THE INFLUENCE OF DIGITAL FILTER TYPE AND NORMALISATION METHOD ON SURFACE EMG DATA DURING DYNAMIC MOVEMENT TASKS

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THE UNIVERSITY OF WESTERN AUSTRALIA

Achieve International Excellence

To my parents

Vijaya Devaprakash and D.F Devaprakash

DECLARATION

I declare this thesis is my own composition, all sources have been acknowledged and my contribution is clearly identified in the thesis. For any work that has been co-published with other authors, I have permission of all co-authors to include this work in my thesis.

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ABSTRACT

In the field of Electromyography (EMG), several different types of filters and normalisation methods have been employed to process the high frequency biological signal. The use of different types of filters and normalisation procedures for the signal processing of EMG data has added complexity when comparing these processed biological signals between studies. Additionally, there are numerous ways in which researchers analysed processed EMG data to obtain clinically relevant meaning. One example is co-contraction ratios, which like the EMG signal processing methods, vary extensively in the literature making comparisons between studies difficult at best.

To first understand the influence of normalisation method on the characteristics of a processed EMG signal, we processed EMG data using an underdamped Butterworth filter, then normalised these data using three commonly used methods in the literature; common clinically relevant dependent variables like mean total muscle activation (TMA) and directed co-contraction ratios (DCCR) were calculated from the processed data. The data was normalised using the peak muscle activation obtained from a combination isokinetic dynamometry trials, functional movement trials and dynamic calibration trials (COMB), peak muscle activation obtained from the functional movement trial only (FUNC), and average peak muscle activation obtained from straight line running trials (SLRm). From these analyses, results showed that the type of normalisation method employed significantly influences the clinical interpretation of a TMA and to a lesser extent DCCR estimates.

To then understand the influence of filtering approach on the characteristics of a processed EMG signal, data was processed separately using a critically damped and underdamped Butterworth filter and normalised using the COMB normalisation method. Significant differences in integrated EMG (IEMG) were observed, with the critically damped filter reporting values greater than those estimated with an

underdamped Butterworth filter. Interestingly, results showed that the clinical interpretation of the total muscle activation (TMA) and directed co-contraction ratios (DCCR) did not differ as a result of filtering approach, likely because these data were normalised to a maximal muscle activation value calculated within the experiment. Visual analysis of both processed signals (prior to normalisation) suggested the roll-off of the underdamped Butterworth filters were superior to that of a critically damped filter making it the digital filter of choice for the signal processing of EMG data.

A secondary aim of this thesis was to investigate the influence of co-contraction ratio algorithms (agonist vs. antagonist muscles crossing a joint) on the clinical interpretation of processed EMG data. Results showed the clinical interpretation of the data is influenced by the co-contraction ratio algorithm used. The DCCR algorithm published by Heiden et al., appeared to be the most appropriate algorithm for assessing the magnitude and directionality of a joint's co-contraction during clinical movement assessments.

The general conclusions from this research were that the standards for reporting EMG data established by the International Society of Electrophysiology and Kinesiology (ISEK) should incorporate recommendations on the methods associated with the filter type used to process EMG data, the methods used to normalise the data and the co-contraction ratio algorithms used to estimate the co-contraction between agonist vs. antagonist muscles crossing a joint. The standardised implementation of such recommendations will serve to reduce the complexity associated with between studies comparisons utilising EMG for the clinical assessment of movements like walking gait, running, jump-landing and change of direction tasks. Thereby facilitating researchers using EMG for clinical research to more effectively compare and reproduce results, together with building on previous findings.

EXECUTIVE SUMMARY

Chapter three

Title: The influence of digital filter type and normalisation method on surface EMG data during dynamic movement tasks

Purpose: Determine if the choice of digital filter and normalisation method used to process EMG data has any influence on the clinical interpretation of results. Secondly, determine if the co-contraction ratio algorithm used influences the clinical interpretation of processed EMG data.

Methodology: Sixteen (22.2 ± 2.9 years. 167 ± 10 cm, 66.3 ± 6.7 kg) athletes from the Australian women's National field hockey team participated in this study. Out of which, twelve athletes completed the UWA sidestepping protocol along with dynamic calibration and isokinetic dynamometry normalisation trials. The dynamic calibration trials included in the study were single leg squat (SLSQ), counter movement jump (CMJ) and single leg drop jump (SLDJ). Surface electromyography (sEMG) data were recorded from nine lower limb muscles and processed with an underdamped Butterworth filter as per the ISEK guidelines. Following this, the data was normalised using three different normalisation methods commonly used in the literature. The three different methods of normalisation employed in this study are the COMB method which takes the peak muscle activation obtained from a combination of isokinetic dynamometry, functional movements assessed and dynamic calibration trials; FUNC method uses the maximum muscle activation value obtained from the functional movements assessed and the straight line run method (SLRm) method which normalises the running trials with the mean peak muscle activation obtained from planned straight line running trials (PSLR). From the three different sets of normalised data, mean total muscle activation (TMA) and directed co-contraction ratio (DCCR) were calculated and compared using one way repeated measures analysis of variance (ANOVA). *Post-hoc*

Sidak tests ($\alpha = 0.05$) were also conducted in order to evaluate the differences between each normalisation method. The raw sEMG data were also filtered using a critically damped filter, and then normalised using the COMB method. Mean total muscle activation (TMA), directed co-contraction ratio (DCCR) and integrated EMG (IEMG) calculated separately using an underdamped Butterworth and critically damped filters were compared using a paired sample t-test ($\alpha = 0.05$). From the sEMG data filtered using an underdamped Butterworth filter and normalised using the COMB method; co-contraction ratios were also calculated as per the three common employed algorithms in the literature.

