NEURAL NETWORK-BASED MUSCLE TORQUE PREDICTION USING MECHANOMYOGRAPHY DURING ELECTRICALLY-EVOKED KNEE EXTENSION AND STANDING IN SPINAL CORD INJURED PATIENTS

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DISSERTATION SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING SCIENCE

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NEURAL NETWORK-BASED MUSCLE TORQUE PREDICTION USING MECHANOMYOGRAPHY DURING ELECTRICALLY-EVOKED KNEE EXTENSION AND STANDING IN SPINAL CORD INJURED PATIENTS

ABSTRACT

This study sought to design and deploy a torque monitoring system using an artificial neural network (ANN) with mechanomyography (MMG) for situations where torque cannot be independently quantified. The MMG signals from the quadriceps were used to derive muscle torques during prolonged functional electrical stimulation (FES) assisted isometric knee extension contractions and during standing in spinal cord injured (SCI) individuals. Three individuals with motor-complete SCI performed FES-evoked isometric quadriceps contractions on a Biodex dynamometer at 30º knee angle and 100mA stimulation current until the torque declined to a minimum required for ANN model development. Two ANN models were developed based on two different inputs; RMS and RMS-ZC. The performance of the ANN was evaluated by comparing its predicted torque against the actual torque derived from the dynamometer. MMG data from 5 other individuals with SCI who performed FES-evoked standing to fatigue (i.e. until the knee angle reached 30º flexion), were used to test the RMS and RMS-ZC ANN. RMS and RMS-ZC obtained from the FES standing experiments were then provided as inputs to the developed ANN models to determine the predicted torque during the FES-evoked standing. The average correlation between the knee extension predicted torque and the actual torque outputs were 0.87±0.11 for RMS and 0.84± 0.13 for RMS-ZC. The average accuracies for predicting 50% torque drop for both models were 79±14% for RMS and 86±11% for RMS-ZC. The two models revealed significant trends in torque decrease, both suggesting a critical point at 50% torque drop where there were significant changes observed in RMS and ZC trends. Based on these findings, it can be concluded that both RMS and RMS-ZC models performed similarly well in predicting knee extension torque in this population. However, interference was observed in the ZC values towards the end of the knee buckling. The developed ANN model could be used to predict muscle torque in real-time thereby providing possibly safer automated FES control of standing in persons with motor-complete SCI.

Keywords: functional electrical stimulation, mechanomyography, neural network, spinal cord injuries, torque prediction

RAMALAN TORK OTOT BERDASARKAN RANGKAIAN NEURAL MENGGUNAKAN MEKANOMYOGRAFI SEMASA MENGUCUPAN EXTENSI LUTUT DAN BERDIRI ANTARA PESAKIT TUNJANG SARAF

ABSTRAK

Penyelidikan ini adalah untuk mereka dan mengunakan sistem pengawasan tork yang berfungsi dengan rangkaian saraf tiruan (ANN) dengan mekanomyografi (MMG) dalam situasi di mana tork tidak dapat diukur secara bebas. Isyarat MMG dari quadriceps telah digunakan untuk memperoleh tork otot semasa kuncupan extensi lutut isometri dibantu oleh stimulasi electrikal fungsian (FES) di kalangan individu yang mengalami kecederaan tunjang saraf (SCI). Tiga individu dengan kecederaan motor penuh kecederaan tunjang saraf telah melakukan kuncupan quadriceps isometri di atas dinamoter Biodex pada sudut lutut 30º dan simulasi arus 100 mA sehingga tork menurun ke kadar minima yang diperlukan untuk membangunkan model ANN. Dua model ANN telah dibangunkan berdasarkan dua input berbeza; RMS dan RMS-ZC. Keberkesanan ANN telah dilakukan dengan cara membandingkan tork yang diramalkan dengan tork sebenar dari dinamometer. Data MMG dari lima individu lain dengan kecederaan tunjang saraf yang melakukan aktiviti berdiri sehingga letih dengan bantuan FES (sehingga sudut lutut melepasi 30º), telah digunakan untuk menguji model RMS dan RMS-ZC ANN. RMS dan RMS-ZC yang diperoleh dari ujikaji berdiri dengan FES telah digunakan sebagai input untuk model ANN yang telah dibangunkan untuk mengenalpasti ramalan tork semasa aktiviti berdiri dengan bantuan FES. Purata korelasi antara ramalan tork extensi lutut dengan pengeluaran tork sebenar adalah model 0.87±0.11 untuk RMS dan 0.84± 0.13 untuk model RMS-ZC. Kedua-dua model menunjukkan haluan bermakna semasa penurunan tork, kedua-dua model mencadangkan penurunan tork 50% dari maksima sebagai titik kritikal di mana perubahan ketara dapat dilihat dicorak RMS dan ZC. Berdasarkan penemuan ini, kedua-dua model RMS dan model RMS-ZC dapat

disimpulkan untuk meramalkan tork dari extensi lutut dengan perlaksaan yang sama. Namun, gangguan dapat dilihat dari data ZC di penghujung semasa lengkokan lutut. Model ANN yang dibangunkan dapat digunakan untuk meramalkan tork otot semasa, mungkin akan dapat memberikan kawalan FES automatik yang lebih selamat semasa aktiviti berdiri dengan individu kecederaan tunjang saraf.

Kata kunci: simulasi elektrik gunaan, mekanomyografi, rangkaian neural, kecederaan saraf tunjang, ramalan tork

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	: Artificial Neural Network
ARV	: Average rectified value
CWT	: Continuous Wavelet Transform
EMG	: Electromyography
FES	: Functional Electrical Stimulation
FFT	: Fast Fourier Transform
ISNCSCI	: International Standards for Neurological Classification for Spinal Cord Injury
MC	: Maximum Contraction
MF	: Mean Frequency
MLP	: Multilayer Perceptron
MMG	: Mechanomyography
MPF	: Mean Power Frequency
PTP	: Peak to peak
RMS	: Root mean square
SCI	: Spinal Cord Injured
SLP	: Single layer Perceptron
SNR	: Signal to Noise Ration
SVR	: Support Vector Regression
ZC	: Zero Crossing

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

This chapter introduced the main idea of the study in general. There were 8 sections in this chapter. The first chapter focused on the contextual information of the study. Sections 2 and 3 discussed the motivation and the problem statement of this study respectively. Section 4 discussed the objectives that needed to be achieved. Section 5 introduced the hypothesis of the study. Section 6 highlighted the aims of the study while section 7 reviews the scope in this study. The organization of the section, in general, was discussed in section 8.

1.1 Background Study

Spinal cord injury (SCI) happened when an injury happened to the spinal cord most commonly because of accident. SCI causes the communication between the brain and the body to be disturbed (Kirshblum et al., 2011). Results from SCI can be temporary or permanent loss of the ability to perform physical or sensate functions depending on how bad the damage to the spine (Furlan, Noonan, Singh, & Fehlings, 2011) due to disruption to the message transmission from the brain to the designated body part (Kirshblum et al., 2011). The spinal cord injury can be differentiated as complete and incomplete based on the movement and sensation occurs and the area of injury or the area below the injury (Kirshblum et al., 2011). The effects of the spinal cord injury may include loss of mobility, loss of sensation, poor bowel control, spasms, or intense pain (Kirshblum et al., 2011).

The levels of injury can be assigned according to the severity of the injury towards the body function. International Standards for Neurological Classification of Spinal Cord Injury (ISNCSCI) grading is used to define the seriousness of the injury (Kirshblum et al., 2011). Grade A is the level where there is a complete disability of motor and sensory function, Grade B is an incomplete sensation from the area of injury and below, Grade C is there is the ability for muscle movement, but it is restricted and most of the muscle below the injury area is unable to move against gravity. Grade D is where most of the muscle below the injury area are able to move against gravity while Grade E is the normal muscle movement for a healthy individual (Kirshblum et al., 2011).

It is common for individuals to experience medical complications after SCI and this can cause disturbance to the individual's health and the process of rehabilitation. The common complications that can happen are pressure ulcers, bladder infections, autonomic dysreflexia and respiratory infections (Haisma et al., 2007). These complications may cause negative impacts not limited to the individual's health, but also on the social interactions, employability and general quality of life. Such complications may also cause death for some sections of SCI patients (Soden et al., 2000).

Individuals with SCI require a rehabilitation method to facilitate daily tasks. Functional Electrical Stimulation (FES) has been widely utilized in rehabilitation engineering as an artificial muscle activation in order to restore muscle function lost due to spinal cord injury (Ahmad et al., 2012). FES designed for a spinal impaired individual in their daily task (Sedel, Nizard, & Meunier, 1995). This is done by electrically stimulating the muscle to provide artificial contraction (Hamid & Hayek, 2008). The intensity of the stimulation must be regulated to prevent extreme muscle fatigue that will lead to muscle failure.

Application of FES had been seen through the history where the first version of FES was used with a live electric ray to deliver electric current in form of pain treatment approximately 2000 years ago. In recent years, there are two types of stimulation devices which are the implanted and non-implanted devices usually used in clinical setting. Cardiac peacemaker is one of the examples of the implanted device where the device is implanted in the chest or belly to provide electrical stimulation to the cardiac muscle to control of the heart rhythms (Nielsen, Gerdes, & Varma, 2015).

FES is commonly used because of its therapeutic effect on the SCI individuals by training the injured muscles in order to regain partially or fully its lost function (Hamid & Hayek, 2008). FES is used commonly in spinal cord injury individuals to restore the muscle function. Electrical stimulation can be applied through a surface or implanted electrode to provide contraction stimulation to the paralyzed muscle provided fibre depolarization is achieved (Ferrarin & Pedotti, 2000).

The method of monitoring muscle fatigue that was being investigated in this thesis was mechanomyogram (MMG). MMG is a measurement of the mechanical activity of contraction muscles by detecting the muscular sound (Islam, Sundaraj, Ahmad, & Ahamed, 2013). The origin of the muscle sound used to distinguish the physiological aspect of the muscle could be trace to 1665 by Grimaldi who has then signified the sound as the motion of the animal spirit (Grimaldi, 1665).

The MMG principle is to record the mechanical changes of muscle during a contraction (Weir, Ayers, Lacefield, & Walsh, 2000). MMG has been considered as the mechanical counterpart to the muscle activity of the electromyography (EMG) (Beck et al., 2004). MMG also provides information such as forces the muscle produced, the stiffness and the fluid pressure (Barry, Geiringer, & Ball, 1985). MMG signal during specific activities such as walking, standing up and reaching is captured to monitor the muscle fatigue (Laufer, Ries, Leininger, & Alon, 2001). The MMG sensors were placed on the skin surface of the muscle involved in the activity.

There are three main physiological events that reflected from the signal which are the gross lateral movement of the contracting muscle during the start of the contraction, a smaller resulting vibrations at the resonance frequency of the muscle and the changes of the shape of the active muscle fibre (Orizio, Gobbo, Diemont, Esposito, & Veicsteinas, 2003). Muscle sound from previous work usually implicated its properties such as the muscle vibration, muscle acceleration, and the dimension change to evaluate the muscle contractions and its conditions.

The system used to predict the onset of fatigue is the Artificial Neural Network (ANN) which is a system that is built from a huge number of connected neurons. Neurons are the processing elements that are able to process data and to represent knowledge. Through training, the ANN can detect patterns and with the developed models the ANN can make decisions regarding any new type of pattern the ANN has not seen without any human interaction.

A definition of ANN explained by Haykin (Haykin, 1998), ANN is a colossal parallel group of simple processing units that accept information from its surrounding with the processing of learning and the information is stored within its connections. ANN definitions highlight the processing elements and the learning algorithms (Eberhart, 2007). Learning can be explained as changing the synaptic weight to obtain information at more effective accuracy (Eberhart, 2007). ANN was also able to change its very own topology (Haykin, 1998).

Processing elements were conceived from the idea, neurons in the animal nervous system. The neuron obtains stimulus and converts the knowledge into synaptic weights, adding them and finally, produced a single output response. ANN can be defined into 3 basic elements which are the synaptic weight, summing function which combines the input according to the weight in respective connections, and activation function which produce the output (Haykin, 1998). The ANN was adopted from the four structures of the biological neuron shape albeit in the minimal structure, which is made out of dendrites, synapse, cell body, and axon.

ANN are distributed, adaptive and usually nonlinear learning machines made from various processing elements and each processing elements connects either from other processing elements or to itself. The topology is used to define the connection in the system. Weights are the parameters that can be adjusted to control the signal in each elements' connections. The processing elements gather all the signal from the elements to generate an output that is non-linear to the function of the sum. The output from the processing elements could be in three situations; a system output, the signal is sent to different processing elements or the signal is sent back to itself.

In the ANN, the prediction and function approximation are comparable. Usually, the input data will generate a single output. The use of ANN in prediction requires the training of the network to determine the output of the future values of the output of a variable given from the past observation of the data.

ANN tackles highly non-linear functions and does not require any understanding of the nature of the relationships of the functions (Sibanda & Pretorius, 2012). This is the benefits of the ANN over regression analysis. Linear regression does not work if the relationship between the variables is non-linear. Non-linear regression can be used provided the relationship of the nonlinearity is found and the non-linear elements are consistent through the measurement. However, highly non-linear relationships exist in the everyday world and traditional regression does not bode well due to the presence of scattering data or noise. Hence, it is why ANN offers an important outlook on these relationships.

1.2 The Motivation of The Study

Researchers described the importance of muscle fatigue detection in order to prevent muscle injury. This situation is more critical for the SCI individuals as their muscle are usually weaker due to inactivity of the muscle (Al-mulla, Sepulveda, & Colley, 2011). There was a need for an automated system that will remind the user that the muscle was about to reach fatigue state (Al-mulla et al., 2011). This resulted in improving the training and avoid injury due to strain. Researchers have not been able to measure muscle performance during activities such as standing because there is no adequate tool to directly quantify knee and hip extensor torques during the stance.

With the use of MMG, the muscle activity can be quantified over time and thus its performance could be assessed. The monitoring and characterizing muscle fatigue bring significant information regarding the human and computer interactions, sports injuries and performance, ergonomics and prosthetics. An automatic system that able to forecast and distinguish muscle fatigue when it happens is very useful commonly in situations related to SCI rehabilitation where fatigue has heightened the injury risk while an individual with spinal injury would not be able to sense the muscle fatigue. The automatic system guides the individuals during training and serves as an indicator to when the fatigue sets and to maintain a favorable fatigue state, hence, encourage improvement to the muscle while evading redundant strain to the muscle to minimize injury.

1.3 Problem Statements

The application of FES is for SCI individuals with a neuromuscular disability to execute daily activities. By electrically stimulating the muscle, the muscle undergoes contraction and the force is generated. However, the force would decrease as the muscle fatigues and muscle performance would decline (Tarata, 2009).

Muscle stimulated by the FES will contract due to the introduction of electrical current to the muscle. However, muscle stimulated tends to get fatigue quickly due to the reversed recruitment order of the stimulated motor neurons which limits certain applications in FES (Rabischong & Guiraud, 1993). Muscle fatigue is known as the disability to sustain or provide the intended muscle strength (Enoka & Duchateau, 2008). This may lead to performance drop in individuals. Muscle fatigue can occasionally aid muscle growth seen in bodybuilders. However, most of the time localised muscle fatigue is harmful by causing serious injury at the high level of muscle fatigue. Therefore, muscle fatigue detection is the main topic for this research and literatures were found based on detection of muscle fatigue.

