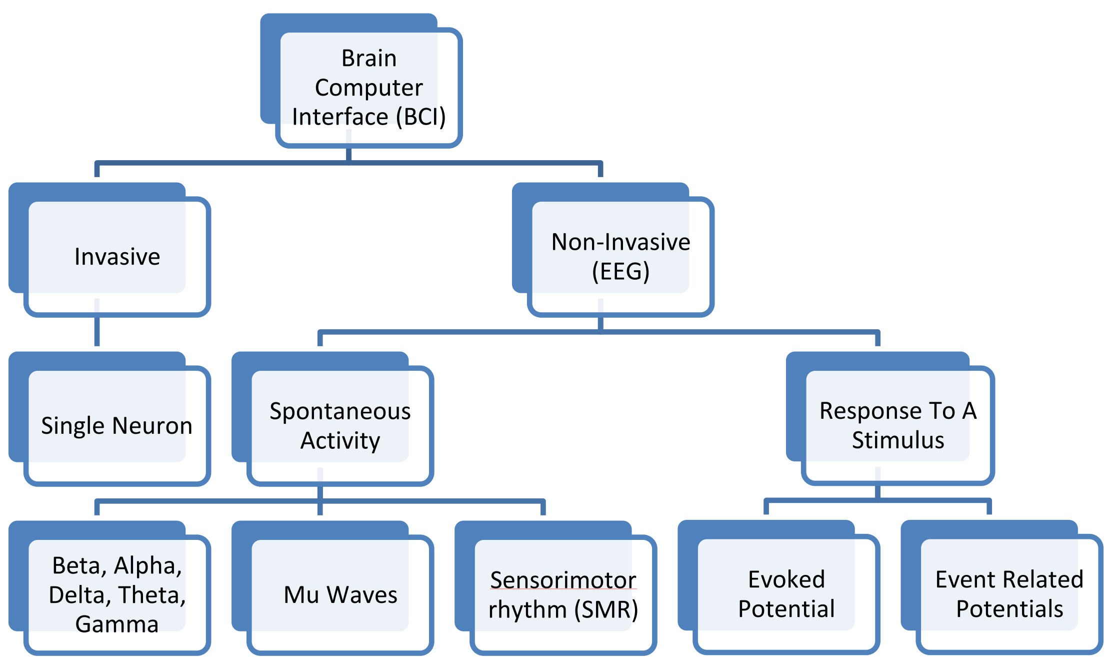


Figure 2.1: Types of Brain Computer Interface used related to brain activity monitored.

2.2 Brainwave States

There are several brainwave states operate simultaneously at a time with one of the states being dominant [6]. The waves are EEG component which occur spontaneously. Relationship between brainwave states and level of consciousness are represented in Table 3.

Table 2.1: Brainwave state and level of consciousness

BRAINWAVE STATE	**FREQUENCY**	**STATE OF MIND**
Beta	12 – 30 Hz	- Hightened state of alertness - Focus - Mind actively engaged - Eg : conversation, playing sports
Alpha	7.5-12Hz	- State of relaxed mental awareness - Reflection - Contemplation, Visualization, problem solving, accessing deeper level of creativity
Theta	3.5 – 7.5 Hz	- Deep relaxation, meditation - Creativity, stress relief , light sleep, dreaming
Delta	0.5 – 3.5Hz	- Deep dreamless sleep - Associated with healing
Gamma	31Hz and up	- High level information processing

Mu waves occur in alpha wave frequency range, with the maximum amplitude recorder around motor cortex area. This wave will be suppressed when a person move or have an intent to move [7]. It will be even suppressed when a person observes another person performing a motor action.

Sensorimotor Rhythm (SMR) can be detected by monitoring the brain activity recorded over the sensorimotor cortex which is modulated by actual movement, motor intention or motor imaginary. These modulations are manifests by decrease in alpha (also known as Mu rhythm) and beta frequency bands accompanied by increase in the gamma frequency band. It is also known as Event-Related Desynchronization (ERD).

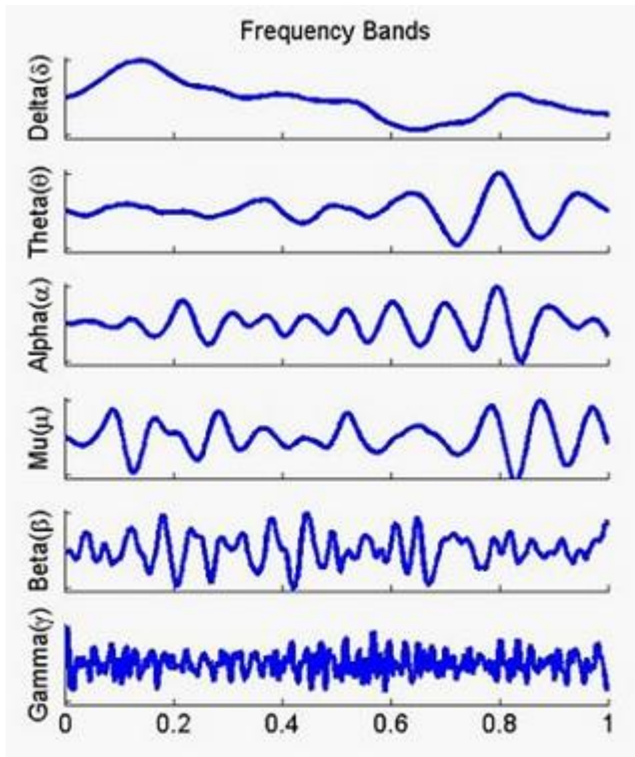


Figure: 2.2: Example of different type of brainwaves (Lotte, 2009)

Information gathered from these brainwaves make it possible to develop application related to the state of mind as listed out in Table 2.2 below.