Results: The main findings from this study are that the choice of normalisation method has a large influence on the clinical interpretation of the TMA and DCCR. The COMB method of normalisation produced significantly lower estimates of mean TMA when compared with the FUNC and SLRm methods ($p < 0.05$). The flexion extension (F/E) and semimembranosus/biceps femoris (SM/BF) DCCR obtained from COMB method produced clinically different information when compared to the values obtained from FUNC and SLRm method of normalisation. For instance, the SM/BF DCCR value obtained from COMB method of normalisation indicated that the biceps femoris muscles were more active when compared to the semimembranosus muscle during the pre-contact (PC50) and weight acceptance (WA) phase of all trials. However, the other two methods of normalisation indicated that SM muscle was more active. The Mean TMA and DCCR obtained separately from sEMG data processed using an underdamped Butterworth and critically damped filter were not significantly different for the majority of dependent variables tested. Only the IEMG of all nine muscles were significantly lower when calculated using an underdamped Butterworth filter when compared with the values calculated using a critically damped filter ($p < 0.05$). All three co-contraction ratio algorithms assessed resulted in differing clinical interpretations.

Conclusion: The COMB method of normalisation is most suitable as it always identified the peak muscle activation of each muscle measured during the clinical movement assessment. The co-contraction method devised by Heiden et al., was considered to be the most appropriate co-contraction ratio algorithm tested as it provided information associated with both directionality and relative magnitude of co-contraction between the agonist and antagonist muscles.

Significance: This is the first study to, 1) compare the effect of digital filtering type and normalisation method for the signal processing of sEMG data and 2) examine its impact on clinical interpretation of the results. It is also the first study to calculate and compare three different co-contraction ratio algorithms commonly employed in the literature to assess for variation in clinical interpretation resulting from algorithm choice. The results obtained from this study enable us to make recommendations towards the use of a particular digital filter, normalisation methods for the signal processing of EMG data and also recommend towards the use of DCCR method published by Heiden et al. for calculation of co-contraction ratios across joints. Our intention is that these recommendations will provide increased uniformity in the methods used for the signal processing of EMG data to improve the ability for researchers to reproduce, verify and build upon previously published data.

Thesis impact: The results obtained in this study would be submitted to the Journal of Electromyography and Kinesiology; which is the journal responsible for framing guidelines associated with sEMG/EMG processing methods. Our results indicate the improvements are required to the currently available ISEK guidelines. Specifically, recommendations on the filter type, normalisation method employed, as well as the co-contraction algorithm adopted for the analysis of clinical movement assessments should be addressed. Such recommendations will serve to mitigate the complexity associated

with comparison of EMG data for future research involving the analysis and reporting of sEMG data.

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Statement of Candidate Contribution

The work involved in designing, conducting and analysing the study described in this thesis was primarily performed by Daniel Devaprakash. The thesis outline and experimental design was planned and developed by the candidate with consultation from Dr. Cyril J Donnelly, Dr. Jacqueline Alderson, Dr. James J Dunne (Stanford University) and Ms. Gillian Weir. The final thesis was drafted by the candidate with Dr. Cyril J Donnelly, Dr. Jacqueline Alderson and Dr. James J Dunne providing editorial feedback.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

A rupture to the anterior cruciate ligament (ACL) is considered to be one of the most severe knee injuries an athlete can sustain in sport; often leading to hospital admission for the surgical reconstruction of the ligament (1). Injury surveillance has shown that injuries to the ACL predominantly occur during non-contact situations such as sidestepping or single leg landing tasks (2). During non-contact sidestepping tasks, peak valgus and internal rotation moments are significantly elevated when compared with straight-line running (3). These are the loading patterns which are known to elevate ACL strain in-vivo (4). Given that the ACL can only rupture when the load acting on the ligament is greater than its tissue tolerance, injury prevention frameworks generally focus on reducing loads applied to the ligament by changing an athlete's technique or increasing the activation/strength of the muscles supporting the knee during non-contact sporting tasks like sidestepping (5,6). Specifically, Besier and colleagues have shown that the muscles surrounding the knee joint are capable of providing support to the knee joint during non-contact sidestepping tasks and are instrumental for mitigating the load (i.e., moments) acting on the knee ligaments such as the ACL (7). To attain clinically relevant muscle activation information during non-contact sidestepping tasks, surface electromyography (sEMG) is generally used to record time varying muscle excitation data (mV). After recording muscle excitation data, there are multiple signal processing steps required to obtain muscle activation estimates. Common clinically relevant dependent variables to assess muscular support during non-contact sidestepping tasks are mean total muscle activation (TMA) (6,8), directed co-contraction ratio (DCCR) (6,8) and integrated EMG (IEMG) (9). These variables enable us to understand the way in which muscles crossing the knee joint are used to support the joint from external loading (i.e., moments) (8) and also the energy consumption associated with muscular contraction. In order to obtain reliable, clinically meaningful information from muscle

excitation estimates, sEMG data have to be processed according to the guidelines specified by ISEK (10). These guidelines have been established in order to effectively and efficiently remove random and systematic noise from the recorded biological signal, including movement artefacts, environmental noise and heart rate artefact (applying high pass filter at 30 Hz when analysing sEMG data of trunk and upper limb musculature) (11). However, during the signal processing steps of an electromyogram there is the potential for the characteristics of the signal to be compromised and for these undesirable effects to directly influence the clinical interpretation of the processed signal.

1.2 STATEMENT OF THE PROBLEM

The guidelines provided by ISEK for the processing of sEMG signals does not advocate the use of any particular filter (critically damped vs underdamped Butterworth filter) or normalisation method (manual muscle testing, using the peak obtained from the functional movement tasks or dynamic calibration tasks) to process sEMG data. For the purpose of this study, we assessed three different methods for the normalisation of sEMG data recorded from nine muscles of the lower limb during running tasks such as planned straight line running (PSLR), planned sidestepping (PSS) and unplanned sidestepping (UPSS) trials. Underdamped Butterworth and critically damped filters were used to process the sEMG signal, where specific clinically relevant dependent variables (anterior cruciate ligament injury risk classifiers) were then compared. Based on the findings, we provided empirical data towards future recommendations by the ISEK surrounding the type of digital filter to be used for the processing of sEMG signals and the most appropriate normalisation procedure employed for studies involving clinical movement assessments like running, sidestepping and/or landing tasks. Recommendations are also be made towards the use of a co-contraction ratio

algorithm that provides important information in terms of magnitude and directionality of co-contraction between the agonist and antagonist muscles' crossing the joint during clinical movement assessments where joint loading and injury risk elevated.