Due to lack of research regarding muscle fatigue monitoring in SCI during FES; especially during a quiet standing contraction, it is important that such model is developed to integrate along with FES in view to optimize the training efficiency while minimizing the risk of injury to the individual during FES standing. In order to monitor muscle fatigue, there are many types of parameters that can be used to describe the neuromuscular fatigue such as the torque output and the muscle characteristic such as the contraction strength and the frequency of the contraction. However, the usefulness of the parameters in regard to ANN model has yet to been tested during FES evoked standing training.

Therefore, in this study, the aim was to design an artificial neural network (ANN) that could predict the torque exerted around the knee joint by the quadriceps muscle by taking inputs from certain MMG parameters, namely the root mean square (RMS) and zero crossings (ZC). The models were designed to predict the knee torque during FES isometric knee extension. Second, we sought to apply the ANN models to multiple sessions of FES standing challenges. This was done to determine the accuracy and reliability of the ANN models based on RMS and RMS-ZC inputs to predict the knee torque produced by the quadriceps in FES isometric knee extension and standing.

1.4 Objectives of the study

There are three objectives that need to be met during the course of the study which are:

a) Design a neural network system model based on MMG sensor predicting the knee torque produced during FES isometric contraction and quiet standing.
b) Identify the correlation and accuracy for prediction between predicted torque output and the actual torque output in ANN models.
c) Compare the ANN model's performance to estimate a selected point of torque.

1.5 Hypotheses of the study

In order to test the effectiveness of the ANN models to predict muscle fatigue, three hypotheses were introduced. The hypotheses were (i) the initial torque predicted would be higher than the final torque predicted, (ii) the predicted torque output pattern would be reduced throughout the stimulation and (iii) the pattern of RMS and ZC before and after the 50% torque drop point would not be the same.

1.6 Aim of the study

In this study, the main aim of the research was to develop an automated system to serve as the muscle fatigue monitoring based on the generated torque during an FES isometric contraction in individuals with spinal cord injury. With the use of MMG, the muscle activity can be quantified over time and its performance assessed. Therefore, the aim of the study was to design an ANN that could predict the torque exerted around the knee joint by the quadriceps muscle by taking inputs from certain MMG parameters, namely the RMS and ZC. The models were designed to predict the knee torque during FES isometric knee extension. ANN models were then used to apply in multiple sessions of

FES standing challenges. This was done to determine the accuracy and reliability of the ANN models based on RMS and RMS-ZC inputs to predict the knee torque produced by the quadriceps in FES isometric knee extension and standing. Finally, this study aimed to compare the ANN model's performance to determine the input(s) that best predicted the performance of isometric knee extension and standing. In other words, the ANN's accuracy to predict knee torque produced by the quadriceps was tested during FES isometric knee extension and the developed model was then deployed in an FES standing activity. It was hypothesized that the knee extension torque could be modelled through MMG-derived RMS and ZC, which would enable the prediction of torque in activities where torque cannot be physically measured, such as upright stance.

1.7 Scope of study

The study aimed to design an ANN model to estimate torque during FES evoked contraction during seated and standing. The ANN model accepts inputs from MMG depending on the ANN model used and the output would be the knee joint torque. The ANN model will benefit the SCI individuals and physiotherapist as the monitoring system will enable the FES evoked contraction training to have optimal benefits with little to no risk of injury. This study focused only on the quadriceps muscle of the SCI subjects and the activities involved in this study were FES evoked standing and FES seated contraction on a dynamometer. The implementation of the model in a FES device or MMG sensor is not within the scope of this study.

1.8 Organization of the Thesis

This thesis consisted of six chapters that covered the data collection to training and testing the ANN model to predict torque in SCI individuals. The overview of the contents of each chapter in the thesis are as listed:

Chapter 1: This chapter introduced the problem faced by SCI individuals during rehabilitation training and the needs for a monitoring system for muscle fatigue. This chapter also introduced to the background studies related to this study as well as the scope of the study and the study objectives.

Chapter 2: This chapter reviewed the past researches and experiment done about SCI, MMG, and FES. Hence, this chapter contained information that related to this study which ensured a better understanding of the topic subject.

Chapter 3: This chapter detailed the methodology used to achieve the study's objective.

Chapter 4: This chapter showed the test results from the testing of the ANN models in both FES evoked seated and standing contraction.

Chapter 5: This chapter discussed the impact of the test results from the experiment and the effectiveness of the ANN model to estimate torque.

Chapter 6: This chapter discussed the conclusion and the future work that can be done following this study.

CHAPTER 2: LITERATURE REVIEW

This chapter included the critical studies based on the past researches related to the study. There were six sections in this chapter. The first section discussed the FES and the parameters related to the FES and how the changes to the parameters affected the muscle contraction. The second section defined the muscle fatigue that occurred during the training. The third section discussed the related information regarding mechanomyography (MMG) and its parameters. The fourth section was on the planning of the study experimental setup based on the past studies. The fifth section discussed the techniques and parameters used to process the data obtained from the experimental phase and finally, the sixth section discussed the systems used to predict the knee torque during FES training.

2.1 Functional Electrical Stimulation

The main field of this research was regarding the improvement that can be made in the field of rehabilitation. FES is commonly used because of its therapeutic effect on the SCI individuals by training the injured muscles in order to regain partially or fully its lost function (Hamid & Hayek, 2008). FES activated the nerves by utilizing electrical currents. The principle behind FES was that electrical stimulation excites the motor nerve attached to the muscle to contract.

2.1.1 FES waveform

The FES is supplied in different types of waveform to provide excitation to the neurons (Popovic, Keller, Pappas, Dietz, & Morari, 2001).

The waveforms can be distinguished into direct current (DC), alternating current (AC) and pulse-shaped current (C). Figure 2.1 shows the different type of stimulation used in the FES devices.

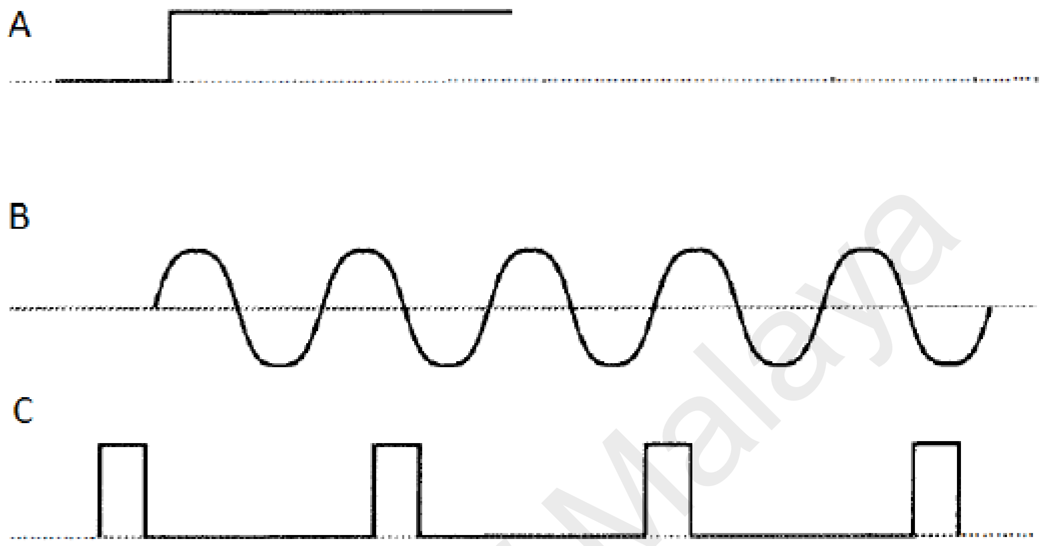

Figure 2.1 Stimulation waveform pattern (A is DC, B is AC and C is pulse-shaped stimulation) (Agnello, 2011)

DC waveforms are known to treat neuralgia and improve circulation as well as electrolysis and tool for a process of transfer of ions through the skin also known as iontophoresis (Agnello, 2011). However, DC waveforms do not provide the necessity to generate muscle contractions but provide muscle twitches related to the beginning and end of the DC waveform. AC waveforms are known as a constantly changing direction of the current flow. This includes shapes like square, triangle, trapezoidal and sinusoidal. AC waveforms lack the electrical silence between phases similar to DC waveforms and both are not used for therapeutic stimulation (Masdar, Ibrahim, & Jamil, 2012).

Stimulus waveforms are generally available in two types of shape which are monophasic and biphasic. Monophasic pulses like DC moves the current in a single direction. This type of pulses might cause electrode deterioration and tissue damage on the skin when applied on the skin over a long period of time (Masdar et al., 2012). This is due to the changes in ionic distribution and tissue breakdowns and burns due to the polarization. The monophasic waveforms are still being used in short-term FES stimulation despite the shortcomings. Biphasic waveforms can reduce the unequal ion transfers and biphasic waveforms are available in two types (symmetrical and asymmetrical). Monophasic and biphasic (symmetrical and asymmetrical) are shown in Figure 2.2.

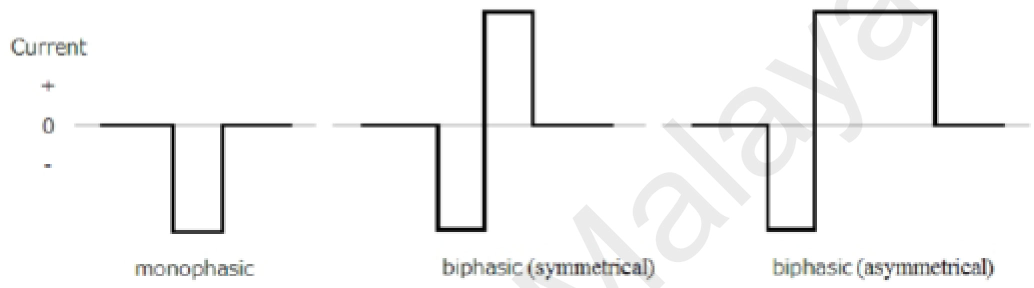

Figure 2.2 Pulse shape stimulation waveforms (Agnello, 2011)

Single direction of the current is able to depolarize excitable tissue and the opposite direction of the current in lower current amplitude but in longer duration may able to lower the neural excitation. Overall, a biphasic waveform is best used for the longer duration of FES.

2.2 Muscle Fatigue

SCI individuals with neuromuscular disability utilize FES to execute daily activities such as walking, cycling, and standing up as well as muscle strengthening and cardiovascular reconditioning, endurance, improving range-of-motion (ROM) and gait control, enhancing limb function, wound healing, improving blood flow and sensory awareness and reduce pain and osteoporosis (Petrofsky, 2004). By stimulating the muscle, the muscle will contract and generates force. However, the force will decrease when the muscle fatigue and thus, muscle performance will decline (Tarata, 2009).

Muscle contraction was stimulated with the introduction of electrical current to the muscle. However, muscle stimulated tended to get fatigued quickly due to the reversed recruitment order of the artificially stimulated motor neurons which limits certain applications in FES (Rabischong & Guiraud, 1993).

Muscle fatigue is known as the disability to sustain or provide the intended muscle strength (Enoka & Duchateau, 2008). This may lead to a drop in performance in the individuals. Fatigue is a general symptom that occurs in many people and it is related to health conditions. Such a condition can be said as feeling tired that is overwhelming while performing voluntary tasks (Gruet et al., 2013). Muscle fatigue can last several hours, and it reduces the ability of the muscle to contract and to produce force.

Fatigued muscle has less ability to absorb energy than non-fatigued muscle prior to the muscle are stretched to a high degree of risk to injury (Mair, Seaber, Glisson, & Garrett, 1996). Often time, fatigue is related to the muscle not able to reach the set level of maximum contraction (MC) (Merletti & Parker, 2004).

When muscle activated to lift a load, the muscle contracts and shortens (Faulkner, Larkin, Claflin, & Brooks, 2007). Isometric contractions required the muscle activation, but the length of the muscle does not change. Contrary to eccentric contraction where the muscle will lengthen when active. An eccentric contraction occurs when the individual is performing an action such as walking.

Muscle fatigue occured when the muscle is exposed to a strong muscle activity and differences of muscle characteristic between individual are significant and that there is no exact way to define a precise muscle fatigue threshold (Robert, 2006) because of the difficulty to isolate the different mechanism of fatigue. Muscle fatigue is related to the muscle not be able to reach a set level of MC force which the muscle is unable to maintain its current task (Barry & Enoka, 2007). Researchers defined that the individual may still be able to sustain the activity after the onset of muscle fatigue but the definition of muscle fatigue is an engineering perspective where fatigue occurs over time and it is constantly developing as the muscle physiological factors change before finally unable to produce any more force (Barry & Enoka, 2007). This can be used as the basis for determining the muscle fatigue threshold where a certain percentage from the MC during an experiment can be used to determine that the muscle has fatigue. Another parameter that can be used to indicate muscle fatigue is the joint angle (Barry et al., 1985; Guo, Zheng, Huang, & Chen, 2008).

There are two stages of muscle fatigue which are fatigue and non-fatigue where fatigue relates to the fatigue during a muscle contraction while non-fatigue is the status of the muscle during contraction prior the fatigue sets (Al-mulla et al., 2011). The first stage of fatigue which is non-fatigue, the muscle that is well rested is able to produce the highest force and when the muscle starts to fatigue, a new muscle fiber recruitment happens (Al-mulla et al., 2011; Al-Mulla, Sepulveda, Colley, & Al-Mulla, 2009). However, there is a third type of fatigue which is transition-to-fatigue (M R Al-Mulla et al., 2009). The transition-to-fatigue is an attempt to predict the occurrence of fatigue during an exercise. This recruitment period is known as Transition-to-Fatigue where an increase in motor unit action potential firing rate. The Transition-to-fatigue continues until the actual fatigue occurs. Resting period is also important to ensure that the muscle is well rested.

2.3 Mechanomyogram

2.3.1 Muscle sound

Muscle sound has been used to investigate the muscle condition since 1665 by Grimaldi. He alluded to the sound as the motion of animal spirits. Wollaston, in 1810, reported quantitatively the frequency of muscle sound in the range of 14 to 35 Hz. Oster and Jaffe studied the time and frequency domains analysis characteristics of the muscle sound during evoked and voluntary contraction (Oster & Jaffe, 1980).

The frequency of the muscle sound was quantitively described to be between 14Hz to 35Hz, Wollaston described the frequency based on the use of analogy (Wollaston, 1810). Time and frequency domain analysis of the muscle sound during evoked and voluntary contraction was characterized by Oster and Jaffe who described that the muscle sound's dominant frequency is within the 25Hz with a variation of 2.5Hz plus or minus (Oster & Jaffe, 1980).

2.3.2 Properties of MMG

MMG is a measurement of the mechanical activity of contraction muscles by detecting the muscular sound (Islam et al., 2013). The muscle sound is related to the essential property of the muscle contraction with the help of a stethoscope and microphone where the sound is known as a form of MMG. The MMG was identified as the supportive mechanical signal to the more established electromyogram (EMG) in researching muscle activities (M. Stokes & Blythe, 2001). The amplitude of the MMG is related to the force produced by the muscle, a small change of force can also be reflected in the MMG amplitude (Beck, 2010). Hence, small changes during muscle fatigue can be reflected through the MMG amplitude (Beck, 2010).