Table 2.2: Related work done associate with brainwave state.

Researchers	**Summary**
Solis-Escalante et al(2009) [8]	Analysis of sensorimotor rhythms for the implementation of a brain switch for healthy subjects *Device: Single channel dry sensor mobile EEG system from Neurosky. - Using ERD during a motor task and event-related synchronization (ERS) after the termination of the task. - Support Vector Machine (SVM) used as classifiers.
Mak, Chan and Savio (2013) [9]	Evaluation of Mental Workload in Visual-Motor Task: Spectral Analysis of Single-Channel Frontal EEG - Consistent increase in EEG activities in upper alpha band was induced by significant increase in mental workload. - First 30s show significant connection between EEG activities and mental workload. - Mental workload level associated with the task was more dominated by the number of sharp directional changes than the actual time taken to complete the task.
Jimenez et al (2011) [10]	Classification Of Cognitive States Of Attention And Relaxation Using Supervised Learning Algorithms - Low Beta, Medium Beta, High Beta, Alpha, Delta and Gamma were analyzed in this study. - Data extracted was classified using KNN, LDA, C4.5 and Naïve Bayes .

Researchers	Summary
Hyunjin et al (2013) [11]	Emotion Recognition Of Serious Game Players Using A Simple Brain Computer Interface - Using neurosky mindwave to extract delta, theta, alpha, beta and gamma frequency band power as well as attention and meditation levels. - Accuracy reached 66.04% to classify emotional states (activated, engaged, pleasant and neutral.
Vourvopoulos, A, Liarokapis, F (2011) [12]	Brain-Controlled NXT Robot: Tele-operating a Robot through Brain Electrical Activity - Use attention and meditation level obtained from Neurosky Mindset to control speed of robot. - Use Emotiv Epoc Headset to determine direction of robot.
Chin-Teng Lin et al (2010) [13]	A Real-Time Wireless Brain–Computer Interface System for Drowsiness Detection - Alpha and Theta Rhythms are used to detect drowsiness

2.3 Evoked Potentials (EP) & Event Related Potentials (ERP)

Both Evoked Potentials (EP) and Event Related Potentials (ERP) are time locked to a specific stimulus. An Event Related Potentials (ERP) is the brain response when given specific stimulus such as sensory, cognitive or motor event [14]. Example of ERP component is P300 wave which surfaces as a positive deflection in voltage with delay around 250 to 500ms [15] when given stimulus. P300 is associated with process of decision making. While Evoked Potentials (EP) is an electrical potential recorded from the nervous system following a stimulus. Evoked potential (EP) tests measure the electrical activity of the brain in response to stimulation of specific sensory nerve pathways [16]. Example of EP testing is Visual Evoked Potentials (VEP) which is effectively used to confirm a diagnosis of multiple sclerosis [17]. To conclude, EP can be considered associated with physical stimulus while ERP involve other aspect such as memory, expectation and attention, among others.

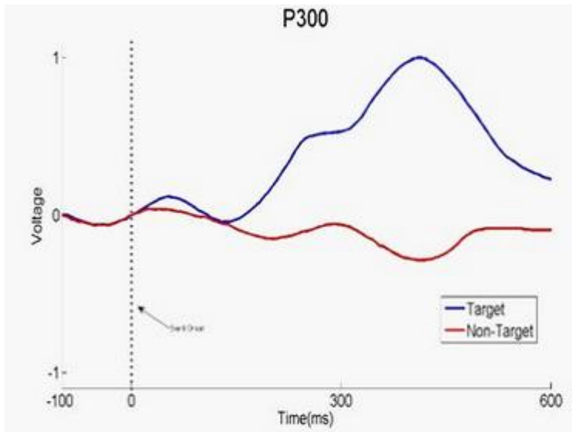
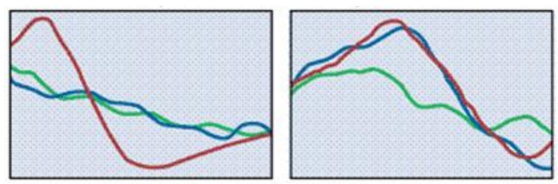


Figure 2.3: P300 wave occur approximately 300ms after given stimulus [17].

Several works done by harnessing EP and ERP is shown in Table 2.3 below.