1.3 AIMS AND HYPOTHESIS

Chapter 3: The influence of digital filter type and normalisation method on surface EMG data during dynamic movement tasks

Aims

- Determine whether it is necessary to conduct a series of dynamic calibration, isokinetic and functional movement tasks in order to obtain the peak muscle activation (within the experiment) of lower limb muscles during clinical movement assessments (i.e., non-contact sidestepping, straight line running).
- Determine if the choice of normalisation method influences the magnitude of mean TMA estimates and the directionality and magnitude of DCCR values calculated during a common clinical movement assessment.
- Determine if sEMG data processed using an underdamped Butterworth or critically damped filter produces similar TMA, DCCR and IEMG estimates during a common clinical movement assessment (i.e., non-contact sidestepping, straight line running).
- To determine if commonly used co-contraction ratio algorithms produce similar clinical interpretations of processed sEMG data during a common clinical movement assessments.

Hypotheses

- Peak muscle activation values (in mV.) from nine muscles of the lower limb will be elicited during the SLSQ, CMJ and SLDJ dynamic calibration trials.
- sEMG data normalised using the COMB (combination of dynamic calibration, functional movement and isokinetic dynamometry) method will produce the lowest estimates of mean TMA of the lower limb muscle groups compared with FUNC and SLRm methods; however, no changes will be observed in the DCCR estimates.
- sEMG data processed using an underdamped Butterworth filter and critically damped filter will provide similar mean TMA, DCCR and IEMG values; leading to similar clinical interpretation of results.
- DCCR method would be the most effective co-contraction ratio method when compared with the methods developed by Lloyd and Buchanan (12) and Hamstra-Wright et al. (13) due to its ability to provide complete information in terms of magnitude and directionality of co-contraction between the agonist and antagonist muscles.

1.4 LIMITATIONS

- sEMG data provides information only about the electrical activity produced during a muscular contraction. The electrical activity does not provide information about muscle force generated through the active muscle fibres, nor the series and parallel elastic component of a muscle. Caution should be taken when using sEMG data to represent the magnitude of muscle support provided to a joint when external loads are applied.

- A processed biological signal may contain low levels of systematic noise as digital filters used to process are not capable of eliminating the systematic noise completely from the biological signal of interest.

1.5 DELIMITATIONS

- The sEMG data were obtained from a study involving elite level female athletes and therefore may not be transferrable to non-elite female athletes.
- The sEMG data were recorded from a healthy adult cohort and therefore may not be transferrable to children or pathological populations.
- The findings (comparison of normalisation methods) may only be applicable for studies assessing running and change of direction tasks.

1.6 LIST OF ABBREVIATIONS

Abbreviation	Definition
A/D	Analog/Digital
ACL	Anterior cruciate ligament
ADP	Adenosine diphosphate
ANOVA	Analysis of Variance
ATP	Adenosine triphosphate
BF	Biceps Femoris
BW	Butterworth filter
Ca^{2+}	Calcium ions
C_{crit}	Correction factor
CD	Critically damped filter
CMJ	Countermovement jump
CNS	Central nervous system
COMB	Combination method of normalisation
DC	Direct current
DCCR	Directed co-contraction ratio
EMG	Electromyography
F/E CCR	Flexion/Extension co-contraction ratio
F/E DCCR	Flexion/Extension Directed co-contraction ratio
F/E HW	Flexion/Extension Hamstra-Wright co-contraction ratio method
F_{crit}	Corrected cut off frequency
FUNC	Functional method of normalisation
GAS	Gastrocnemius
GL	Gluteals
Gmax	Gluteus Maximus
Gmed	Gluteus Medius
HAM	Hamstrings
Hz	Hertz
IEMG	Integrated EMG

ISEK	International Society of Electrophysiology and Kinesiology
KJM	Muscles crossing the knee joint
LG	Lateral Gastrocnemius
M/L CCR	Medial/Lateral co-contraction ratio
M/L DCCR	Medial/Lateral Directed co-contraction ratio
M/L HW	Medial/Lateral Hamstra-Wright co-contraction ratio method
MG	Medial Gastrocnemius
MUAP	Motor unit action potential
mV	Millivolt
mV.s	Millivolt.seconds
MVC	Maximal voluntary contraction
MVE	Maximal voluntary effort
MVIC	Maximal voluntary isometric contraction
N/A	Not applicable
Na^+	Sodium ions
PC50	Pre-contact phase (50 milliseconds prior heel contact)
PCSA	Physiological cross-sectional area
P_i	Inorganic phosphate
PNS	Peripheral nervous system
PSLR	Planned straight line running
PSS	Planned sidestepping
QUAD	Quadriceps
RF	Rectus Femoris
RMS	Root mean square
RoM	Range of motion
sEMG	Surface Electromyography
SENIAM	Surface ElectroMyography for the Non-Invasive Assessment of Muscles (SENIAM)
SLDJ	Single leg drop jump
SLR_Mean	Straight line running method of normalisation
SLSQ	Single leg squat
SM	Semimembranosus

SM/BF CCR	Semimembranosus/Biceps Femoris co-contraction ratio
SM/BF DCCR	Semimembranosus/Biceps Femoris Directed co-contraction ratio
SM/BF HW	Semimembranosus/Biceps Femoris Hamstra-Wright co-contraction ratio method
TMA	Total muscle activation
UPSS	Unplanned sidestepping
UWA	The University of Western Australia
VL	Vastus Lateralis
VM	Vastus Medialis
WA	Weight acceptance
°	Degrees
ζ	Damping ratio

Reference list chapter one

1. Gianotti SM, Marshall SW, Hume PA, Bunt L. Incidence of anterior cruciate ligament injury and other knee ligament injuries: a national population-based study. J Sci Med Sport. 2009 Nov;12(6):622–7.