2.3.3 Applications of MMG

MMG is used in research of sensor development, signal processing, characterization of muscle activity, development of prosthesis or switch control, diagnosis of a neuromuscular disorder and medical rehabilitation tool (Islam et al., 2013). MMG has advantages over EMG which are MMG is easy to implement and does not contain power line interference as well as having the highest signal to noise ratio (SNR)(Islam et al., 2013). Moreover, MMG indicates the force production of the muscle which is an important factor to access muscle fatigue while EMG reflects the electrical activity of the muscle (Beck, 2010). MMG is used as a development tool in order to find the abnormalities from the designated baseline. MMG is useful in detection for muscle fatigue during sustain contraction (Jensen, Jorgensen, & Sjogaard, 1994). Even though MMG has been commonly used in research on muscle fatigue during isometric contractions, the usability of MMG for postural control after fatigue made it significant in various fields such as occupational therapy and ergonomics while using the wireless technology can give a new area for real-time clinical examinations during daily activities (Beck, 2010).

The method of combining MMG and EMG is especially used to estimate noninvasively the physiology of the muscle during a contraction and the fatigue occurrence (Esposito, Orizio, & Veicsteinas, 1998).

The production of sensitive, light, cheap sensors and advanced signal analysis method, obtaining low-frequency vibration of due to the muscle activities in the form of MMG had made the MMG more feasible. The signal has been found out to be able to be seen on the skin surface during changes to the shape and size of the active muscle fibre. The changes to the muscle fibre caused a pressure wave resulting from voluntary or evoked contraction and the signals due to the pressure waves were demonstrated to contain a high number of information of the neuromuscular parameters that cause contraction. This behavior made the MMG a reliable muscle function assessment (Claudio Orizio et al., 2003).

Current EMG used as the signal to investigate and observe skeletal muscle activities has not been successfully providing satisfactory information when it comes to the mechanical index of muscle contraction (Sasidhar, Panda, & Xu, 2013). Hence, this lack of information limited to the understanding of the neural control of the muscle function

(Farina, Merletti, & Enoka, 2013). The EMG signal also is not able to suitably quantify the muscle function during an electrically evoked muscle contraction (Braz, Russold, & Davis, 2009). Thus, there is a need for a sensor that is sensitive to the muscle mechanical activities and does not react to electrical noise. MMG fulfilled both criteria. MMG has advantages over EMG which MMG is easy to implement and does not contain power line interference, hence it is able to work in conjunction with FES whereby EMG has not able to, in process of examining neuromuscular properties (Malek & Coburn, 2012). Moreover, because of the propagating characteristics through the muscle tissue, the MMG sensor does not need to be placed at a precise or specific location (Alves & Chau, 2008). MMG also does not incline to the changes of the skin impedance from sweating, this is because MMG is a mechanical signal (Xie, Zheng, & Guo, 2009).

The MMG signal can be utilized to determine muscle fibre typing (Herda et al., 2010), assess muscle force (Sarlabous, Torres, Fiz, Morera, & Jané, 2013), investigating muscle fatigue (Hendrix et al., 2010), determine the resonance frequency of the muscle (D. T. Barry & Cole, 1990) and to assess properties during a muscle contraction (Gorelick & Brown, 2007). An observation had been done on the mechanical landscape of the muscle fibre activities that cause contraction which can be better differentiated and characterized with the signal response that is fundamentally mechanical (Gerdle, Karlsson, Day, & Djupsjöbacka, 1999).

The amplitude of the MMG is related to the force produced by the muscle, a small change of force can also be reflected in the MMG amplitude (Beck, 2010). Hence, small changes during muscle fatigue can be reflected in MMG amplitude (Beck, 2010). MMG is used in research of sensor development, signal processing, characterization of muscle activity, development of prosthesis or switch control, diagnosis of a neuromuscular disorder and medical rehabilitation tool (Islam et al., 2013).

2.3.4 MMG Parameters

MMG indicates the force production of the muscle which is an important factor to access muscle fatigue while EMG reflects the electrical activity of the muscle (Beck, 2010). MMG is used as a development tool to find the abnormalities from the designated baseline. Two features of MMG are the RMS which is the magnitude of the muscle contraction and Mean Frequency (MF) which is the frequency of muscle contraction (Yang, Kumar, & Arjunan, 2009). The two indications can be used to study the muscle fatigue based on the experiment.

RMS is correlated to load as increasing MC will increase the RMS value of the MMG (Akataki, Mita, Watakabe, & Itoh, 2003). RMS value represents the motor activation (J P Weir et al., 2000). RMS is an important parameter to monitor muscle fatigue due to its correlation to the force of contraction of the muscle (Barry, Geiringer, & Ball, 1985). Variance, on the other hand, represents the magnitude of the muscle contraction (Tanaka, Okuyama, & Saito, 2011). The decreasing value of variance indicates that the muscle is fatigue. Both RMS and variance are in the time domain (Tanaka et al., 2011). The other domain of the signal is frequency domain which is known as spectrum. Mean Power Frequency (MPF) is the common parameter that has been used to represent muscle conditions. Decreasing MPF indicates the muscle is fatigue (M. Tarata, Spaepen, & Puers, 2001). The usage of MMG had gained traction due to the resistance to electrical noises and it is flexible in its sensing technology. Literature review emphasises the robustness of the MMG signal that is typically underrated. Besides a few remote studies with differences seen such as in Herda and Cooper who established that the MMG amplitude to force relationship failed to differentiate the voluntary activation capacity among individuals (Herda & Cooper, 2013).

The data obtained from the MMG signal can be in either time or frequency domain and each domain will be represented by the time or domain respectively. In the time domain, the amplitude is identified as the voltage values and the amplitude can be retrieved as peak to peak (PTP), RMS and average rectified values (ARV). The amplitude is importantly known as the variables in motor unit recruitment during a contraction process (Orizio, Gobbo, Diemont, Esposito, & Veicsteinas, 2003).

Two features of MMG are the RMS which is the magnitude of the muscle contraction and MF which is the frequency of muscle contraction (Yang et al., 2009). The two indications can be used to study the muscle fatigue based on the experiment.

Power spectra of MMG signals can be obtained from the signal through the fast Fourier transform (FFT) or by using discrete Fourier transform (DFT) algorithm in order to obtain the frequency domain of the same signal. MPF and mean power frequency (MDF) are the most widely used variables that are obtained from the frequency domain (Madeleine & Arendt-Nielsen, 2016). Mean Power Frequency (MPF) is the common parameter that has been used to represent muscle conditions. Decreasing MPF indicates the muscle is fatigue (M. Tarata et al., 2001).

In isometric contractions, an increased in MMG amplitude can be seen when force production is low which was around 10% to 40% of the MC and during the high level of muscle force which is around 50% to 80% MC, there was no change in MMG amplitude (Perry et al., 2016). The same observation was reported by another research group (Rodriguez-Falces & Place, 2013).

In addition to that, at a higher level of muscle force resulted to decrease in MMG amplitude (Claudio Orizio et al., 2003). A linear relationship was reported between the contraction muscle and the RMS amplitude of the MMG (Oster & Jaffe, 1980) and it was proven by the correlation of amplitude of MMG signal and motor unit activation during a voluntary contraction as well as FES contraction (Beck, 2010).

There was a linear relationship with the MMG amplitude and knee torque during an incremental evoked contraction on the first dorsal interosseous muscle reported that in a healthy subject, and the muscle fibre type was proposed as the reason for the pattern and as a conclusion the MMG-torque was dependent on muscle fiber and structure (Petitjean, Maton, & Fourment, 1998) (Stokes & Dalton, 1991; Yoshitake & Moritani, 1999). Firing rate of the active motor units of the muscle during the FES contraction was related to the frequency domain of the MMG (Orizio et al., 2003). Hence, both time and frequency domain of the MMG signal can be investigated in order to access muscle control strategy which is related to the muscle force production during a FES contraction (Orizio, 1993). Torque output produced by the muscle during a FES contraction was affected by three factors which were a degree of muscle unit recruitment, the firing rates (Petitjean et al., 1998) and the contractile properties of the muscle unit (Yoshitake, Shinohara, Ue, & Moritani, 2002).

Besides the RMS and MF stated above, another parameter that can be obtained by the time domain of the MMG data is the Area to Amplitude ratio (RAA) (MT Tarata, 2009). The parameter was computed from the time domain as the average of ratios of the area to amplitude over a considered time period (MT Tarata, 2009). The RAA was calculated between the consecutive transversals of the isoelectric line known as phases (MT Tarata, 2009). RAA is said to be more efficient computationally compared to FFT or wavelet technique (MT Tarata, 2009). However, this parameter of computation has not been supported by other researchers.

From the reviewed literatures, the changes following parameters can be observed in order to monitor the muscle fatigue during a contraction. The summary for the parameters from MMG can be found in Table 2.1.

Table 2.1 Summary of Parameters and the relationship with increasing muscle fatigue.

Parameters	Definition	Relationship with muscle fatigue
RMS	The amplitude of muscle activation (Weir et al., 2000).	Decreased with increasing fatigue (Barry, Geiringer, & Ball, 1985).
PTP	Amplitude in motor unit recruitment during contraction (Claudio Orizio et al., 2003).	Decreased PTP shows fatiguing muscle (Perry et al., 2016).
Variance	Magnitude of muscle contraction (Tanaka et al., 2011).	Decreased value means the muscle is fatigued (Tanaka et al., 2011).
MPF/MDF	Represent the muscle condition (Madeleine & Arendt-Nielsen, 2016).	Decreased with increasing fatigue (M. Tarata et al., 2001).

2.4 Experimental Setup Considerations

Past researches revealed the effectiveness of the method and its significance for the investigated research in order to design a test protocol that will be able to achieve the research's objectives. This includeed the experimental setup, the techniques used to investigate the MMG parameters that were related to muscle fatigue.

An experiment for muscle fatigue required the subject to perform a set of activities corresponding to the selected limb with the sensor attached to the skin to pick up the changes occurs in the signal due to the movement (Al-mulla et al., 2011). The signal will then be recorded and processed. This suggested setup will be the foundation of the experiment for the research where instead of contraction that was generated by the subject, the contraction will then be provided by the FES device (Al-mulla et al., 2011). Researches used the sensor EMG during an experiment procedure along with the goniometer signal that later is used to compare with the reading of the EMG (Al-Mulla et al., 2009). The readings were then divided into three states of muscle which are Non-Fatigue, Transition-to-Fatigue, and Fatigue. The fuzzy classifier was used to determine the state of muscle and the identification of Transition-to-Fatigue is important for detecting and predicting muscle fatigue (Al-Mulla et al., 2009).

2.4.1 Sensors placement

Placement of electrode and sensors were important for this experiment as such to minimize cross movement of the signal between the nearby muscle in order to achieve a reliable and stable contraction and signal (Stoykov, Lowery, & Kuiken, 2005). The best placement for sensors was when the signal amplitude was the highest and had a bigger standard deviation of signal noise (Gerdle et al., 1999).

The accelerometer was used in order to monitor the surface oscillations of the tibialis anterior muscle in order to investigate the MMG changes prior and post-fatigue (Orizio, 1993). It was found that MMG is suitable for recording muscle changes while studying the effect of muscle fatigue (Orizio, 1993).

The setup from Figure 2.3 can be used as the experimental set up for the research and can be modified to observe a knee torque from the dynamometer and amplitude from the MMG with one set of constant current and knee angle during an isometric FES contraction.

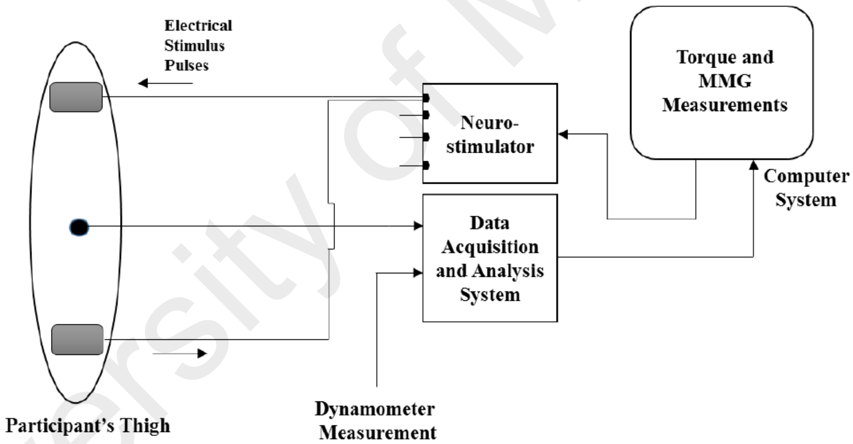

Figure 2.3 Experimental setup schematic (Ibitoye, Hamzaid, & Abdul Wahab, 2016)

In the stimulation protocol, the FES electrode was placed 8cm distal to the targeted area over the muscle belly near the location of the motor points (Botter et al., 2011). The position of the electrode should be slightly adjusted in order to achieve maximum response and this can be done by palpating the muscle response and force production and that the electrode was recommended to be placed 5cm proximal to the patella (Levin, Mizrahi, & Isakov, 2000). A 10-minute recovery period between trials was able to minimize the risk of cumulative muscle fatigue (Thomas, Griffin, Godfrey, Ribot-Ciscar, & Butler, 2003).

During the simulation, the torque measurement from the dynamometer and the MMG signal recording attached directly to the muscle belly for obtaining the maximum muscle surface oscillation were simultaneously run from the beginning (Olusola et al., 2016). The purpose of the two measurements was recorded together that was in order to obtain the parameters with respect to time. Which then the author was able to observe the torque and MMG simultaneously at a specific time. The author also used the stimulation pulse width of 400μs and frequency of 30Hz. The foundation of the protocol by the author can be replicated such as the FES stimulator setting and the position of the muscle up until the dynamometer isometric contraction (Olusola et al., 2016).

2.4.2 Training settings

MMG signal obtained from the muscle activity during a dynamic activity is similar to those in isometric contractions. However during dynamic contraction factors such as changes in production of torque, muscle length and tissue thickness may affect the amplitude and frequency can cause difficulty in understanding the motor control strategies and thus fewer studies of muscle fatigue during dynamic contractions for the use of MMG (Beck et al., 2005).

Isokinetic dynamometers had been commonly used in muscle force assessment during a research as they were able to obtain the torque through the limb motion with good reliability (Sisto & Dyson-Hudson, 2007). The disadvantage with the dynamometers is that it was not mobile and expensive therefore the dynamometers are not suitable for home usage.

The subject was seated on a calibrated isokinetic dynamometer using restraining straps over the thigh, pelvis, and trunk in order to minimize unnecessary movement and to make sure that the contraction is recorded on the target muscle based on Brown and Weir's suggestions(Brown & Weir, 2001) . The stimulation should be done carefully to ensure the knee extensor's moment does not exceed the range for the required torque in order for the individual to stand (Brown & Weir, 2001). This was as a safety precaution to avoid risking a bone damage in the subject. The maximum torque production should not exceed more than 75Nm as it is an average value for torque generated around the knee for FES assisted standing (Gerrits et al., 2005) and the current amplitude of the FES should be in the range of 100 to 120 mA (Kagaya et al., 1995).

2.5 Signal Processing

The raw data were obtained at a sampling rate of 1 kHz and it is digitally band-pass filtered from 20 to 200Hz in order to remove the artifacts related to the body movement (Goldenberg, Yack, Cerny, & Burton, 1991). Peak torque can be obtained from the dynamometer for each contraction at the selected intensity of the stimulation. As for the MMG signal, the author extracted the MMG-RMS, PTP value and MMG frequency such as the peak frequency.