Table 2.3: Related work done associate with EP and ERP

Researchers	**Summary**
Farwell et al (2001) [18]	Using brain MERMER testing to detect knowledge despite efforts to conceal - Using brain waves as lie detector.  (a) (b) Figure 2.3: P300 wave showing (a) Suspect guilty and (b) Suspect not guilty - Suspect given known information (red), unknown information (green) and information related to crime (blue). - Suspect guilty if the blue and red lines closely correlate.
Campbell et all (2010) [19]	NeuroPhone: Brain-Mobile Phone Interface using a Wireless EEG Headset - A sequence of contact's photo from address book was flashed . - P300 component will trigger if the flashed photo matched the person whom the user wishes to dial.
Yuanqing Li et al (2013) [20]	A Hybrid BCI System Combining P300 and SSVEP and Its Application to Wheelchair Control - P300 combined with SSVEP to produce a "go/stop" command to control wheelchair in real time.

2.4 Signal Acquisition

The brain activities can be recorded by placing electrodes on the scalp. The electrodes placements for EEG measurement follow International Standard Procedures 10/20 System as shown in Figure 2.4.

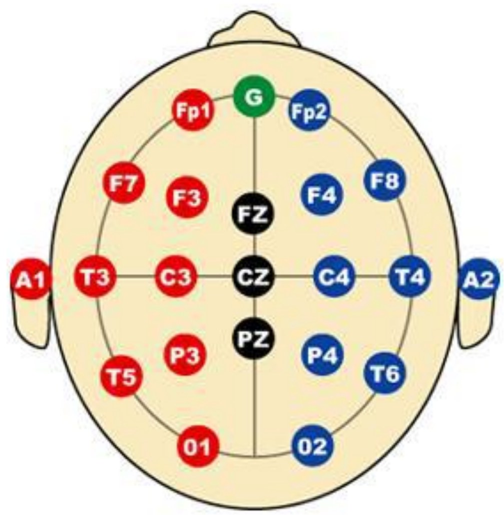


Figure 2.4: The standard 10/20 electrode placement system for EEG (McGill, EEG-Introduction)

Nowadays, there are variety selections of mobile EEG headset using dry electrodes and make it easier to design consumer based product by making use advancement in brainwave acquisition tools. In order to collect brainwave data, Neurosky Mindwave Mobile is used in this research. The sensor placement for Mindwave Mobile target FP1 (as shown in Figure 2.4) because it offers EEG clarity since this is the forehead area with minimal hair. The location stated also offers higher cognitive processes such as Attention and Meditation algorithms. FP1 placement also enables blink detection given the proximity to the eye.

2.5 Data Measurement

EEG band power values from Mindwave Mobile are indications of relative amplitudes of the individual EEG bands. Usually, volt-squared per Hz $\left(\frac{V^2}{Hz}\right)$ unit is used to indicate power spectrum band. However, since the value from mindwave mobile have undergone a number of complicated transforms and rescale operations from the original voltage measurements, there is no longer a simple linear correlation to units of Volts.

In their currently output form, they are useful as an indication of whether each particular band is increasing or decreasing over time, and how strong each band is relative to the other bands. EEG power band are displayed in exponential values since it represent a power spectrum, which mean the lower-frequency bands (such as delta and theta) will be exponentially larger values than the higher-frequency bands (alpha and beta)

Beside EEG band power values, raw EEG wave samples can also be obtained from Mindwave Mobile using Mindset Communication Protocol. The output is sampled at 512 Hz, which mean there are 512 data can be plot in one second. The formula for converting raw values to voltage is:

$$\frac{rawValue\times\left(\frac{1.8}{4096}\right)}{2000} \tag{2.1}$$

This is due to a 2000 times gain, 4096 values range and 18V input voltage.

2.6 EEG Analysis

The most applied method for signal processing and analysis would be the Fourier Transformation and extraction of band power [21]. It is possible to separate different EEG rhythms by using an algorithm based on Discrete Fourier Transfrorm (DFT) as shown in equation 2.2. .

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-i2k\pi\frac{n}{N}} \qquad , k = 0, \dots, N-1 \tag{2.2}$$

and the inverse of it

$$x_n = \frac{1}{N} \sum_{n=0}^{N-1} X_k \, e^{i2k\pi\frac{n}{N}} \tag{2.3}$$

Typically, the fast Fourier Transform (FFT) is used to compute the DFT and its inverse. FFT is an algorithm that can compute the DFT and produce exactly the same result but much faster compared to evaluating the DFT directly. This is the reason why FFT is much more preferred to analyze EEG signals.

2.7 Classification Task

There are several types of classification used in BCI research. One of the common methods is Neural Network. However, although neural network are great at nonlinear problems, EEG wave are generally presumed to be linear [22].

A linear classifier, Support Vector Machine, SVM was chosen for this research as it is the simplest classifier that might work.

For pattern recognition mapping,

$$X \longmapsto Y, \tag{2.4}$$

$$x \in \mathcal{X} \tag{2.5}$$

$$y = \mathcal{Y} \tag{2.6}$$

where $x \in \mathcal{X}$ is some object and $y = \mathcal{Y}$ is a class label.