2. Koga H, Nakamae A, Shima Y, Iwasa J, Myklebust G, Engebretsen L, et al. Mechanisms for noncontact anterior cruciate ligament injuries: knee joint kinematics in 10 injury situations from female team handball and basketball. Am J Sports Med. 2010 Nov;38(11):2218–25.

3. Besier TF, Lloyd DG, Ackland TR, Cochrane JL. Anticipatory effects on knee joint loading during running and cutting maneuvers. Med Sci Sports Exerc. 33(7):1176–81.

4. Donnelly CJ, Elliott BC, Ackland TR, Doyle TLA, Beiser F, Finch CF, et al. Research in Sports Medicine : An An Anterior Cruciate Ligament Injury Prevention Framework : Incorporating the Recent Evidence. 2012;(July):239–62.

5. Donnelly CJ, Lloyd DG, Elliott BC, Reinbolt JA. Optimizing whole-body kinematics to minimize valgus knee loading during sidestepping: implications for ACL injury risk. J Biomech. Elsevier; 2012 May 11;45(8):1491–7.

6. Donnelly CJ, Elliott BC, Doyle TLA, Finch CF, Dempsey AR, Lloyd DG. Changes in muscle activation following balance and technique training and a season of Australian football. J Sci Med Sport. Sports Medicine Australia; 2014 May 14.

7. Besier TF, Lloyd DG, Ackland TR. Muscle activation strategies at the knee during running and cutting maneuvers. Med Sci Sports Exerc. 2003 Jan;35(1):119–27.

8. Heiden TL, Lloyd DG, Ackland TR. Knee joint kinematics, kinetics and muscle co-contraction in knee osteoarthritis patient gait. Clin Biomech (Bristol, Avon). Elsevier Ltd; 2009 Dec;24(10):833–41.

9. Inman VT, Ralston H, De CM Saunders J, Bertram Feinstein M, Wright Jr EW. Relation of human electromyogram to muscular tension. Electroencephalogr Clin Neurophysiol. 1952;4(2):187–94.

10. International Society of Electrophysiology and Kinesiology. Standards for Reporting EMG Data. J Electromyogr Kinesiol. 2014 Oct;24(5):I – II.

11. Drake JDM, Callaghan JP. Elimination of electrocardiogram contamination from electromyogram signals : An evaluation of currently used removal techniques. 2006;16:175–87.

12. Lloyd DG, Buchanan TS. Strategies of muscular support of varus and valgus isometric loads at the human knee. J Biomech. 2001 Oct;34(10):1257–67.

13. Hamstra-Wright KL, Swanik CB, Sitler MR, Swanik K a, Ferber R, Ridenour M, et al. Gender comparisons of dynamic restraint and motor skill in children. Clin J Sport Med. 2006 Jan;16(1):56–62.

CHAPTER TWO

EXTENDED LITERATURE REVIEW

2.1 SKELETAL MUSCLE FUNCTION

Skeletal muscle is a connective tissue which receives electrical impulses from alpha motor neurons and undergoes excitation-contraction coupling in order to generate force through the musculotendinous unit (1,2). Muscles perform a wide range of functions to enable human movement. For example, they behave as physiological torque actuators, converting chemical energy into mechanical work. They also function to resist or 'brake' motion, absorbing energy within the parallel and series elastic components of muscle. Furthermore, muscles behave as "isometric struts", enabling elastic energy stored in tendons to be released during dynamic movements (3). At the knee, muscles play a vital role; they support the joint from external forces (i.e., moments), ultimately reducing the load acting on the ligaments during dynamic tasks such as unplanned sidestepping and single leg jump landing tasks (4–8). It is well understood that the muscle's ability to support external loads acting on the body is dependent on various parameters such as the physiological cross-sectional area (PCSA), its line of action (i.e. fibre pennation angle), force-length and force-velocity property, moment arm length, and the rate at which the motor unit action potentials (MUAP) are produced to generate force through the active muscle tissue (2,9).

2.2 MOTOR NEURON – STRUCTURE AND FUNCTION

Motor neurons transmit action potentials to muscle tissue, thus initiating a muscular contraction. The nervous system is composed of functional units known as neurons (10). Any cell which consists of a cell body, dendrites and an axon falls under the broad category of a neuron. For example, the highly complex Purkinje cells found in the cerebellum and the comparatively simple bipolar cells found in the retina both belong to the neuron family (10). The dendrites of a neuron are projections which arise from the cell body (soma) of a neuron (Figure 2.1) and are said to account for ~ 95% of

the surface area of the cell body (2,10). The dendrites have a rich concentration of ligand gated ion channels and are responsible for receiving synaptic input from neighbouring neurons. A single neuron can have up to 50, 000 dendrites (2,10).