The data obtained were quantified by using the correlation coefficient (r) and standard error of measurement (SEM%) (Joseph P Weir, 2005) which was the percentage of the mean values. This was to investigate the consistency of the parameters. The meaning for the correlation coefficient is as follows: > 0.90 – very high reliability, 0.70 to 0.89 – high reliability, 0.50 to 0.69 0 moderate reliability (Sundmacher, Gotz, & Vogt, 2014).

The authors also conducted a polynomial regression analysis to test the correlation between the MMG-RMS versus FES torque, FES torque against the intensity of the stimulation and MMG-PTP against the stimulation intensity. The observation of the model of best fit for the said relationships was also being investigated by using the polynomial regression (Beck et al., 2004). The highest coefficient of determination (R^2) was used in order to conclude the reliability of fit of the selected regression model. The following method can be used in order to investigate the correlation between the relationship of MMG-RMS against knee angle which is obtained by the accelerometer.

The results obtained from research conducted by the author showed that at different angles the correlation coefficient ranges from moderately to very high reliability which is from 0.65 to 0.97. The SEM% has a value of 10.1 to 31.6% of the relative mean values. The amplitude produced by subjects in research done showed that at higher current intensity, the amplitude is higher but at both intensities, the frequency of the muscle contraction remains the same.

2.6 MMG muscle fatigue monitoring system

The magnitude of muscle force or the torque generated around the joint during a FES contraction has been used in healthy individuals (Brocherie, Babault, Cometti, Maffiuletti, & Chatard, 2005). As a method to further enhance the FES technology in therapeutic and functions, the user should be able to monitor the muscle force or torque in real time (Braz et al., 2009). With the ability to monitor muscle force in real time, the FES system will be able to self-adjust the characteristic of the stimulation based on the level of muscle fatigue and to control the level of muscle force needed to be produced in order to execute an activity.

The author used the MMG signal due to its characteristic to quantify the mechanical equivalent of the EMG output during a muscle contraction (Orizio, 1993). MMG signal had been able to detect muscle fatigue in able-bodied subjects (Gobbo, Ce, Diemont, Esposito, & Orizio, 2006) and hence supported the idea that the MMG signal may be used to estimate the torque in the joint during FES contraction (Ibitoye, Hamzaid, Zuniga, & Abdul Wahab, 2014).

A computational technique was proposed to quantify the MMG signal and then compared the accuracy of the model through a contraction. An artificial network model for elbow flexion estimation based on the force generated by the MMG during an isometric voluntary contraction achieved the accuracy of 0.892 and 0.883 in another research in respect of cross-correlation (Youn & Kim, 2010).

The model was subject dependent, and the authors suggested that support vector regression is used. Simulation of the knee torque was designed via Support Vector Regression (SVR) (Youn & Kim, 2010). This was because of the good generalization in the corresponding field. The input of the SVR will be MMG amplitude, level of the electrical stimulation and knee angle.

2.6.1 Support Vector Regression (SVR)

One study validated the performance of the SVR model by using a dynamometer available commercially and calibrated and used to record the knee torques during an isometric contraction supported by the FES contraction. The authors used eight able-bodied male volunteers. The subject preparation was done based on the recommended setup for voluntary isometric knee torque measurement (Brown & Weir, 2001). The dynamometer seat must be adjusted to align the lateral femoral condyle to the axle of the dynamometer (Bickel, Slade, VanHiel, Warren, & Dudley, 2004). The author obtained the RMS and PTP amplitudes during the contraction form 2s epoch of the 4s MMG as well as the torque recording at a different level of contraction.

Choosing the right parameter for the model is vital for the accuracy of the SVR model. High variety of different possible combination of the SVR parameters caused difficulty to obtain the most optimal SVR parameter (Cherkassky & Ma, 2004). The author used a hybrid optimization search technique which has been recommended (Yıldız, 2009). The technique approach can be described by first noting several SVR parameters such as regularization factor C (bound on the Lagrangian multiplier), λ (conditioning parameter for quadratic programming methods), ε (epsilon) and η (kernel option) and the related kernel functions. The computational method was repeated for all SVR kernel function with increasing parameter's values.

The author then proposed the optimal parameters for the Support Vector Regression model which is detailed in Table 2.2. The flowchart in Figure 2.4 summarized the method used by the author in order to obtain the optimal SVR parameters.

Table 2.2 Optimal Parameters for SVM Regression Model (Ibitoye et al., 2016)

C	879
λ	2^{-15}
ε	0.1205
Kernel option	54
Kernel	Gaussian (RBF)

The author used MATLAB software with SVR coding for the computational work. Training and testing of the model require the data to be partitioned into 2 subsets which are training and testing subsets with the subset ratio of 7:3 (Shamshirband et al., 2014) (Akande, Owolabi, & Olatunji, 2015). The Gaussian kernel function is also used as it is considered an optimal parameter that able to measure performance and hence applied the data to the SVR kernel function for building an efficient knee torque estimation model.

In order to measure the SVR estimation accuracy, the author calculated the coefficient during the training and testing with the root mean square errors (RMSE). The coefficient of determination estimated from the research was 94% in training and 89% in testing cases while the RMSE was 9.48 and 12.95 respectively (Ibitoye et al., 2016).

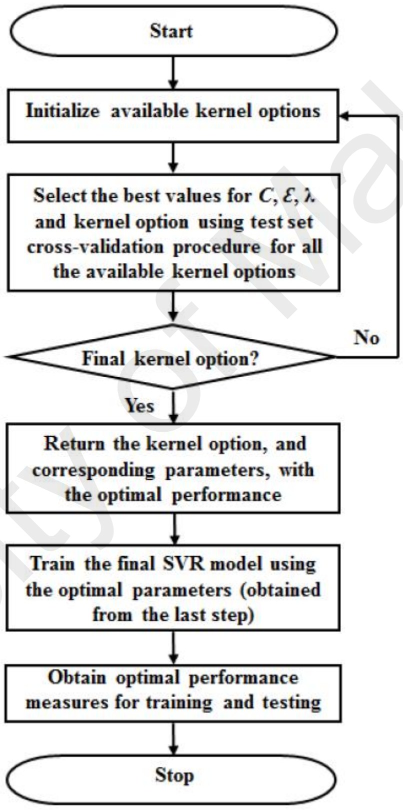

Figure 2.4 Flowchart of obtaining Optimal SVR Parameters (Ibitoye et al., 2016)

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The knee torque estimation obtained from the SVR modeling was parallel with the experimental data performed by an isokinetic dynamometer. These findings are able to be used in a closed-loop FES system for a series of functional task utilizing MMG as a source for a feedback signal as well as SVR algorithm for joint torque estimation.

2.6.2 Continuous Wavelet Transform algorithm (CWT)

The journal reviewed the continuous wavelet transform (CWT) algorithm to detect the muscle activity through the usage of MMG signals. The similarities and differences between the CWT coefficients of the MMG and specific thresholds from the baseline signal were identified from the baseline signal in order to estimate the timing of the muscle activity.

The author was investigating the muscle activity of the upper limb while this research is focusing more on the lower limb and the muscle fatigue. However, the CWT algorithm could be investigated in this research in order to identify the algorithm for muscle fatigue detection.

There were two tasks for event detection form biomedical signals which are online detection algorithm and offline analysis to identify the exact timing of the event (Staude & Wolf, 1999). Common detection involved three components which were signal conditioning, event detection, and post-processing c. This is shown in Figure 2.5.

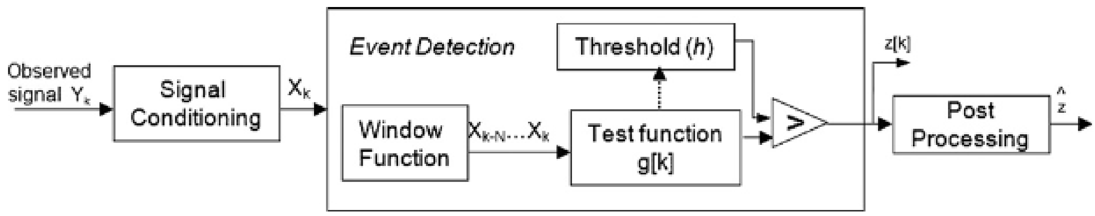

Figure 2.5 Components of event detection (Staude & Wolf, 1999)

Signal conditioning removed the motion artifact and electromagnetic interference by band-pass filtering (Staude & Wolf, 1999). The detection unit was used to identify the event of interest and alert at the time instants when the event is observed. Offline post-processor tested for the chances for a more accurate estimation of the detection time with methods such as the duration of the changed state, rising amplitude or pattern observed by the neural networks or fuzzy rules (Staude & Wolf, 1999).

The author tested the hypothesis that CWT analysis was able to estimate the timing of muscle activity based on the MMG signals by introducing a multi-scale, multi-threshold CWT- based test function and the author compared the CWT method with the existing event-detection test functions. The analysis included test functions that compute the signal's rectified amplitude (Dietz, Colombo, & Müller, 2004), RMS and maximum CWT coefficients.

The proposed multiple-threshold CWT was where the CWT coefficient at each scale is compared to a specific threshold from the baseline signal and the event detection unit monitor the sample for any coefficients that is more than the threshold.

2.6.3 Fuzzy Logic

EMG activity in biceps muscle from ten subjects during an isometric contraction until fatigue was investigated and the author classified the fatigue into three classes of fatigue used in the prediction and detection of fatigue (Al-Mulla & Sepulveda, 2010). During the experiment, the subject was attached with sensor electrodes which were EMG electrodes and goniometer in order to measure the elbow angle during the experiment.

The fuzzy logic was classified and labeled into three classes in order to verify the output of muscle state. In Figure 2.6, the reading of the goniometer is superimposed into the fuzzy logic in order to verify the outcome.

This input for the fuzzy logic can be adopted for knee extension to detect the muscle fatigue based on the knee angle input. The rules for the fuzzy logic were made based on the elbow angle and the elbow angular oscillation in order to monitor the level of muscle fatigue.

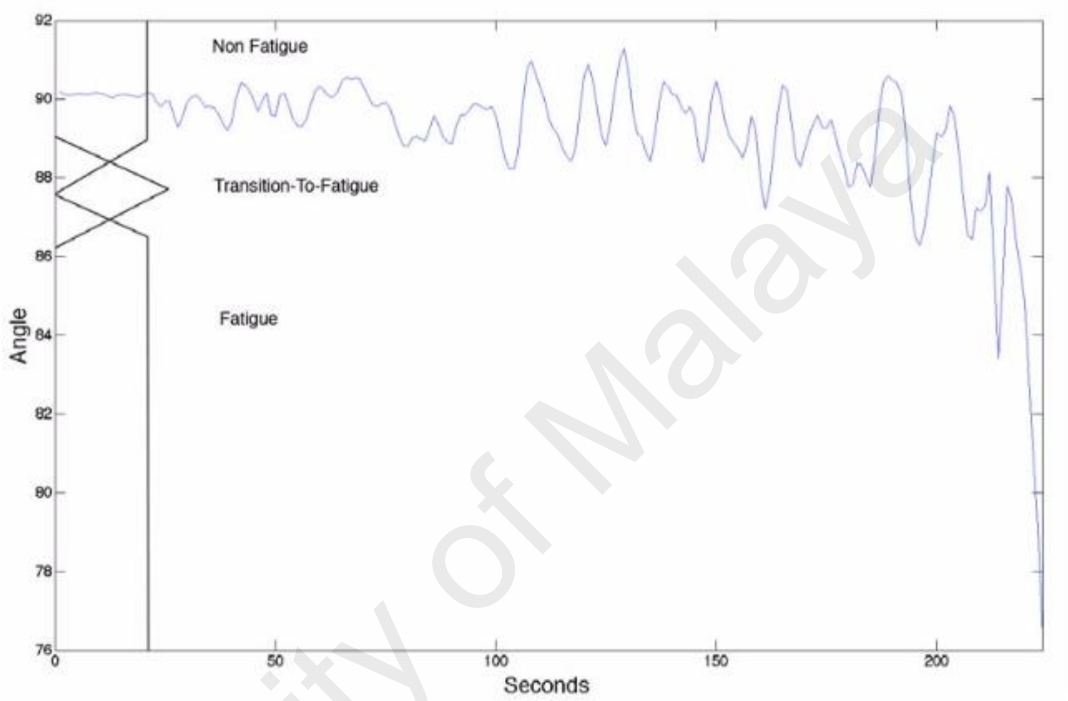

Figure 2.6 Fuzzy Logic Classification for Goniometer (Al-Mulla & Sepulveda, 2010)

The author used elbow angle and angular oscillation while the research is using knee angle and torque produced by the quadriceps muscle (Al-Mulla & Sepulveda, 2010).

This can be used as the base fuzzy logic rules for the research. The rules are stated in Table 2.3.

Table 2.3 Fuzzy Logic Rules (Al-Mulla & Sepulveda, 2010)

Rules	Input 1 (elbow angle)	Input 2 (angular oscillation)	Decision
1	Non-Fatigue	Low	Non-Fatigue
2	Non-Fatigue	High	Transition-to-fatigue
3	Transition-to-fatigue	Low	Transition-to-fatigue
4	Transition-to-fatigue	High	Transition-to-fatigue
5	Fatigue	Low	Fatigue
6	Fatigue	High	Fatigue

2.6.4 Artificial Neural Network

Based on the various characterization above, a thorough definition of ANN had been made (Guresen & Kayakutlu, 2011). ANN is a system which contains at least one of start node or start element, one end node or end element and at least one processing element. Every node must be the processing elements except for the start and end nodes. The state variable ni must be related to node i respectively. The learning algorithm was used to form the model to the desired output based on the provided input. Each start node must be connected to at least one node.

ANN as a system can be explained with three graphical representations (Haykin, 1998); a block diagram to describe the network functionality, a signal-flow graph which describes the signal flow between the elements in the network and the architectural graph to describe the general layout of the system. As for the mathematical definition of the ANN, the following can be used to explain the elements in the network.

A state variable n_i is related to each of the node i, a real number of weight w_{ik} which is related to the link from i to k. The bias v_i can be found at each node i. The transfer function $fi[n_k,w_{ik},v_i,(i\neq k)]$ is known for each node I that determines what is the state of the node as this function is made out of its bias, weights of the incoming signal and the state of the responding nodes.

There are many types of neural networks, one of the types is feed-forward neural networks. This is the earliest and the simplest form of ANN. The information in this system moves in a single direction which is forward. The direction beginning from the start node to the hidden node and finally, to do the output nodes. There is an absence of cycles or loop throughout the network. Single layer perceptron (SLP) and multi-layer perceptron (MLP) are the examples of feed-forward neural networks.

Figure 2.7 shows the basic schematics of a feed-forward neural network.