For a simplest case, 2 class classification,

$x \in \mathcal{R}^n, y \in \{\pm 1\}.$ (2.7)

For training and prediction model, input/output sets $\mathcal{X}, \mathcal{Y}$.

Training set $(x_{1,}y_{1,}), \dots, (x_{m,}y_{m,})$ (2.8)

For generalization, given a previously seen $x \in \mathcal{X}$, find $y = \mathcal{Y}$. In other word, want to learn classifier: $y = f(x, \alpha)$, (2.9)

Where α are the parameters of the functions. For example, to choose model from the set of hyperplanes in $\mathcal{R}^n$, then

$f(x, \{w, b\}) = sign(w.x + b)$ (2.10)

2.7.1 Linear Classifiers

A linear classifier has the form

$f(x) = w^T x + b$ (2.11)

In 2D the discriminant is a line as shown in Figure 2.5. w is the normal and known as the weight vector while b is the bias.

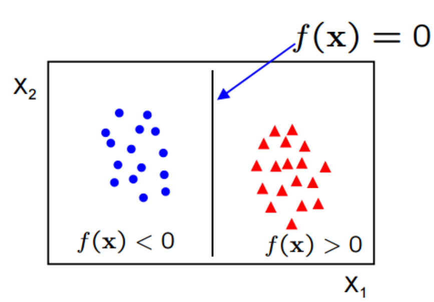


Figure 2.5: Linear classifier in 2D

In 3D the discriminant is a plane as shown in Figur 2.6 and in nD it is a hyperplane.

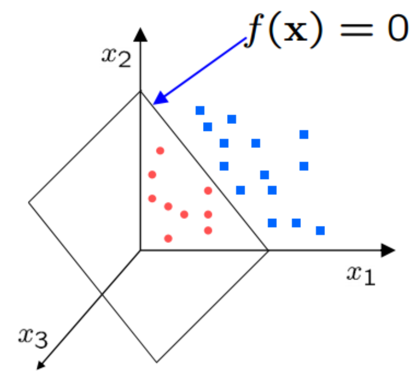


Figure 2.6: Linear classifier in 3D

For a K-NN classifier, it was necessary to `carry' the training data. For a linear classifier, the training data is used to learn w and then discarded. Only w is needed for classifying new data.

2.7.2 Support Vector Machine

SVM maximize the margin around the separating hyperplane. The decision function is fully specified by a subset of training samples, the support vectors as shown in Figure 2.7.

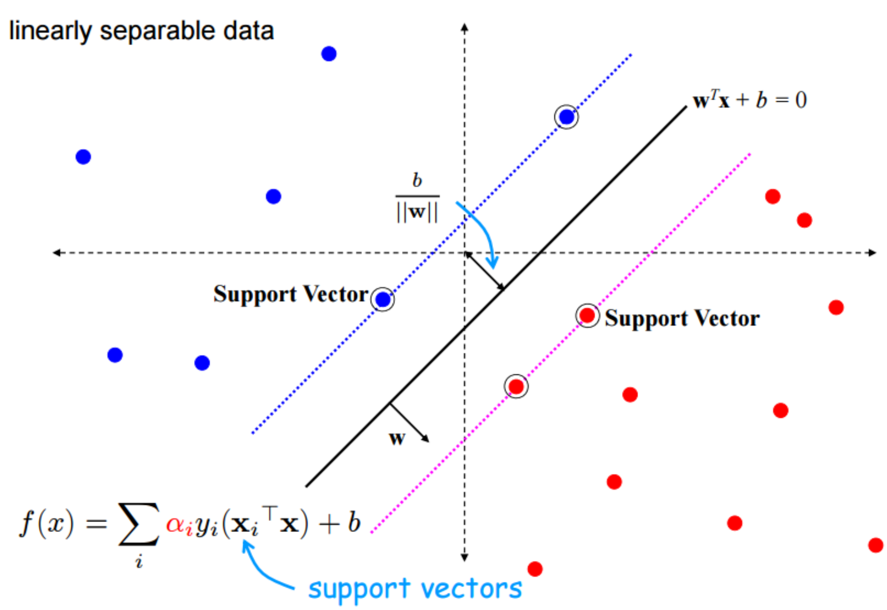


Figure 2.7: Support vectors in a linearly separable data

$$w^T x + b = 0 \tag{2.12}$$

$$c(w^T x + b) = 0 \tag{2.13}$$

Since equation 2.12 and 2.13 define the same plane, we have the freedom to choose the normalization of w.

$$w^T x_+ + b = +1 \tag{2.14}$$

$$w^T x_- + b = -1 \tag{2.15}$$

Choose normalization such that the resulting is as shown in equation 2.14 for positive and equation 2.15 for negative support vectors respectively. Then the margin is given by

$$\frac{w}{\|w\|} \cdot (x_+ - x_-) = \frac{w^T(x_+ - x_-)}{\|w\|} = \frac{2}{\|w\|} \tag{2.16}$$