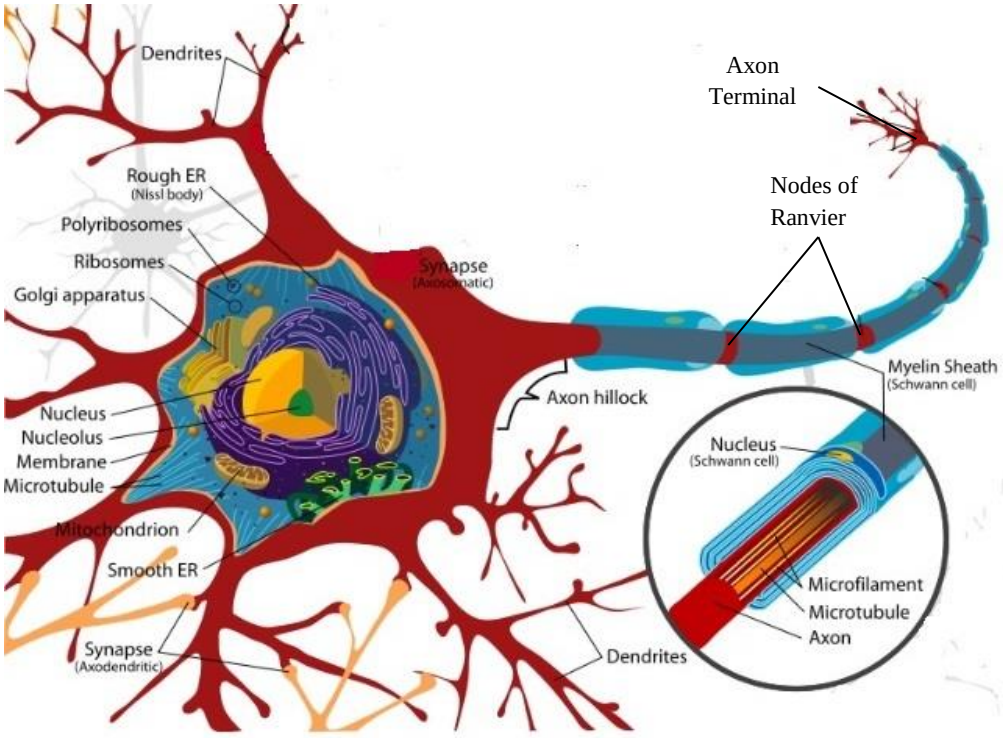

Figure 2.1 Structure of a neuron. Adapted from Mariana Ruiz Villarreal (11)

The cell body of a neuron houses various cell organelles such as mitochondria, ribosomes, Golgi bodies and rough endoplasmic reticulum (Figure 2.1) (1). Similar to the dendrites, the cell body also has a rich concentration of ligand gated ion channels (10). The cell body and initial segment of the axon both play a major role in transforming synaptic inputs received by the dendrites into an action potential (1,2). This phenomenon occurs only when the synaptic inputs received as graded potentials exceed a given threshold value. These two components also control the rate at which action potentials are released; thereby modulating the force produced at the muscle level (1).

The role of an axon is to transfer the action potential to a neighbouring neuron or muscle/gland cell (10,12). This process occurs at a very high speed due to the layer of myelin wrapped around its surface (Figure 2.1) (10). Oligodendrocytes are responsible for wrapping myelin sheaths around the axons of neurons found in the central nervous system (CNS) and the Schwann cells perform similar function in neurons found in the peripheral nervous system (PNS) (1). Unlike the dendrites and cell body, the axon has a high concentration of voltage gated ion channels (in the Nodes of Ranvier) that facilitate the rapid transmission of action potentials across the length of the axon.

Depending on their function, neurons are classified into sensory or motor neurons (10). The sensory neurons operate in the afferent pathway and are responsible for providing sensory information to the CNS (12). They originate from sensory receptors and attach to the CNS via the dorsal root. Conversely, motor neurons operate in the efferent pathway and send neural impulses to the skeletal muscle, eventually exiting the spinal cord through the ventral root (12). Motor neurons can be further classified as somatic or autonomic (10). The somatic motor neurons innervate muscle fibers and are responsible for voluntary movements, whilst the autonomic motor neurons are responsible for innervating internal organs. In the case of a somatic motor neuron, the cell body is in the ventral root of the spinal cord and its axon directly innervates the corresponding muscle fibre (10). Somatic motor neurons are further classified into alpha and gamma motor neurons (1,10). The alpha motor neurons innervate muscle fibres responsible for voluntary movement (extrafusal fibres), and gamma motor neurons innervate muscle spindles (intrafusal fibres) which provide information about the length and rate at which a muscle fibre shortens (1,10). For autonomic neurons, action potentials generated by one neuron are transferred to another within the PNS (10). A single motor neuron can innervate around 3 – 1000 muscle fibres (i.e., ‘motor unit’) (2), through the neuromuscular junction (12). The force produced by a muscle fibre as a

result of a single action potential is known as a “muscle twitch” and the maximum force that can be produced by a muscle as a result of a series of action potentials is known as “tetanic tension” (1).

2.3 EXCITATION – CONTRACTION COUPLING

Excitation-contraction coupling is a term used to describe the outcome of a muscle excitation by the motor neurons and the subsequent events leading to muscular contraction, which results in force production through the musculotendinous unit. When the action potential reaches the nerve terminal, acetylcholine is released (at rest, the electric potential is -60 mV inside the cell). The Ach molecule diffuses into the muscle fibre via the neuromuscular junction and attaches to the neuromuscular end plates causing an increase in the movement of Sodium (Na^+) ions across the sarcolemma. This movement is responsible for altering the membrane potential (depolarisation) from -60mV to + 40mV, leading to the generation of an action potential in the muscle fibre (1). The action potential travels along the sarcolemma, which it then enters via the transverse tubules (T tubules). This leads to the release of Calcium (Ca^{2+}) ions from the sarcoplasmic reticulum. The Ca^{2+} ions bind with the troponin C molecules and this causes troponin C molecules to attach to the region of the troponin I molecule which binds to the actin molecule. These events facilitate the tropomyosin molecule to change its configuration, ultimately uncovering the myosin binding sites on the actin molecule, which allows actin and myosin molecules to interact with each other (1). The change in Ca^{2+} ion concentration returns to a resting level as soon as the action potential has passed because the ions are returned to the sarcoplasmic reticulum via Ca^{2+} pumps located on the membrane of the sarcoplasmic reticulum. This process prepares the cell for another depolarization wave.