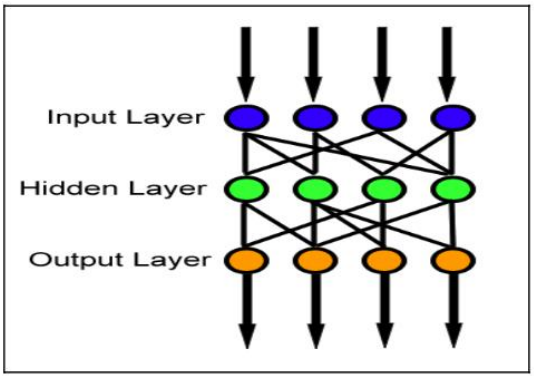

Figure 2.7 Schematics of the feed-forward neural network (Sibanda & Pretorius, 2012)

SLP network is made of one layer of output nodes. The output received the input through a series of weights. The sum of the resulting products of weights and inputs is then calculated on each node and determined if the value is above a selected threshold. The firing of neuron will then starts and the activation or deactivation value will be taken by the neuron. The neurons with this mode of activation function are known as McCulloch-Pitts neurons or threshold neurons (Graben & Wright, 2011).

MLP on the other hands contains multiple layers of computational units that are interconnected in a feed-forward way (Calcagno et al., 2010). There are many learning techniques that are used to train this network, the most prominent use is the back-propagation.

Back-propagation technique is where the output values of the system are compared with the correct values where the error between the output and the correct answer are computed in an error function (Calcagno et al., 2010). The adjustments are made to the weights on every connection to obtain a smaller value of error function. A common method for non-linear optimization to adjust the weights is known as gradient descent.

Neural network training was done when a running a series of information from the input layer to the output layer with a hidden layer in between the two layers. An information passed from a neuron will go through transfer functions. Transfer functions are usually found in form of log function, sigmoid function or a scale function.

The sigmoid function is commonly utilized as a transfer function (Calcagno et al., 2010). The reason being the sigmoid transfer function introduces non-linearity to the network's calculations as well as it is a simple derivative function (Calcagno et al., 2010).

A weight is assigned every time a value is moved from one layer to the other layer. Summation of all the inputs is done by the neurons on the hidden layer. The values are then modified by the transfer function. The values are passed to the output layer with its transfer function and weights. As values move from the input to the output, the weight connecting the nodes are adjusted with the back-propagation algorithm during the learning period so that the resulting outputs will be the closely match to the predicted outputs.

The neural network has been known to perform various tasks. These tasks include prediction, function approximation, or pattern classification. The prediction tasks the neural network to predict the future trend in a time series from the past conditions. Function approximation is a method to model the relationship between variables while pattern classification is organizing data into its own discrete classes.

2.7 Summary

The literature review discussed extensively the usage of FES in helping patients suffering from SCI to partial or fully regain their motion and as a method of rehabilitation. Past researches also showed the potential risk of injury that can occur should the muscle gets too fatigued. Muscle fatigue could have a beneficial effect but at a higher level of fatigue, the risk of injury is great and not ideal for SCI.

The application of MMG to monitor torque production and muscle fatigue has been studied in the past. The MMG could be in form of an accelerometer or a microphone used to record the muscle sound. MMG is useful to quantify the force production.

There are 2 domains that can be extracted from MMG; the time domain and frequency domain. Each domain has their own parameter. These parameters for example; RMS and Mean Average Amplitude for time domain and Mean power frequency for frequency domain.

In order to design the experimental procedure that can achieve the objectives set, past studies were reviewed in order to help with the placement of sensors, type of data collections, method of data processing and also the type of torque monitoring system that is currently on use.

There are not many studies that used ANN to detect muscle fatigue and there are no studies on ANN that detect torque during a standing experiment with FES. We can conclude that the time domain will be used due to the simple processing method such as RMS and also frequency domain mostly records the frequency of the FES pulse, not the muscle contraction. ANN was chosen as the monitoring system due to lack of previous studies and the simple MLP can be trained without the need for a high number of training data.

CHAPTER 3: METHODOLOGY

The aim of this study was to first design an artificial neural network (ANN) that could be used to predict the torque exerted by the quadriceps muscle by taking inputs from the MMG parameters, namely the RMS and ZC. The models had been designed to predict the knee torque during FES isometric knee extension. The next step was to apply the ANN models to FES standing activity. Second, we aimed to determine the accuracy and reliability of the ANN models based on RMS and RMS-ZC as inputs in predicting the knee torque produced by the quadriceps in FES isometric knee extension and FES standing. Finally, this study aimed to compare the ANN model's performance to determine the input that best fit into the ANN model for isometric knee extension and standing. In other words, the ANN accuracy to predict torque produced by the quadriceps was tested during FES isometric knee extension and the developed model was tested in FES standing activity. It was hypothesized that the knee extension torque could be modeled through MMG-derived RMS and ZC, which would enable the prediction of torque in activities where torque cannot be physically measured, such as upright stance.

This chapter discussed the participants, medical ethics, equipment, experimental setup, and the processing method used in view to achieving the objectives set in the introduction chapter of the study.

The methodology was divided into three components, the first being data collection where the SCI study participants performed electrical stimulation-evoked isometric knee extension to obtain their muscle MMG signal parameters and torque. The second part was ANN model development and signal processing of the captured MMG data signal obtained from the first phase to prepare the signal as input for the ANN model. The third phase was the utilization of the ANN model in an actual FES-evoked standing experiment performed by the SCI participants.

3.1 Participants

The subjects for this experiment were five individuals with SCI (ISNCSCI A and B) who were trained FES users and non-sensate due to the sensory deficit of their injury. The subjects were briefed about the research protocol before providing their informed consent to participate. Table 3.1 describes the subjects that were used to obtain the data set for training data, testing data and standing data sets.

Table 3.1 Subject distribution for ANN design and standing procedure

Subject	ANN Design	Standing Procedure
1	/	/
2	/	/
3		/
4		/
5	/	/

3.2 Medical Ethics

The data collection for the first phase of the experiment was approved by the University of Malaya Medical Centre Medical Research Ethics Committee (Ethics Number: 1003.14 (1)) and the standing experiment had been approved by the University of Malaya Medical Centre Medical Research Ethics Committee (MECID.NO: 20164-2366).

3.3 Phase 1: Knee Extension Training data collection

This experiment was conducted to obtain the mechanical signal and torque during an isometric FES contraction of the quadriceps muscle in three SCI individuals. The torque data were recorded with a dynamometer (System 4; Biodex Medical System, Shirley, NY, USA) and the MMG data were recorded on MMG sensor (Sonostics BPS-II VMG transducer, sensitivity 30V/g). The subjects were asked to complete the isometric knee extension protocol for two sessions with 48 hours between each session of data collection. The experiment was conducted at the Department of Rehabilitation Medicine, University Malaya Medical Centre.

The data obtained from the experiment were then used as the foundation to design a neural network system in MATLAB toolbox to predict torques. The neural networks were tested on with the MMG data obtained during the FES standing contraction without torque data in Phase 3. The next phase of the experiment involved training the system and validating the system.

3.3.1 Equipment & Materials

The validation of the ANN model was done by comparison with isometric knee torque data obtained from the commercially available dynamometer (System 4; Biodex Medical System, Shirley, NY, USA). The test protocol set on the dynamometer was Isometric knee extension and 900 seconds of recovery between each trial. Three trials were conducted for each for the left leg and right leg. The isometric contraction angle was set at 30º from the straight leg position.

3.3.2 FES evoked muscle contractions and knee torque measurement

The subjects were familiar with the FES activity and therefore no familiarization session was done prior to data collection. The FES stimulation of square-wave pulses was provided at 30 Hz and 200μs pulse duration with the stimulation current of 100mA. The stimulation was provided by a commercial neurostimulator (RehaStimTM, Hasomed GmbH, Magdeburg, Germany). Electrodes used in this experiment were 9 x 15 cm2 self-adhesive electrodes.

3.3.3 Data Collection Procedure

The subjects were seated on the dynamometer seat and seatbelts were strapped around them to prevent movement from muscles other than the quadriceps interfering with the reading of the MMG. Knee attachment was applied to the leg to measure the torque exerted around the right knee. The knee attachment applied was to measure the torque exerted around the knee joint. The subject's ankle was strapped to a cushion of the knee attachment to hold the leg at a 30° knee angle. Since the armature prevented the leg from moving, the torque signal obtained from the dynamometer fully originated from the subject's muscle and not affected by the gravity. The maximum and minimum flexion and extension were set on the Biodex. The Biodex recorded knee torque at a sampling rate of 500Hz.

The FES electrodes were placed at both ends of quadriceps muscles but not on the tendon area which was around 5cm near the position of the patella and around 8cm distal to the groin area (Levin et al., 2000). Figure 3.1 illustrates the setup for FES induced isometric knee torque measurement. The subject was seated on the Biodex seat such that the lateral femoral condyle was parallel to the dynamometer axle. These body position and the lever arm of dynamometer were consistent throughout the whole study.

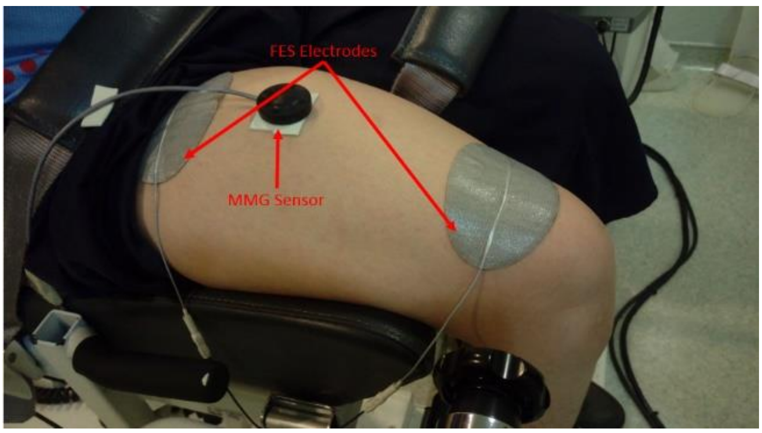

Figure 3.1 FES electrodes and MMG sensor placement on the quadriceps muscle

Once the dynamometer setting was set, the dynamometer guided the knee attachment to 30º knee flexion. The MMG was started first while the dynamometer torque recording and FES stimulation were started simultaneously after. The recording of the dynamometer, MMG, and the simulation was stopped once the torque reading reached well below 50% of the maximum torque and the recovery period began. The same procedure was repeated on the other leg once the third trial had ended with the same settings for dynamometer and Rehamed as well as the recovery period. The subject then repeated the same procedure after 48 hours. To ensure high day-day reproducibility of the protocol, the same researchers and physiotherapists were involved in the experiment for all subjects.

3.3.4 MMG acquisition and processing

Muscle mechanical signals were recorded with the accelerometer sensor. The MMG sensor was placed right on the muscle belly and held onto the muscle belly with a double-sided tape (3M 157 Center St. Paul, MN, USA). Acqknowledge v4.3 data acquisition and analysis software (MP150, BIOPAC Systems, Santa Barbara, CA, Inc) were used to collect the data at 1k Hz frequency. The signal was then filtered with a bandpass filter (20Hz lower cutoff frequency and 200Hz higher cutoff frequency).

The dataset processed from the MMG signal could be in the time or the frequency domain. In the time domain, the amplitude is identified as the voltage values and the amplitude was retrieved as RMS. The amplitude is importantly known as the variables in motor unit recruitment during a contraction process (Orizio, Gobbo, Diemont, Esposito, & Veicsteinas, 2003).

The RMS was the magnitude of the measurement obtained by the MMG and the data was in the time domain. Both parameters (RMS and torque) were then scaled to values in the range of 0 to 1 to simplify the data for preprocessing step for the ANN. The MMG-

RMS were obtained from MATLAB at 1s epoch. Normalization of MMG and torque data, as well as the designing process of the ANN, was done using MATLAB (R2015a, Mathworks, 2015) toolbox.

RMS was correlated to load as increasing MC increased the RMS value of the MMG (Akataki et al., 2003). RMS value represents the motor activation (Weir et al., 2000). RMS is an important parameter to monitor muscle fatigue due to its association with the force of contraction of the muscle (Barry, Geiringer, & Ball, 1985). The equation for the RMS processing was defined as:

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N-1} x_k^2, \;\; for\; k = 1, \ldots., N} \quad (3.1)$$

where xk is the raw signal from each segment and N is the number of samples.

In isometric contractions, an increase of MMG amplitude was observed when force production was low which was around 10% to 40% of the MC. During a high level of muscle force which was around 50% to 80% of MC, there was no change in MMG amplitude (Perry et al., 2016). The same observation was reported by another research group (Rodriguez-Falces & Place, 2013).

A higher level of muscle force resulted to a decrease in MMG amplitude (Claudio Orizio et al., 2003) due to a linear relationship reported between the contraction muscle and the RMS amplitude of the MMG (Oster & Jaffe, 1980). The correlation of amplitude of the MMG signal and motor unit activation was reported during a voluntary contraction as well as FES contraction (Beck, 2010).

The mean frequency shows the frequency feature of the MMG (Cescon, Farina, Gobbo, Merletti, & Orizio, 2004). ZC was used due to the fact that unlike mean frequency, ZC does not require the use of FFT to obtain and the calculation used to obtain

ZC is a simple one (Hagg, 1991). ZC has been defined as the number of times that the MMG signal passed through the horizontal amplitude axis (Zecca, Micera, Carrozza, & Dario, 2002). The equation (3.2) for ZC was as follows:

$$ZC = \sum_{k=1}^{N} sgn(-x_k x_{k+1}),\ for\ k = 1, \dots N \qquad sgn(x) = \begin{cases} 1\ if\ x > 0 \\ 0\ otherwise \end{cases} \qquad (3.2)$$

where x_k was the raw signals of the of the segment and N was the number of samples.

Both MMG-RMS and ZC were taken at the sample rate of N = 1000. While the torque data from the Biodex were averaged to get the mean torque for every 500 torque samples. This was done to obtain the reading of torque, MMG-RMS, and ZC for every second during the stimulated contraction for synchronization.

3.4 Phase 2: Neural Network development

3.4.1 Training data processing and neural network development

The Neural Network system was designed using MATLAB 2015 using the Neural Network fitting toolbox. The ANN system takes MMG inputs to predict the onset of muscle fatigue. Two types of ANN models were developed based on the two types of data sets used to train the model, the first was normalized MMG-RMS only and the second type was normalized MMG-RMS together with normalized MMG-ZC. RMS and RMS-ZC were used as the input for the neural network training and the normalized torque was used for the target data for the desired output of the network. The ANN is trained by feeding the RMS and RMS-ZC signals along with the desired signal data, torque output from the Biodex to the models. The samples obtained from the first session of the 3 subjects were used as training samples. A software G-power was used to determine the suitability of the number of subjects used. Using a priori correlation test with a minimum number of 0.90 correlation of probability which means if the experiment is repeated on similar number of subjects and subject's status, the results will have 90% probability of giving similar outcome, the minimum probability of the number of subjects to give false positive and false negative which were 0.05 and 0.20 respectively, and 0.80 effect size which is to determine if the selected number of subjects are suitable to emulate small or large number of sample. Effect size of 0.8 is the minimum size to represent a large effect on the population (Cohen, 1988). Based on above requirement, at least 6 to 8 samples were minimally required statistically thus this study employed 18 training data and 12 testing samples of various sample size to test the accuracy of the neural network system. The testing samples were obtained from the second session of the experiment for two of the subjects. The samples were arranged in a matrix row.