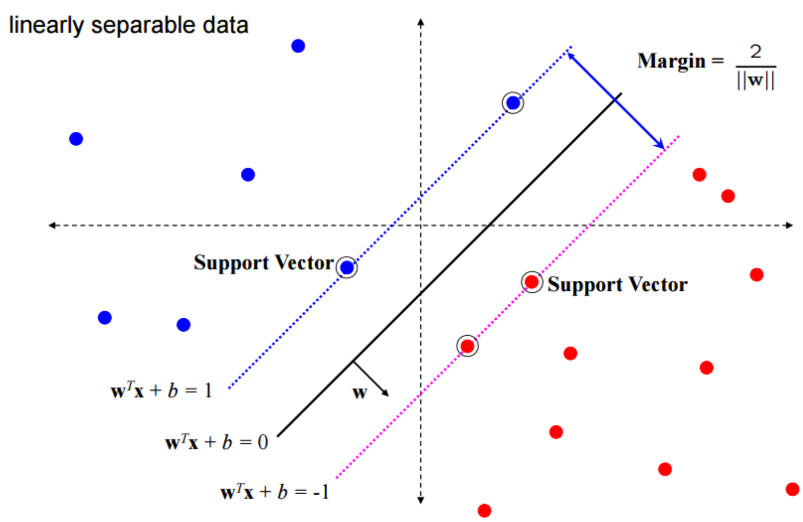


Figure 2.8: Margin in SVM

Figure 2.8 shows clearly how equation 2.12 until 2.15 can be visualize in a linearly separable data.

CHAPTER 3

METHODOLOGY

3.1 System Overview

Method used in the classification of EEG signals to control wheelchair for severe impairment users is shown in Figure 3.1.

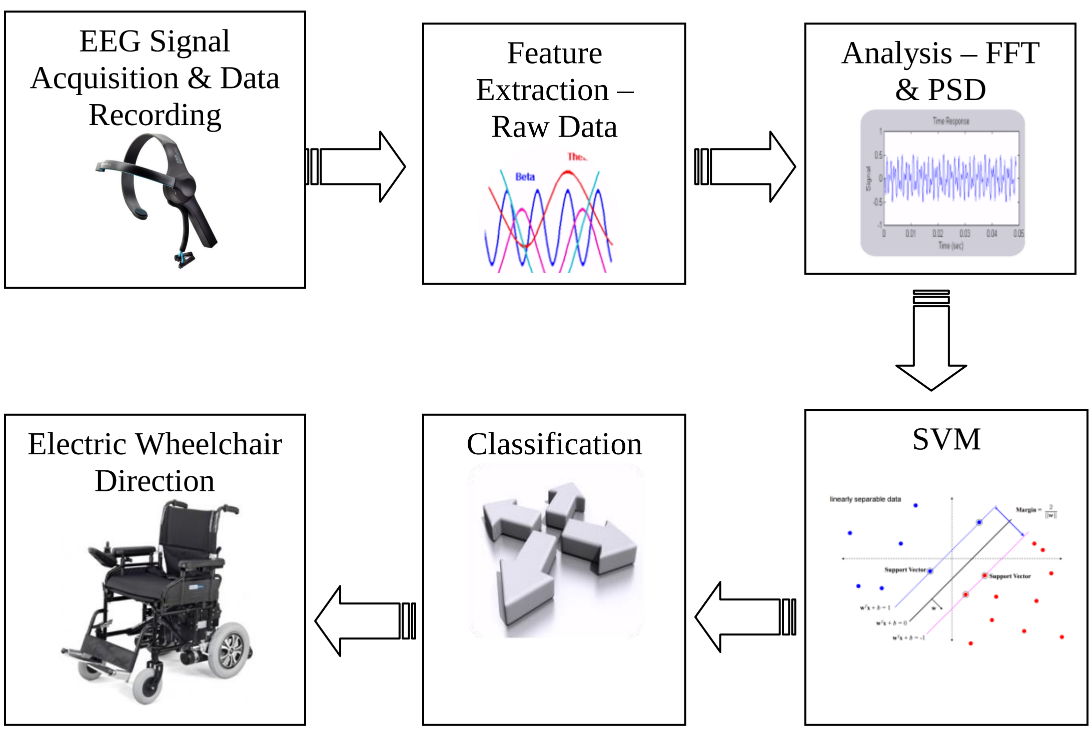


Figure 3.1: Overall diagram showing method used in the classification of EEG signal to control wheelchair for severe impairment users.

EEG signal acquisition process will be done by using Neurosky Mindwave Mobile (M003). Graphical User Interface is used to collect raw data from the Mindwave Mobile to determine whether the data obtained can be mapped out to classify different direction based on user's intention. Fast Fourier Transform will be used to obtain the frequency component in time domain signal from raw data. Data obtained (both in frequency domain and power spectrum) will be tested offline in Phyton using SVM. The output will be classified to four directions: forward, backward, left and right based on user's intention.