Actin and myosin molecules are strongly bound within a muscle fibre (i.e., rigor state). The myosin molecule interacts with the ATP molecule and its binding with the actin molecule weakens. It is the release of P_i that allows for relative movement between actin and myosin, ultimately generating a muscular contraction (i.e., muscle fibre shortening). This is modulated by the molecules known as ATPase which aid in the breakdown of Adenosine triphosphate (ATP) into Adenosine diphosphate (ADP) and inorganic phosphate (P_i). The detachment of P_i from the myosin molecule generates the kinetic energy required to enable the thick filaments (myosin) to pull the thin filaments (actin), thereby, facilitating muscle contraction and subsequent force generation through the fibre (i.e., power stroke) (1). Once the attached ADP molecule is released from myosin, the myosin and actin filaments return to their resting rigor state.

During the cross-bridge cycle, muscle fibres are capable of performing three types of actions; concentric, eccentric and isometric. Concentric contractions involve the muscle producing force while shortening; eccentric contraction occur when a muscle produces force while lengthening and isometric contraction is when a muscle produces force with minimal change in length during the initial stage, thereby shortening the tendon and applying a force on the bone (13).

2.4 ELECTROMYOGRAPHY – AN OVERVIEW

Electromyography (EMG) is a biological signal which represents the sum of the MUAPs that combine to initiate muscular contraction. Therefore, it provides insight on how muscles coordinate to support joints from external forces and facilitate dynamic movement. In the year 1786; Luigi Galvani conducted an experiment to observe the effects of atmospheric electricity on dissected frog skeletal muscles. Galvani observed that the frog muscles began to contract when they came in contact with a metal scalpel. These findings inspired Galvani to conclude that there was indwelling electricity in

animal skeletal muscle and that the observed movement was caused by an externally applied negative charge from the scalpel coming in contact with the positively charged frog leg (14). According to Rasch and Burke, Galvani was the first person to elucidate the presence of electric potential in nerves and muscles (15). This seminal study laid the foundation for a large body of research which has aimed to determine the neuromuscular mechanisms underlying muscle contraction dynamics and force production across a joint (13,16,17).

Duchene (1806 – 1875) investigated the effects of electrical stimulation on facial muscles (18). He was also the first person to show that the antagonist muscles are activated simultaneously with agonist muscles in order to generate/ modulate movement (19). Following this, the Weber brothers were the first to study the reduction in muscle length during a contraction, and the role of bones as mechanical levers (15). The late nineteenth and early twentieth century saw tremendous improvement in the understanding of human movement as a result of the introduction of motion capture devices. During the same period, Alfred Eugen Fick (1829 – 1901) introduced the terms ‘isotonic’ and ‘isometric’ contraction, thereby providing useful insight in the way muscles function (15). The first ever recording of muscle activity during voluntary muscle contraction was made by Marey in 1890, who was believed to have been the first person to coin the term ‘electromyography’ (EMG) (20). The invention of the Audion by De Forest allowed the electronic amplification of EMG signals over a given voltage range and this was viewed as one of the major advancements in the field of EMG (20). In 1944, Inman, Saunders, & Abbott were the first to use EMG to study the function of muscles contributing towards movement at the shoulder joint (21). The use of EMG as a clinical tool then became increasingly prevalent in North America and Europe in the 1950’s as scientists sought to better understand the complex interplay between muscle excitation and movement. With advances in bioengineering (Table 2.1),

the instruments used to record muscle signals became more accessible and feasible for use in research laboratories whose key interests involved modelling muscles to investigate coordination patterns during dynamic activities such as walking, running and cycling.

Table 2.1: Brief overview on the various types of electromyography (EMG) systems used over a period of sixty years (22).

Year	EMG SYSTEM
1950 – 1973	Analogue EMG systems
1973 – 1982	Digital EMG systems
1982 – 1993	Microprocessor controlled EMG systems
1993 – 2001	PC based EMG system
2001 – present	Handheld and Telemetry EMG systems

From an EMG signal, it is possible to study the amplitude and frequency characteristics of the biological signal. The amplitude of the EMG signal can provide insights regarding muscle activity (on/off) and muscle force, whereas the frequency of the EMG signal can provide information pertaining to motor unit recruitment and muscle fatigue (23). Surface EMG (sEMG) signals have extremely varied and broad applications in the field of movement science, bioengineering and biomechanics. They have been used as input signals for the control of exoskeletons (24), EMG driven muscle models (9,25), diagnostic tool in patients suffering from various neurological disorders (26) and they are also commonly used to assess the muscular support offered against the external joint loading during functional movement tasks (4,6,27).

2.5 Filtering of EMG signal

The sEMG technique is a widely used, cost effective, user-friendly, non-invasive technology capable of measuring the excitation characteristics leading to active muscle fibre contractions (18). Despite the relative ease of sEMG data collection, it is highly susceptible to noise from the environment (18), movement artefacts (28), cross-talk from neighbouring muscles (23) and in some cases from other biological signals such as the electrical activity of the heart muscles (29). In general, sEMG has primarily been used to record superficial muscles. The sEMG technique is not suitable for the measurement of muscles with small muscle bellies such as the extra-ocular muscles or the muscles of the inner ear. The electrical activity of deep and/or small muscles are generally studied with more invasive EMG techniques, which utilise fine wire electrodes that are inserted directly into the muscle tissue. Fine wire EMG requires the presence of specialised medical personnel to insert electrodes, and a small, well defined capture volume. This method is not applicable to highly dynamic movements due to the associated risk of muscle damage (30). Despite its advantages as a measurement technique, sEMG is highly susceptible to external sources of systematic noise, thus data collection and processing of these biological signals requires extensive methodological expertise and analogue to digital signal processing knowledge.