A feed-forward network with sigmoid hidden neurons and linear output neurons was used for the development of the ANN. The sigmoid transfer function was utilized as a transfer function due to the transfer function introduced non-linearity to the network's calculations as well as it is a simple derivative function (Calcagno et al., 2010). The type of ANN model developed was the MLP which contained multiple layers of computational units that were interconnected in a feed-forward manner. The three layers used were the input layer, hidden layer, and the output layer with a single input layer and output layer. ANN model training technique involved the output values of the system to be compared with the correct values thus producing the error between the output and the correct answer are computed in an error function (Calcagno et al., 2010). The data set that was used for training and testing the ANN had 516 samples. The percentage of data set was 70% training samples, 15% validations samples and 15% testing samples. These were the default settings for the ANN. The number of hidden neurons was set to 10 so that the output of the ANN models would produce the correlation that is above 0.8.

The network was trained with the Levenberg-Marquardt algorithm (Levenberg, 1944):

$$w = w + \Delta w \tag{3.3}$$

$$\Delta w = [J^T J + \mu I]^{-1} J^T e \tag{3.4}$$

$$e = R - z \tag{3.5}$$

where w is the weight vectors, Δw is the differences between the weight vectors, J is Jacobian matrix that included the first derivatives of the network errors according to the weight, μ was a scale parameter, *I* is the identity matrix, R is the vector of measured torque, z is the vector of predicted torque, and e is a vector of the network errors. Post neural training, the network was deployed with the MATLAB compiler and Builder tools to generate a MATLAB function.

3.4.2 Neural network accuracy test

In order to quantify the performance of the two ANN models, a correlation between the predicted torque output and actual torque output as well as the accuracy of the model were identified. To achieve the objective, the network was tested with all the normalized RMS and RMS-ZC from the second session of the 3 subjects. The output torque was then compared with the actual torque obtained from the Biodex with the 'fitlm' function on MATLAB to obtain the correlation coefficient (r). A critical point of 50% torque drop was chosen in order to test the accuracy of the ANN model by comparing the time for the actual torque in each test data samples to reach 50% torque drop and the time for predicted torque (RMS and RMS-ZC) to reach 50% drop to determine the reliability of the models to detect a specific torque value. The accuracy was obtained from the equation (3.6).

$$\left(1 - \frac{|predicted\ torque\ time - actual\ torque\ time|}{actual\ torque\ time}\right) \times 100 \quad \% \tag{3.6}$$

3.5 Phase 3: testing the neural network model during a standing experiment with FES

3.5.1 Standing protocol

A standing protocol was executed in order to validate the effectiveness of the ANN model to predict the onset of muscle fatigue by predicting knee torque during an FES standing stance in SCI subject. Five individuals with SCI (ISNCSCI A and B) participated in this component of the study. This protocol has been developed by Ibitoye to measure different stimulation frequency effects during a prolonged FES standing (Ibitoye, 2016). All 5 subjects had been familiarized with the FES training and were able to undergo the stimulation as intended in the protocol.

3.5.2 Equipment and Materials

The FES stimulator that was used in the standing experiment was a commercially available neurostimulator (RehaStimTM, Hasomed GmbH, Magdeburg, Germany). The stimulation was channeled to the targeted muscle by 9 x 15 cm^2 size surface adhesive electrodes (RehaStimTM, Hasomed GmbH, Magdeburg, Germany). This protocol was adapted from the procedure reported by Braz and colleagues, in their study (Braz et al., 2015). A harness (Biodex Offset Unweighing System) was used to support the subject's body and prevent the subject from tumbling. In order to ensure that the harness did not influence the subject's weight, researchers ensured that both subject's feet were flat on the ground and not hanging above the ground. The muscle mechanical signal during the standing protocol was recorded with the same MMG accelerometer used in the knee extension experiments. Data acquisition and signal processing were done digitally through Acqknowledge v4.3 software (MP150, BIOPAC Systems, Santa Barbara, CA, Inc).

3.5.3 Experimental Procedure

FES standing was achieved by continuous stimulation of both left and right quadriceps muscle and also the glute muscle. The quadriceps muscles were stimulated in order to achieve stabilization in the knee extension and glutei was stimulated for hip extension and upright posture stabilization. The subject was stimulated at quadriceps (80mA) and glutei (64mA) at 200μs pulse width. The frequency of the stimulation was 35Hz on the one trial and 20Hz on the other trial. During the stimulation, the changes in the knee bend were observed with a goniometer. The stimulation and MMG recorded was then stopped when the knee reached 30º flexion and the subject was then given a 30-min recovery period between the two trials. The MMG signals obtained from the standing protocol was processed similarly to the signal processing in isometric knee extension.

Figure 3.2 Standing Experiment (A) at the beginning of the experiment the legs were straight due to FES stimulation. (B) The knee approaching 30º flexion.

3.5.4 Data Processing

The MMG signal data was bandpass filtered (20Hz to 200Hz) and the data was then processed to obtain the normalized RMS and ZC. The time taken for the RMS to drop to 70%, 50% and 30% of the maximum RMS is taken for t-test comparison with the time taken for the knee bend to reach 30º. This was to determine if the RMS alone was sensitive enough to the changes in torque to maintain the knee angle above the 30º mark. The RMS and RMS-ZC data set were then used as inputs for the ANN models respectively to obtain the predicted torque.

A point where changes in the gradient of the predicted output had been selected as a critical point from both sets of predicted torque to determine the consistency between both models to predict the critical point at a similar time and predicted torque value. The time taken to the critical point was normalized in the range of 0% to 100% stimulation time for all subjects because the overall experiment time differs for each trial and the torque value at the critical point from each standing subject were used in t-test to determine its significance and in order to determine the effectiveness of the ANN to predict knee torque and to compare between the two types of input, few hypotheses had been established to determine the behavior of ANN in standing protocol was similar to isometric knee extension.

The hypotheses were (i) the initial torque predicted would be higher than the final torque predicted, (ii) the predicted torque output pattern would be reduced throughout the stimulation and (iii) the pattern of RMS and ZC before and after the 50% torque drop point would not be the same. To confirm the hypotheses, t-test was used to identify the P values of the following pairs; Initial and Final predicted torque, the gradient of MMG-RMS and MMG-ZC before and after the point where the ANN models predicted a 50% torque drop where there should be a noticeable change to the gradient of MMG-RMS and MMG-ZC once the predicted torque from each model had reached a 50% torque drop from the maximum, and the gradient of the predicted torque. The statistical analysis was done on PSPP (1.0.1, GNU operating system, 2017).

3.6 Summary

The methodology involved 5 SCI (ISNCSCI of A and B), the first phase involved 3 SCI subjects and the third phases used all 5 subjects. The data collections sessions were done in UMMC under the supervision of physiotherapists.

The experiment was divided into 3 phases. All data collection sessions involved applying FES to the subject's quadriceps muscle. The first one was to obtain the training data necessary to develop a model to predict knee torque by accessing MMG inputs. The data collection procedure involves applying FES on the subject while seated on the Biodex to record the torque revolves around the knee joint.

The second part was to train the model by using the data obtained from the first page where the raw MMG data were processed into MMG-RMS and MMG-ZC. These two parameters were used as input for the training model and the torque data obtained from the same session were used as the target data.

The third part of the experiment was the utilization of the ANN model to predict the torque and muscle ability to maintain the standing pose in the FES-evoked standing protocol in SCI subjects. In order to determine the accuracy and the efficiency of the ANN in predicting the knee torque, 3 hypotheses were introduced. The torque output from the 2 ANN models was tested based on the hypotheses.

CHAPTER 4: RESULTS

The results chapter showed data collected throughout the experiment and the results of the test conducted to interpret the data. The first part of the results section presents the normalized MMG-RMS, normalized MMG-ZC, and comparison between the predicted muscle torque output from the ANN and the actual torque output from the dynamometer. The comparison was done in terms of the correlation and the accuracy of the ANN output with 2 types of input (RMS and RMS-ZC). The second part of the result section presents the normalized MMG-RMS, normalized MMG-ZC, the ANN training results and the t-test results of the hypotheses to determine the effectiveness of the ANN to predict the knee torque during a standing contraction

4.1 MMG Data Processing

Figure 4.1 shows the raw MMG data obtained from the knee extension training exercise.

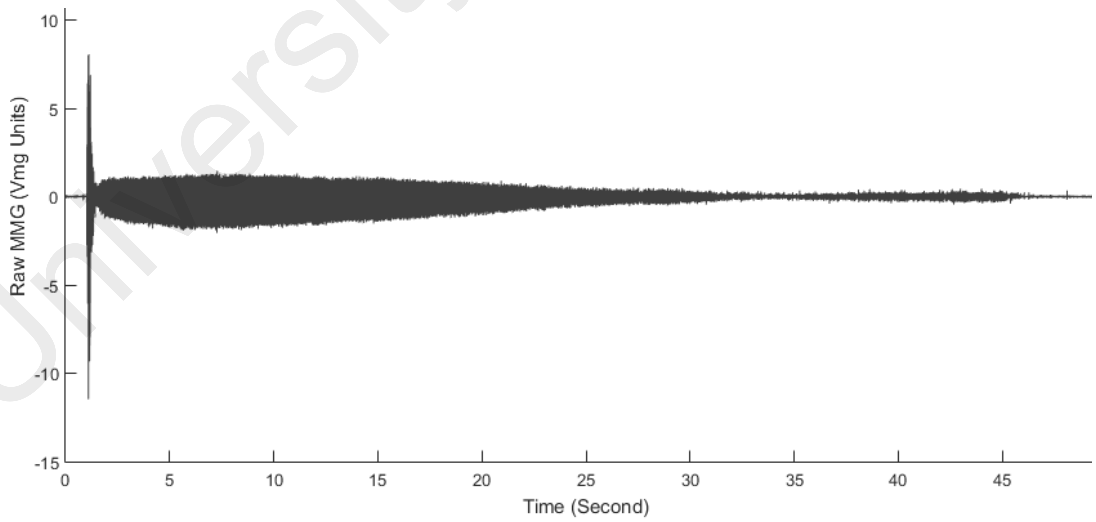

Figure 4.1 Raw MMG Data for Subject 1 Day 1 Left Trial 1

MMG recorded a short time but a significant spike of MMG amplitude (Up to 8 Vmg unit) at the start of the contraction. The MMG unit then began to stabilize itself to the range of ±2 VMG units. The MMG value then started a steady decline until it reached a value close to 0.

The raw MMG data were processed into MMG-RMS and MMG-ZC and then normalized. The processed MMG dataset is presented in Figure 4.2 while Figure 4.3 illustrates the predicted output torque produced by the neural network model and the actual output torque measured by the dynamometer during the data collection part of the research where Model 1 is the ANN model that used RMS as input and Model 2 used RMS-ZC as input. Due to the normalization, the maximum point in the graph was 1 and the minimum point was 0.

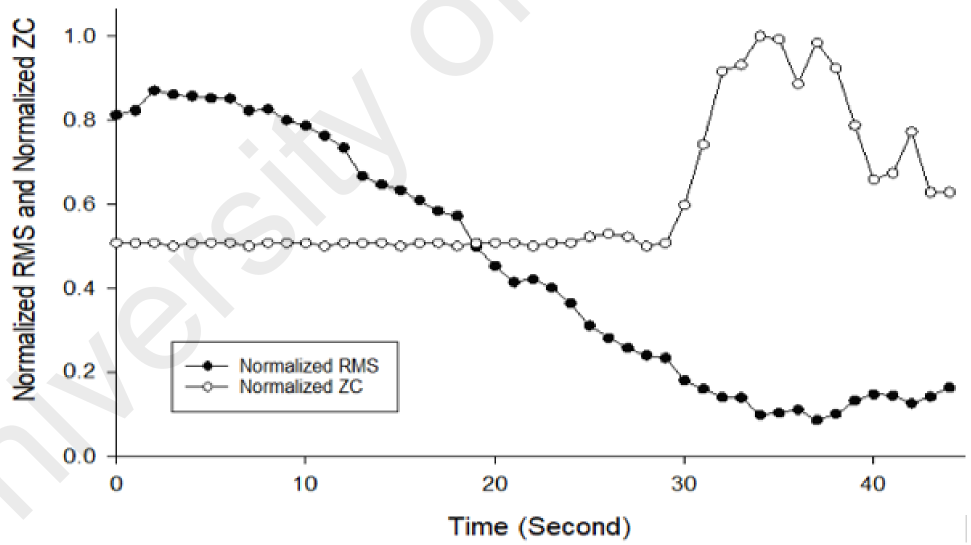

Figure 4.2 Normalized MMG-RMS and Normalized MMG-ZC against time used to be as training data for ANN development from Subject 4 Session 1, Left leg trial 1.

Figure 4.2 shows RMS gradually decreased from the maximum as the stimulation continues and ZC shows a dramatic increase in the frequency of muscle contraction after a certain period towards the end of the session. The gradient of the RMS decrease differed from the start and towards the end of the contraction. The normalized MMG-RMS had a steady decline from the maximum until it reached the value of around 0.2 normalized MMG-RMS which it was then stabilized around that value. In contrast, RMS ZC exhibits a steady value until the 29th-second mark where it rised at a significant value and then dropping around the 38th-second mark.

4.2 Neural Network Training

The two figures below are the results from the training of ANN. Figure 4.3 shows the accuracy training for the Model 1 (RMS). The target data was the actual torque obtained from the Biodex and the output is the value predicted by the ANN model.

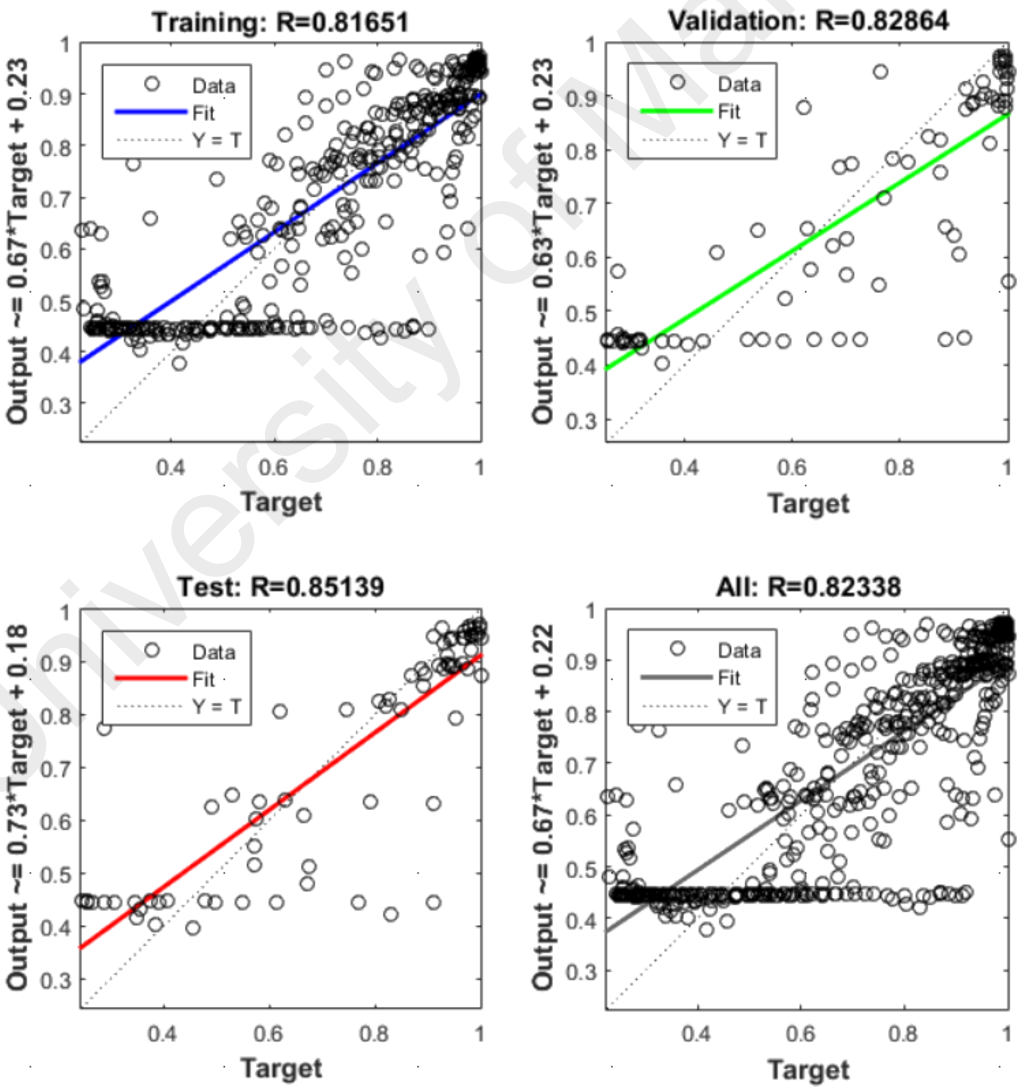

Figure 4.3 Training Results for ANN traning Model 1 (RMS)

The correlation results from the model 1 training yielded 0.82, 0.83 and 0.85 for Training, Validation and Testing Data sets respectively. Overall the correlation between the output data sets and the target data set for Model 1 training was 0.82.