3.2 EEG Signal Acquisition

The main component of Neurosky Mindwave Mobile as shown in Figure 3.2 consist of EEG electrode which is placed at FP1 in 10/20 International Standard Electrode Placement System, and an ear clip to picks up environment noise generated from the body movement and other electrical devices such as laptop and power outlet. The ear clip functions as a ground and reference in order for the Mindwave Mobile to filter out noise and focus on brainwave.

Figure 3.2: Neurosky Mindwave Mobile.

This device was design to be connected with computer using Bluetooth and able to generate output as listed in Table 3.1 below.

Table 3.1: Neurosky Output Protocol

No	Output	Description
1	Raw EEG data	Returns raw EEG data, sampled at 1HZ
2	Delta Power	The ”delta band” of EEG (0.5 - 2.75Hz).
3	Theta Power	The ”theta band” of EEG (3.5 - 6.75Hz).
4	Low Alpha Power	The ”low alpha” band of EEG (7.5 - 9.25Hz).
5	High Alpha Power	The ”high alpha” band of EEG (10 - 11.75Hz).
6	Low Beta Power	The ”low beta” band of EEG (13 - 16.75Hz).
7	High Beta Power	The ”high beta” band of EEG (18 - 29.75Hz).
8	Low Gamma Power	The ”low gamma” band of EEG (31 - 39.75Hz).
9	High Gamma Power	The ”mid gamma” band of EEG (41 - 49.75Hz)

10	Attention eSense	Returns the eSense Attention integer value, between 0 and 100
11	Meditation eSense	Returns the eSense Meditation integer value, between 0 and 100
12	Poor Signal	Returns poor signal level, 0 is good signal, 200 is off-head state.
13	Blink Strength	Returns an integer value between 0-255, indicating the blink strength.

Only raw data used and processed in this research. An attention value was recorded as benchmark. Data will only be recorded when attention value reach certain level.

3.3 Data Recording

Data for both model (imagine mental task and colour visualization) recorded for each participants in office with an uncontrolled environment. Ten-second recordings of six people were gathered for data collection. Each participant performed ten trials to ensure enough trials for both training and testing sets when doing cross-validation. Graphical User Interface (GUI) was design by using Visual C# to record the data. Table 3.2 listed the respective colour and imaginary task assigned to each direction.

Table 3.2: Type of Colour used for different direction

Direction	**Colour**	**Imaginary Task**
Forward	Cyan	Running
Right	Green	Kicking
Left	Black	Juggling
Reverse	Yellow	Singing a song

When GUI started, the first thing to check is whether the mindwave is connected or disconnected. It will be only connected if Mindwave Mobile is on. For signal strength, if the status is bad, probably headset is not worn and if poor means the distance might be too far. GUI can only start recording if the signal is good.

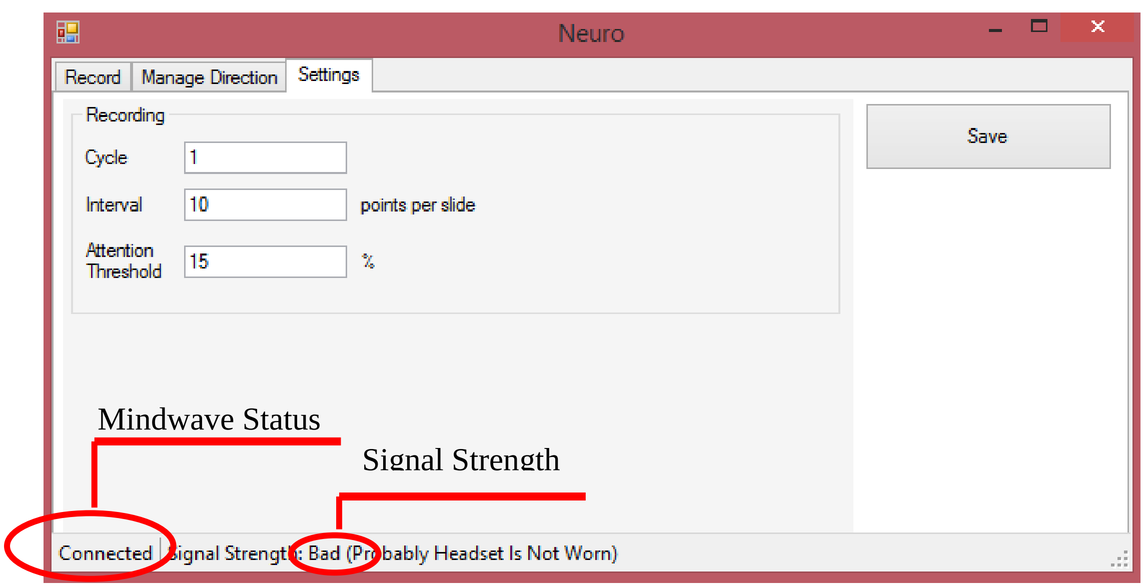


Figure 3.3: Settings in the GUI

Figure 3.3 shows setting tab in the GUI. User can set how many cycle the data need to be recorded. If it is set to two cycles or more, the data will be append into existing data with the same name. After few times of testing, it is decided that only one cycle for each recording will be done because the recording process itself need a lot of concentration and tiring. Interval can be set based on output of 'Power Band' (Delta, Theta, etc) because it gives one output every one second. Literally, if it set to 10, the data will be recorded approximately for 10 seconds. The last one is attention threshold. The value is set to15, means that data will start recording when subject's attention level reach 15% or more.