The signal processing of sEMG relies heavily on digital filters to attenuate systematic noise, while maintaining the frequency characteristics of the signal (31). The characteristics of a digital filter can be assessed by observing its damping response, roll-off, phase distortion and signal attenuation when used to remove high frequency noise from high frequency signals like a step or impulse (31). Through technological advancements in the field of signal processing, many digital filters are available to process sEMG signals, each having unique filter properties, or advantages and

disadvantages. These filters include the Paynter filter (32), Bessel filter (33), moving average filter (34), critically damped filter (35–37) and underdamped Butterworth filter (16,23). Various filters have been used to process sEMG data throughout the literature, with little to no consistency in the signal processing steps and digital filter types between studies (e.g. processing steps, filter types, normalisation techniques, A/D (Analog/Digital) conversion boards, sample rates etc.), making the comparison of results between studies arduous. A summary of selected studies highlighting the different filters used to process EMG signals over 40 years of published research has been provided in Appendix A.

Recognising the need for established guidelines and standards for the processing of sEMG data, the ISEK (38) and the Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles (SENIAM) (39) have independently published recommendations. While both (ISEK and SENIAM) guidelines provide information on the steps involved in processing sEMG data, neither recommend the adoption of a particular filter type or data normalisation procedure during the signal processing steps. This has resulted in different research groups from adopting similar methodologies and subsequently hampering collaborations or comparison of results between research groups and/or studies.

Table 2.2: The processing steps recommended by SENIAM and ISEK to process sEMG signals (38,39).

Processing steps involved in EMG	
SENIAM	ISEK
1. Apply high pass filter at cut off frequencies ranging between 10 – 20 Hz. 2. Apply low pass filter at a cut off frequency of 500 Hz. 3. Rectification of the signal (Full wave or half wave rectification not specified). 4. Amplitude estimation using root mean square (RMS) method. 5. The SENIAM guideline does not provide any recommendation towards normalisation procedure. 6. Sampling frequency should be greater than 1000 Hz. (Note: This might not be suitable if a critically damped low pass filter is applied at 500 Hz).	1. High pass filter at 10 Hz cut off frequency. 2. Apply low pass filter at a cut off frequency of 350 Hz. 3. Full wave or half wave rectification of the signal. 4. Smoothing of the filter with a low pass filter of given time constant (10 ms– 250 ms). i.e. cut off frequencies between 15.92 – 0.64 Hz. 5. Information about the experimental condition of the normalisation method (isometric, dynamic) and justification for adopting the method should be provided. 6. Sampling frequency should be greater than 700 Hz. The guidelines also recommend that it is ideal to sample data at 2500 Hz.

It is important to consider the properties of a particular filter (underdamped vs. critically damped) or normalisation method, and their influence on the clinical interpretation of data. For example, the characteristics of an underdamped Butterworth filter will typically undershoot or overshoot the signal of interest (34,40) , i.e. the filtered values obtained using an underdamped Butterworth filter will result in values that exceed the true value (> 100%) of the original signal. In the field of biomechanics, underdamped low pass Butterworth filters are almost exclusively used to filter kinetic

and kinematic data. They are generally preferred due to their superior ability to attenuate noise and their optimal stability in the band pass region (13). In contrast, when a critically damped filter is applied to a step response signal, the filter does not undershoot or overshoot the original data, leading Robertson and Dowling to postulate that critically damped filters may be more suitable for filtering analogue signals like sEMG and ground reaction forces (GRF) (40) which do not need to be differentiated. However, while critically damped filters may address the signal artefact limitations of underdamped low pass Butterworth filters, it is important to acknowledge that critically damped filters are reported to be inefficacious in removing noise generated as a result of differentiation of the displacement data (40).

In 1977, when filtering recommendations for kinematic signals were established (41); filtering using a higher number of passes was considered to be a laborious process because filters were applied via mechanical transducers (41). Subsequently, the use of an underdamped filter to process kinematic data was preferred as it required less number of passes to attenuate signal noise and it is these underdamped Butterworth filters that have been arbitrarily applied to process sEMG data. Previously, Winter and Yang used critically damped filters (only low pass filter) to process sEMG data and reported that they were unsuitable as a result of time lag (90 milliseconds) created (26). The lag mentioned in the previous study must have been due to the use of a single pass filter to obtain the linear envelope. Today, applying a dual pass filter to a signal can be easily carried out with the help of the functions like '*filtfilt*' in MATLAB (Matlab 2013a, The Math Works, inc., Natick, Massachusetts, USA). The design of low pass (40) and high pass critically damped filters (42) along with the custom software in Matlab (Matlab 2013a, The Math Works, inc., Natick, Massachusetts, USA) is provided in Appendix D.

Over the past 70 years, processed sEMG data has been used as a diagnostic tool in populations suffering from various neurological disorders and also as a kinesiological tool in understanding the function of muscles during dynamic movements. Very few studies have compared the effect of using different filtering procedures to process sEMG data (16,43,44) , however the authors primarily investigated the methodology used to detect a linear envelope rather than the choice of filter type used during the signal processing steps. The study conducted by Kleissen showed that low pass filtering an EMG signal with a low cut off frequency (3Hz) produced EMG linear envelope profiles which were much smoother and had lower cycle to cycle variability. It was also found that the filter with lower cut off frequency had greater associated time lag (16). Hug et al. found that the ideal cut off frequency to obtain a linear envelop would fall within the range of 4 – 10 Hz if the purpose was to study the force-time history of a muscle (44). ISEK guidelines recommend cut off frequency settings (0.8-15.9 Hz) to obtain linear envelopes, and the filtering of data in both forward and reverse direction to negate the time lag artefact that occurs with a one direction filtering pass (13). However, the overall impact of filter choice (underdamped vs critically damped) to process the raw sEMG data and its bearing on the clinical interpretation of the resulting data remain unknown.