Figure 4.4 shows the training results for Model 2 (RMS + ZC). The correlation between the target data set and output were 0.85 for training, 0.89 for validation and 0.84 for testing. Overall, the correlation was 0.85.

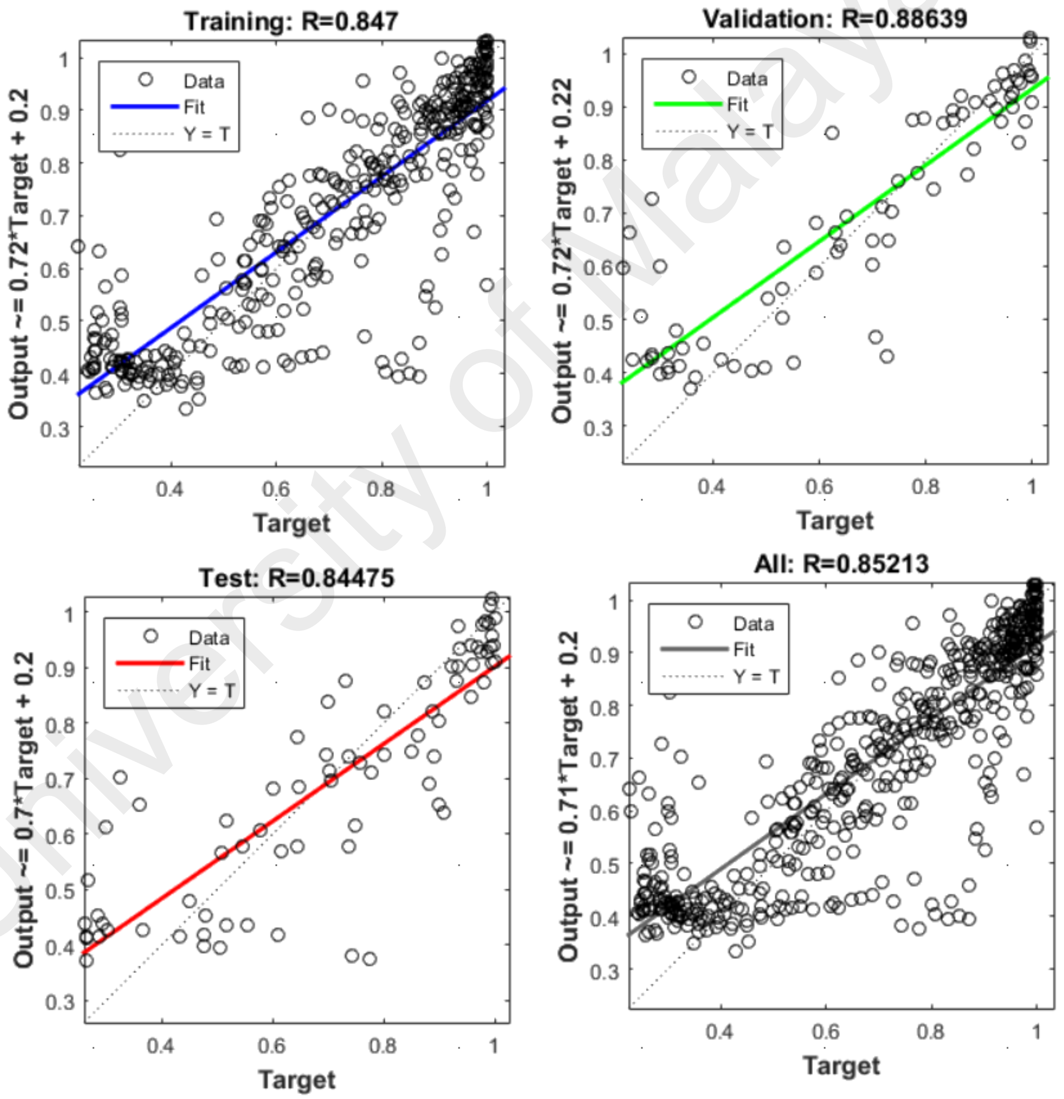

Figure 4.4 Training Results for ANN traning Model 2 (RMS + ZC)

4.3 Model Output of Torque

From the Figure 4.5, the torques from ANN Model 1 and Model 2 are presented on a graph with the actual torque collected from the Biodex.

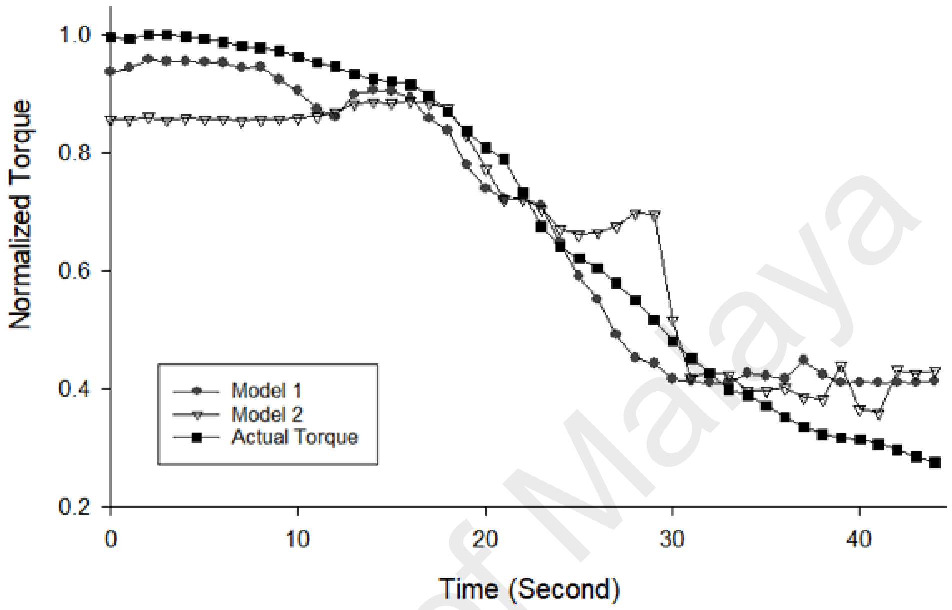

Figure 4.5 Normalized torque measurement from Biodex dynamometer and the predicted torque from two ANN models from Subject 4 Session 1, Left leg trial 1

All three graphs exhibit a decline from the maximum although the actual torque has the smoothest decline among all the 3 parameters.

4.4 Torque and predicted torque from isometric contraction testing

The accuracy of the ANN model to predict the measurement of torque was first tested on isometric knee extension prior to the standing experiment.

The correlation and the accuracy of the ANN model to predict the torque in both subject 1 and 2 have been tabulated in Table 4.1 which shows the mean accuracy and correlation between the two types of inputs.

Table 4.1 Average correlation (R) and accuracy test for two type of ANN models to predict torque during FES isometric knee extension

	ANN model input	
	Model 1: RMS	Model 2: RMS-ZC
R	0.87 ± 0.11	0.84 ± 0.13
Accuracy (%)	79 ± 14	86 ± 11

4.5 Testing the ANN model in FES standing protocol to predict torque

A series of 2-tailed t-test was performed to determine whether the time taken for MMG-RMS to drop to a certain level was significantly different than the time taken for the knee angle to reach 30º at the end of stimulation. The results from the t-test are presented in Table 4.2.

Table 4.2 T-test significance values for time to reach 30%,50% and 70% of MMG-RMS drop compared to the time to 30-degree knee buckle.

MMG-RMS %	P-value
30% MMG-RMS drop vs 30º knee angle	0.01
50% MMG-RMS drop vs 30º knee angle	0.01
70% MMG-RMS drop vs 30º knee angle	0.02

Figure 4.6 shows the predicted torque, which was the output from the ANN model, where model 1 was based on RMS as input and model 2 was from the RMS-ZC input.

4.6 ANN Torque Monitoring in Standing Protocol.

Figure 4.6 shows the torque output from Model 1 and Model 2 in a Trial 1 for subject 5. Both torque outputs from the 2 models initially showed a decline for the first 10 seconds.

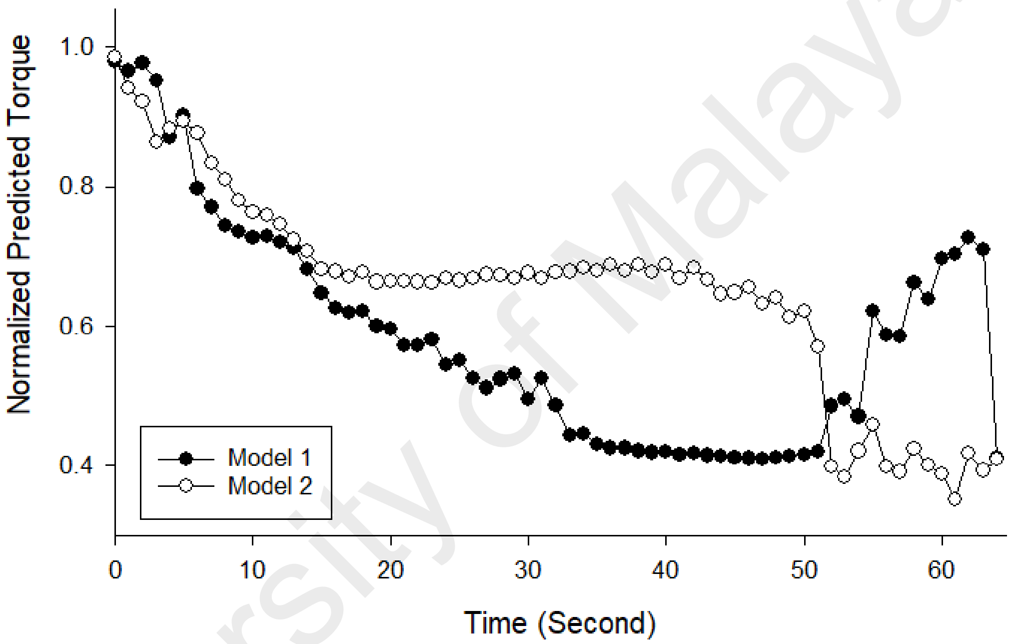

Figure 4.6 Normalized predicted torque for a standing protocol for Subject 5 Trial 1

However, after 10s-mark, model 1 exhibited a steeper decline than the model 2 which was more stable compared. At the end of the data collection, there was an opposite response from the 2 models recorded. Model 1 shows an increase of torque while model 2 shows a decline in torque.

Both torque series mostly satisfied the set hypotheses where (i) the initial predicted torque was higher than the final predicted torque, (ii) the predicted torque output pattern descended throughout the stimulation in most cases, and (iii) the gradient of RMS and ZC before and after the 50% torque drop point were different.

The results from the t-test statistical analysis of the standing protocol based on the said hypotheses are shown in Table 4.3 and Table 4.4 respectively.

Table 4.3 Summary of the t-test done for time to reach a critical point (RMS and RMS-ZC) and the predicted torque at a critical point (RMS and RMS-ZC)

Critical Points at which gradient changes	ANN model input		p-value
	Model 1: RMS	Model 2: RMS-ZC	
Normalized time (%)	44 ± 21	45 ± 17	0.93
Predicted torque (%)	54 ± 14	58 ± 17	0.33

Table 4.4 Summary of t-test statistical analysis for standing protocol from devised hypotheses

Hypothesis	Torque initial vs Torque final		RMS gradient before and after 50% torque drop		ZC gradient before and after 50% torque drop		Predicted torque gradient before and after 50% torque drop	
Model Input	RMS	RMS-ZC	RMS	RMS-ZC	RMS	RMS-ZC	RMS	RMS-ZC
Mean ± SD	Initial Torque 0.95±0.4	Initial Torque 0.93±0.1	Pre50% drop -0.02±0.1	Pre50% drop 0.00±0.00	Pre50% drop 0.00±0.00	Pre50% drop 0.00±0.00	Pre50% drop 0.01±0.10	Pre50% drop 0.01±0.00
	Final Torque 0.53±0.16	Final Torque 0.51±0.15	Post50% drop 0.00±0.00	Post50% drop 0.00±0.00	Post50% drop 0.00±0.00	Post50% drop 0.00±0.00	Post50% drop 0.00±0.00	Post50% drop 0.00±0.00
p-values	0.00	0.00	0.00	0.04	0.18	0.66	0.00	0.01

4.7 Summary

In summary, the MMG showed a depreciation in values as the time goes on. There was a short burst of high amplitude MMG at the instance where the experiment started. This value was not taken into consideration in this study. MMG-RMS and MMG-ZC showed changes to the signal at lower values of torque. MMG-RMS decreased at a steady rate and finally settled while RMS ZC started at a steady rate and experienced a significant increase in the value.

The ANN training results showed that the ANN models were able to predict the knee torque output at a satisfactory performance with 0.82 and 0.85 correlation with the actual torque for Model 1 and Model 2 respectively. Model 1 and Model 2 possessed a similar trend to the actual torque output from the Biodex where the values of the 3 graphs decrease. This, however, the two models' torque output was not showing a smooth decline as the actual torque.

There were high correlations of the torque outputs from the two models respectively and the actual torque output. Model 1 has a correlation of 0.87 ± 0.11 while Model 2 has 0.84 ± 0.13. However, Model 2 has a higher accuracy% of 86 ± 11 compared to 79 ± 14 in Model 1. There was no significant difference between the time taken for the MMG-RMS to record a significant drop and the time where the knee drop reaches 30^{o} knee drop.

In standing procedure, the torque output from the 2 models was discussed and the differences are explained.

CHAPTER 5: DISCUSSION

This chapter critically discussed the results obtained from the procedure. There were 4 sections in this chapter. The first part discussed the relationship of the MMG to the torque and fatigue. The second section discussed the test results of the hypotheses, the third section discussed the performance of the two ANN models in estimating the torque and finally, the fourth section discussed the limitation of the study.