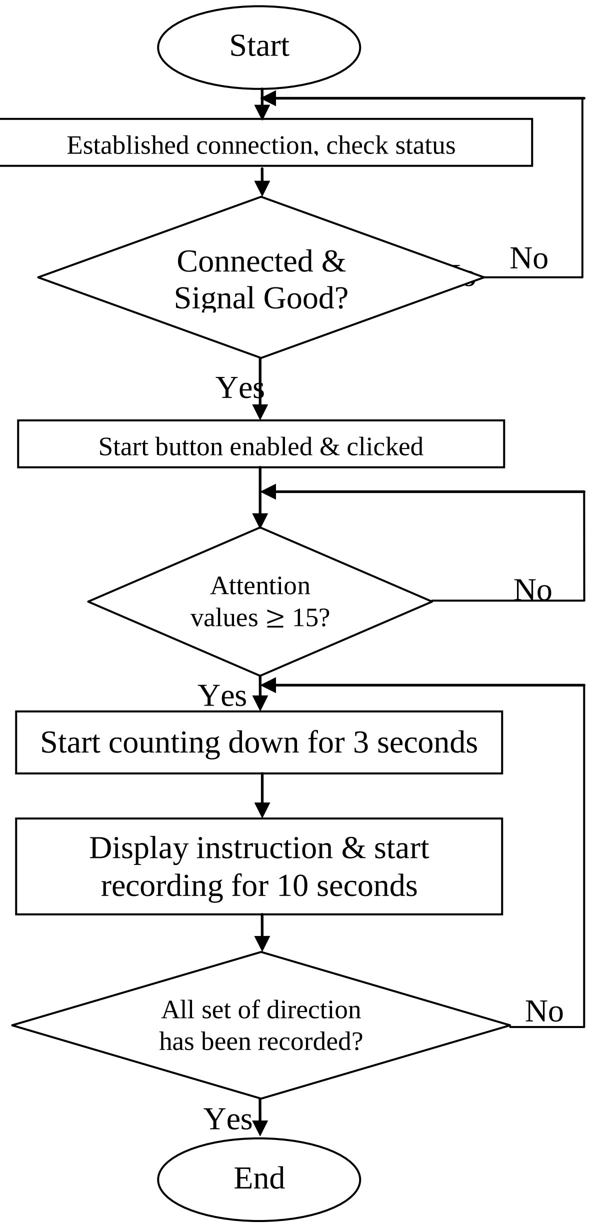


Figure 3.4: Flowchart for data recording.

REFERENCES

[1] R.A, B. (2002). *Computer Input Device Selection Methodology for Users with High-level Spinal Cord Injuries.* The 1st Cambridge Workshop on Universal Access and Assistive Technology

[2] Simpson R. C., Lo Presti E. F., Cooper R. A. (2008) How Many People Would Benefit from a Smart Wheelchair? *Journal of Rehabilitation Research and Development*. 45(1): pp 53–72.

[3] Linda Fehr, W. Edwin Langbein, Steven B Skaar (2000), Adequacy of power Wheelchair Control Interfaces for Persons with Severe Disabilities: A clinical survey, *Journal of Rehabilitation Research and Development*, 37 (3). pp 353-360

[4] Md Razali Tomari (2013), Enhancing Wheelchair Manoeuvrability for Severe Impairment Users, *International Journal Advanced Robotic System*, 10 (92).

[5] Malmivuo, J. & Plonsey,R (1995). *Bioelectromagnetism- Principles & Applications of Bioelectric and Biomagnetic Fields.* New York: Oxford University Press. Retrieved December 14, 2014 from http://www.bem.fi/book/13/13.htm

[6] Immara Institute. *Brainwave States*. Retrieved December 12, 2014, from http://immrama.org/brainwave-technology-for-health-wellness/brainwave-states-alpha-theta-delta-beta-gamma/

[7] Bernier, R., Dawson, G., Webb, S., & Murias, M. (2007, August). *EEG Mu Rhythm and Imitation Impairments In Individuals With Autism Spectrum Disorder*. Brain and Cognition, 64(3), 228–37.

[8] Teodoro Solis-Escalante *, Gernot Mu¨ller-Putz, Clemens Brunner, Vera Kaiser, Gert Pfurtscheller (2009). *Analysis of sensorimotor rhythms for the implementation of a brain switch for healthy subjects.* Biomedical Signal & Control, 159: pp 1-6.