5.1 MMG relationship to torque and fatigue

5.1.1 MMG-RMS to fatigue

The MMG amplitude was a recognizable way to see the relation between MMG and net torque as the decrease of the net torque correlated to the decrease of MMG (Gobbo et al., 2006). The relationship of MMG to the strength of muscle contraction has been established by researchers such as Kimura and Beck (Beck et al., 2005; Kimura et al., 2004). They discovered that with involuntary and electrically evoked contraction, the level of force generated possesses a linear relationship to the RMS amplitude of the MMG. The findings from Kimura and Beck supported the results from the first phase of the experiment where at lower torque level recorded by the Biodex in Figure 4.3 (Torque < 50N.m), the MMG-RMS in Figure 4.2 also recorded a decrease.

In Table 4.2, there were highly significant differences ($P < 0.01$) between 30% and 50% RMS drop to the 30° knee bend during the standing protocol, a 70% drop, however, has a slightly higher chance ($P > 0.02$) to have the similar timing with the knee buckle of 30°. High significant differences show that at any point where the MMG-RMS dropped by 30% and 50%, there was a low confidence level that this occurs during the knee buckle. 70% RMS drop shows a higher confidence that it occurs at the same time the knee buckles.

5.1.2 MMG-ZC to fatigue

The increase of MMG-ZC at lower torque values indicates that the muscle contracts at a higher frequency. This can be seen in Figure 4.2. This observation occurred due to the size principle where the muscle recruitment started from small, slow motor unit towards increasingly larger and faster motor unit (Henneman, Somjen, & Carpenter, 1965). This pattern also supported the finding from Feiereisen (1997) that the pattern of muscle recruitment from small, slow motor unit to bigger and faster motor unit occurs during FES muscle contraction (Feiereisen, Duchateau, & Hainaut, 1997). The increased frequency of the contraction was used as the point where fatigued started to occur which was due to the larger motor units that has a bigger diameter axon and are more prone to fatigue (Bickel, Slade, & Dudley, 2004). This was the point that was used as the endpoint for the point where the muscle was no longer able to maintain its current strength, position, or stance, as the muscle fiber reached the end of its endurance limit.

5.2 Test for hypotheses

5.2.1 Initial Predicted torque against final predicted torque

Individually, for the first hypothesis in the standing protocol that was the initially predicted torque was significantly different than the final predicted torque, both RMS input and RMS-ZC input revealed that they are significantly different ($P<0.01$). The difference shows that at 30° knee bend, there was a distinguishable difference between the mean torque output of all the sessions. The torque at the 30° knee bend was significantly lower than during the initial torque on average for all subjects. The difference is due to the rapid muscle fatigue leads to decrease of RMS and an increased frequency of muscle contraction based on the finding in isometric knee extension (Barry et al., 1985).

5.2.2 Changes to MMG-RMS and RMS-ZC Signals at Lower Torque Output

The second hypothesis that the ANN predicted at 50% quadriceps torque or lower, there was a significant change towards the pattern of RMS where the RMS decreases at the steeper slope and ended up plateauing (gradient is near 0). However, t-test for prediction for both RMS input and RMS-ZC input for the gradient of ZC before and after the predicted 50% torque drop shows that there was no strong significant difference, the P-value for Model 1 was 0.18 and the P-value for Model 2 was 0.66. Compared to isometric knee extension protocol, the standing protocol did not stabilize the legs, and this caused the legs to move and this movement possibly caused the changes in amplitude in the ZC value.

RMS input showed better reliability in predicting muscle fatigue compared to RMS-ZC input due to less disturbance to RMS when there was a leg movement. However, ZC input was able to provide a frequency domain of the muscle contraction as an increased number of contraction indicated the recruitment of fast twitch muscle fiber which was less endurance to fatigue compared to slow twitch fiber (Karlsson, Sjodin, Jacobs, & Kaiser, 1981). ZC together with RMS a better model can be developed that combines both temporal and spectral domain of the muscle signal.

5.2.3 Gradient Pattern of Predicted Torque

The fourth hypothesis was that the gradient of predicted torque for both models of ANN is decreasing throughout the experiment. The RMS input showed a slightly more significant difference compared to RMS-ZC input. Although from Table 4.1 both models showed the same consistency in predicting the torque generally, ANN model performance were different during the fatigued period of the standing experiment where Model 1 had an increased in torque and vice versa in Model 2.

5.3 ANN Models in Predicting Torque

From Table 4.3, the t-test results of P=0.93 indicated no significant difference between the time taken for the predicted torque output pattern to reach the point where there are significant changes to the pattern of the actual torque obtained from the Biodex dynamometer. The value of the predicted torque at the critical time from both models were not significantly different from the value of the torque obtained from the dynamometer with a p-value of 0.33. This indicated that in general both models performed with a consistent level of prediction.

From table 4.4, the ANN models produced torque output during a seated isometric contraction that is almost similar in term of correlation and accuracy, both RMS input and RMS-ZC input has high correlation (R > 0.80) while RMS input has a slightly higher correlation of 0.87±0.11 compared to RMS-ZC of 0.84±0.13. Higher accuracy from RMS-ZC input was due to an increase of ZC value past ~50% of maximum torque. This was because of the transformation of fatigue resistant slow twitch muscle fiber to less fatigue resistant fast twitch muscle fiber (Bickel, Slade, Van Hiel, et al., 2004; Karlsson et al., 1981). This suggests that ANN is a feasible strategy to predict torque without the need of dynamometer.

RMS input showed better reliability in predicting muscle fatigue compared to RMS-ZC input due to less disturbance to RMS when there is a leg movement. However, ZC input was able to provide a frequency domain of the muscle contraction as an increased number of contraction indicated the recruitment of fast twitch muscle fiber which was less endurance to fatigue compared to slow twitch fiber (Karlsson et al., 1981). ZC together with RMS a better model can be developed that combines both temporal and spectral domain of the muscle signal.

At the end of the evoked standing session, the irregular torque predicted by the models, as illustrated in Figure 4.4, could be due to the gravity effect acted during standing. The biomechanics of standing is illustrated in Figure 5.1.

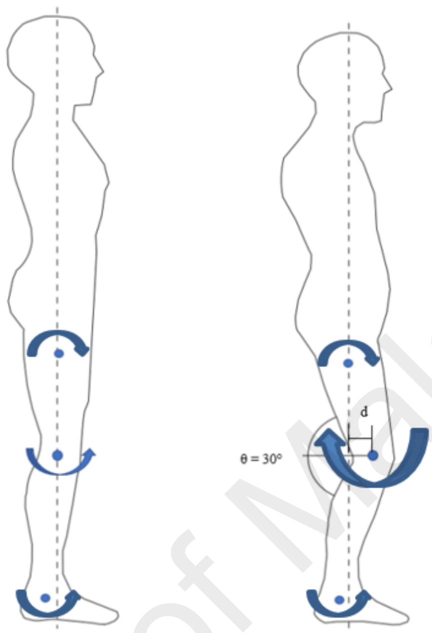

Figure 5.1 Biomechanics of Standing. Left: non-fatigued, quiet standing motion. Small knee extension moment. Right: fatigued, 30º knee angle bend. Large knee flexion moment due to gravity.

It was thought that the amplified torque due to the gravity and the increased distance (d) between the knee joint and the ground reaction force had affected the MMG responses. However, a biomechanical study which includes the study procedure involving biomechanical setups such as ground reaction force plate and a 3D camera system is required to further ascertain this.

The graph from the experiment is shown in Figure 5.2 (Mohd Rasid, 2017). At the end of the contraction when the knee started to bend towards and past the 30° knee angle, there was a high increase of MMG-RMS values. This event supported the idea of increased torque due to gravity.

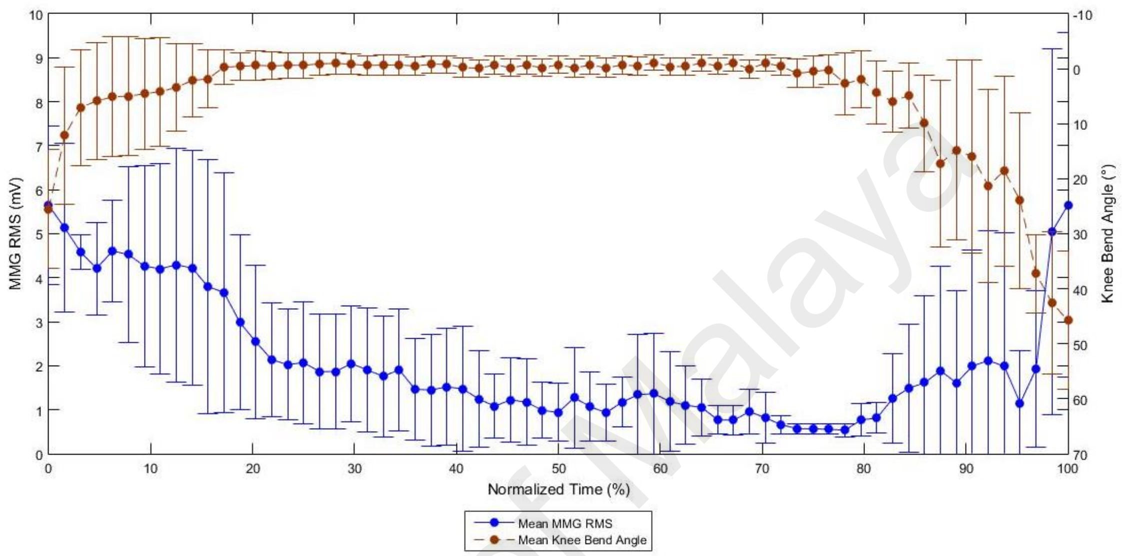

Figure 5.2 Graph of MMG RMS against Knee Bend Angle during FES Standing in SCI subject 4 (Mohd Rasid, 2017)

5.4 Limitation to Study

This research was limited as presently the ANN model to predict the torque only during quiet standing and isometric knee extension was analyzed. Future studies should include a wider movement pattern such as sit-to-stand movement, which is another nonmeasurable torque movement. Different types of inputs such as PTP and ARV in the time domain and MPF in the frequency domain could be investigated as well as different types of computer software networks such as support vector machine (SVM). To our knowledge, there has not been any investigation on ANN model that is trained to predict torque in FES standing experiment using MMG. Hence, this study has demonstrated that an ANN model is feasible in predicting torque during isometric knee extension and FES standing and thus may contribute to the improvement of the automated control FES during rehabilitation in SCI. Finally, the effect of pulse width on the MMG or fatigue was not studied in this research, however, other literature suggested that the pulse width has no significant effect on the muscle fatigue but it affects the maximum muscle force production (Jailani & Tokhi, 2012).

5.5 Summary

This study sought to investigate the practicality of using ANN models to predict the knee extension torque during isometric contraction and standing stance using RMS and RMS-ZC as inputs to the ANN. The testing on isometric knee extension revealed that the ANN model used to predict knee torque from the MMG muscle signal of the quadriceps muscle was reliable. RMS-ZC input ANN model showed a higher accuracy compared to RMS input ANN model which shows that in isometric knee extension, RMS-ZC was more suitable than RMS as input to the ANN model. This also suggests that ANN is a feasible strategy to predict torque without the need of dynamometer.

The transformation explains the ZC graph where the increase in the number of contraction leads to the decrease of torque recorded by the dynamometer. However, model 2 has a higher accuracy compared to model 1 (79±14% for model 1 compared to 86±11% for model 2). This result reflected increased ZC value due to the higher frequency of contraction due to the torque drop of 50% and recruitment of faster, more fatigable motor unit.

CHAPTER 6: CONCLUSION

As for the conclusion, FES is a valuable rehabilitation training method to help SCI patients partially or fully recover from the injury. FES helped rehabilitation process by facilitating blood flow and prevent muscle atrophy. However, there is a need for a monitoring system for SCI training with FES. This is vital to maximize the effectiveness of the training while minimizing the risk of injury to the patient. There are many methods to monitor muscle performance during FES training from monitoring joint angle and torque to using sensors such as EMG and MMG.

However, in FES evoked standing stance, measuring the torque generated around the knee joint is not practical due to lack of suitable attachment of the Biodex dynamometer that enabled such feat. Hence, MMG was used with ANN to enable prediction of the muscle fatigue. To develop the ANN for monitoring knee torque, the ANN must first be trained with known desired output in order to map the input of the MMG to the unknown knee torque.

MMG data from the data collection procedure must first be processed before training and 2 parameters of the MMG was extracted which were RMS and ZC. RMS shows the muscle strength based on its amplitude while ZC presents the frequency of the muscle vibration.

Testing of both data showed a high accuracy and reliability on monitoring knee torque in standing stance FES contraction. However, while Model 1 showed a better reliability in predicting torque due to the less disturbance from movement artifact, Model 2 reflects the frequency domain of the muscle as well leading to a more critical representative of the torque and the muscle fatigue.

The limitations of the study were acknowledged. More actions such as sit to stand, cycling can be trained with similar ANN model. This is to enable a wider range of motion where the usage of ANN to predict muscle fatigue can be used. Different parameters of MMG can be used and the performance of such a model can be compared to the one from this study.

Overall, the results of the study show that ANN can be useful in the field of rehabilitation where the muscle performance can be assessed when the commercially available equipment was not suitable to be used. In addition, the study could be used as a basis for an online FES model that can identify and predict the knee torque. This would enable a better control for FES that will significantly increase the effectiveness of the FES training.

6.1 Recommendations for future work

As for the recommendations for the future work of this study, there are 3 potential areas that can be explored to further improve the research. First, more subjects can be recruited in order to have a higher number of training data to enable higher more generalized results on the population of SCI. Second, a prediction based on knee angle and MMG would have a better effect on determining muscle fatigue in FES evoked standing stance and third, the integration of the ANN model with FES to enable control and safety to the patients during FES training such as gradually lower down the current intensity when the muscle is approaching fatigue to have a longer duration of the contraction.

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LIST OF PUBLICATIONS AND PAPERS PRESENTED

- **Dzulkifli, M.A.**, Hamzaid, N.A., Davis, G.M., Hasnan, N. (2018). Neural Network-Based Muscle Torque Estimation Using Mechanomyography during Electrically-Evoked Knee Extension and Standing in Spinal Cord Injury. Frontiers in Neurorobotics (Published)

- Mohamad Saadon, N.S., Hamzaid, N.A., Hasnan, N. **Dzulkifli, M.A.**, Davis, G.M. (2018). Electrically Evoked Wrist Extensor Muscle Fatigue throughout Repetitive Motion as Measured by Mechanomyography and Near-Infrared Spectroscopy. Biomedical Engineering / Biomedizinische Technik (BMT) (Published).

Proceedings

- **Dzulkifli**, **M.A**., Ibitoye, M.O., Hasnan, N., Davis, G.M., Hamzaid, N.A. Muscle Fatigue Monitoring using Mechanomyography in FES-Evoked Contractions and Standing among Individuals with Spinal Cord Injury, Rehabweek London 2017.
- Mohamad Saadon, N.S., Hamzaid, N.A., Hasnan, N. **Dzulkifli, M.A.**, Gan, K.B., Teoh, M., and Davis, G.M. (2018). Muscle Oxygen Saturation Correlates with Muscle Mechanomyography during Prolonged Electrical Stimulation-Evoked Wrist Extension Exercise. The 10th International Conference on Robotics, Vision, Signal Processing & Power Applications (ROVISP2018), 14th August-15th August 2018, Penang. (In Press)