[9] Joseph N. Mak, Rosa H. M. Chan, Savio W. H. Wong (2013). *Evaluation of Mental Workload in Visual-Motor Task: Spectral Analysis of Single-Channel Frontal EEG.* Industrial Electronics Society, IECON 2013 - 39th Annual Conference of the IEEE , pp.8426-8430, 10-13 Nov. 2013

[10] Jimenez, C.O.S., Mesa, H.G.A., Rebolledo-Mendez. G. de Freitas, S., "*Classification of cognitive states of attention and relaxation using supervised learning algorithms*," *Games* Innovation Conference (IGIC), 2011 IEEE International, pp.31-34.

[11] Hyunjin Yoon; Sang-wook Park; Yong-Kwi Lee; Jong-Hyun Jang. *Emotion recognition of serious game players using a simple brain computer interface.* ICT Convergence (ICTC). 2013 International Conference on. 14-16 Oct. 2013. IEEE. pp.783-786.

[12] Vourvopoulos, A. , Liarokapis, F., "*Brain-Controlled NXT Robot: Tele-operating a Robot through Brain Electrical Activity*," Games and Virtual Worlds for Serious Applications (VS-GAMES), 2011 Third International Conference , pp.140-143, 4-6 May 2011.

[13] Chin-Teng Lin, Che-Jui Chang, Bor-Shyh Lin, Shao-Hang Hung, Chih-Feng Chao, and I-Jan Wang, "*A Real-Time Wireless Brain–Computer Interface System for Drowsiness Detection*," IEEE Trans. on Biomedical Circuit and system, pp. 214 – 222, 2010.

[14] Luck, Steven J. (2005). *An Introduction to the Event-Related Potential Technique*. The MIT Press.

[15] Polich, J. (2007). *Updating P300: An integrative theory of P3a and P3b*. Clinical Neurophysiology, 118(10), 2128-2148.

[16] MS (National Multiple Sclerosis). *Evoked Potentials (EP).* Retrieved December 14, 2014 from http://www.nationalmssociety.org/Symptoms-Diagnosis/Diagnosing-Tools/Evoked-Potentials

[17] Reinhold Scherer, Josef Faller, David Balderas, Elisabeth V. C. Friedrich, Markus Proll, Brendan Allison, and Gernot Muller-Putz (Feb 2013). *Brain-Computer interfacing: more than the sum of its parts.* Soft Computing, 17(2):317–331.

[18] Farwell LA, Smith SS (2001), *Using brain MERMER testing to detect knowledge despite efforts to conceal*. J Forensic Sci 46 (1): 135-143.

[19] Andrew T. Campbell, Tanzeem Choudhury, Shaohan Hu, Hong Lu, Matthew K. Mukerjee!, Mashfiqui Rabbi, and Rajeev D. S. Raizada (2010). *NeuroPhone: Brain-Mobile Phone Interface using a Wireless EEG Headset,* In Proceedings of the second ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds (MobiHeld '10). ACM, New York, NY, USA, pp 3-8.

[20] Yuanqing Li, Jiahui Pan, Fei Wang, Zhuliang Yu, "*A Hybrid BCI System Combining P300 and SSVEP and Its Application to Wheelchair Control,*" Biomedical Engineering, IEEE Transactions. Vol 60, no.11, pp.3156-3166, Nov. 2013

[21] Lotte, F., Congedo, M., L´ecuyer, a., Lamarche, F., & Arnaldi, B. (2007, June). "*A review of classification algorithms for EEG-based brain-computer interfaces".* Journal of neural engineering, 4(2),Available from http://www.ncbi.nlm.nih.gov/pubmed/17409472

[22] Klaus-Robert Müller, C. W. (June, 2003). Linear and Nonlinear Methods for Brain–Computer Interfaces. " *IEEE Transaction On Neural Systems and Rehabilitation Engineering"*, 165-169.

[23] Jagdish Tripathy, F. K. (2006). "Influence of Colour Hue on Fractal EEG Dimensions". *International Conference on Biomedical and Pharmaceutical Engineering.*

[24] Cooley, J. W., & Tukey, J. W. (1965). An algorithm for the machine calculation of complex Fourier series. *American Mathematical Society* , pp. 297-301.

[25] *Discrete Fourier Tranform (numpy.fft)*. (02 November, 2014). Retrieved 10 June, 2015, from SciPy.org: http://docs.scipy.org/doc/numpy/reference/routines.fft.html#module-numpy.fft

[26] Ball, T. K. (2009). Signal quality of simultaneously recorded invasive and non-invasive eeg. *Neuroimage , 3,* pp. 708-716

[27] Carlos. (4 April, 2014). *fft: significant peak in 0 Hz component*. Retrieved 16 June, 2015, from Matlab Central (Matlab Answers): http://www.mathworks.com/matlabcentral/answers/124471-fft-significant-peak-in-0-hz-component

[28] Pedregosa, F. e. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* (12), 2825-2830.

[29] Merril, N. (15 May, 2014). *Classifying EEG Data With Machine Learning*. Retrieved 8 June, 2015, from UC Berkeley School of Information: http://people.ischool.berkeley.edu/~nick/svm-tut.html

[30] Vidaurre, C. a. (2010). Towards a cure for BCI illiteracy. *Brain topography* , *2*.