2.6 Normalisation of EMG signal

Once the data is filtered, it has to be normalised. Normalisation is an essential step in processing sEMG data as it enables intra-subject, inter-subject and intra-muscle comparisons (45). This stage of processing is of paramount importance due to its ability to decrease the variability (both intra and inter) and increase the reliability of the processed sEMG data (26,45,46). The normalisation process is achieved by dividing the sEMG linear envelope by the peak muscle activation value and in some cases by the

mean activation obtained from either manual muscle testing procedures such as maximal voluntary isometric contraction, isokinetic dynamometry trials (47), functional movement assessed (i.e. walking, running, sidestepping) (26) or specific dynamic calibration trials (e.g. countermovement jump, all-out sprint task performed in a bicyle-ergometer) (45,48,49). This process should effectively result in muscle activation values between zero and one, thereby providing relative muscle activation.

While ISEK (38) and SENIAM (39) guidelines recommend reporting of the methodology for signal processing of sEMG data, the guidelines do not advocate the use of any specific normalisation procedure. An extensive review of normalisation methods by Burden provides a detailed report examining the approaches employed over the past 25 years (47). This review revealed that researchers have used a variety of methods to elicit maximal muscle activation, resulting in a limited number of studies using similar methodologies. Rudolph et al. initially used maximum voluntary isometric contraction (MVIC) and found that the peak muscle activation values obtained were lower than the muscle activation values obtained during the functional movement trials assessed (i.e., walking and jogging) (50,51). These researchers then adopted a protocol that normalised sEMG signals by using peak muscle activation values from a combination of MVIC (manual muscle testing) and functional movement trials (50,51). Two studies (48,49) have normalised sEMG data (recorded during cycling) with the peak sEMG RMS value obtained from an all-out sprint cycling task and one of them that it was not possible to elicit maximal muscle activations of all muscles of interest from a single task (48). Studies adopting a single dynamic calibration trial to elicit maximal muscle excitation values have been criticised for the same reason (47).

Hence, it is unknown if a series of muscle specific dynamic calibration trials can help in identifying greater muscle activation values when compared with those obtained

from the traditional approaches such as isometric, isokinetic and functional methods. Methodological studies have only compared the peak muscle activation and normalised sEMG data obtained from different normalisation procedures (46,52,53). To date, only one study has explored the effects of normalisation methods on the clinical interpretation of results (54). The study analysed the ability of three different normalisation procedures to detect differences in muscle activation values between the injured and non-injured leg in participants with ACL injury during walking trials. The study revealed that clinical interpretation in terms of muscle activation value can vary as a function of normalisation method (54). The study only analysed walking trials, hence, the findings cannot be transferred to sidestepping or drop landing tasks without further analysis.

Peak muscle activations obtained by MVIC and from functional movements(walking, running) are the most common methods used to normalise sEMG data (55). Of the two approaches, the MVIC normalisation method has been shown to have higher reliability and sensitivity, thus making it the most commonly employed approach in the literature (47,54). However, though reliable, several studies have observed lower magnitude peak muscle activation (mV) from MVIC trials when compared with those obtained during dynamic and functional trials (50,51,56), therefore raising doubts about the ability of MVIC normalisation approaches in eliciting peak muscle activation (100%). Previous studies have explored the use of superimposed burst techniques or twitch interpolation methods to elicit ‘true’ peak muscle activation level (57,58). Despite being seen as effective when applied correctly, these methods are not generally used in clinical research environments due to the high levels of technical proficiency required to successfully implement such techniques and their inconsistency in eliciting ‘true’ peak muscle activation values across all participants tested (57,58). The MVIC method of normalisation appears to be a suitable approach to normalise

sEMG obtained during walking trials as the muscle excitation levels are relatively low and unlikely to supersede the muscle activation levels recorded during manual muscle testing. However, it may not be an appropriate method of normalisation muscle activation during high velocity dynamic tasks such as running and sidestepping.

Another type of normalisation method, commonly used in clinical sport settings (i.e., high velocity movements) involves the use of isokinetic dynamometers to produce peak muscle activation. The major limitation of this method is that the testing procedure requires expensive dynamometry systems, which are time expensive when setting them up to record peak muscle activation levels from multiple joints and degrees of freedom. Using a dynamometer, Kellis and Baltzopoulos found that sEMG muscle activity of the knee flexors and extensors was elevated during concentric contractions when compared with eccentric contractions, and that muscle activity increased with velocity during concentric contractions, whilst decreasing during eccentric contractions (59). However, Burden and colleagues showed that the peak muscle activation of the biceps brachialis obtained during isokinetic trials was independent of the type of muscular contraction and angular velocity of movement (55). Therefore, among the different experimental dynamometry set-up positions and the influence of factors such as specific contraction types, contraction velocities and muscle groups tested; there is potential that obtaining maximum muscle activations for each muscle group tested may not be achieved when using time and cost expensive dynamometry systems.

Ball and Scurr normalised sEMG data of the *Triceps Surae* muscles during a 20 metre sprint using the peak muscle activation obtained from a number of methods such as isometric, isotonic, isokinetic, functional and dynamic methods (45). The authors reported that the dynamic method of normalisation was the most appropriate as the normalised activation of sEMG data were always below 100% and displayed acceptable

reliability between both days and weeks. It should be important to note that all other normalisation methods except the dynamic and functional methods produce muscle activation values greater than 100% MVC (45). Although the results obtained were applicable only to the *Triceps Surae* muscle group, further research is warranted to determine the most appropriate normalisation method for the major muscle groups of the lower limb, to determine if the choice of normalisation method can influence interpretation of a clinical movement assessment like running, sidestepping and landing.

Another commonly used method to normalise sEMG data is the functional normalisation method which utilises the peak muscle activation value obtained from the movement assessed (e.g., walking, running). Yang and Winter showed that this method of normalisation reduces inter-subject variability and is considered to be suitable for normalising sEMG data obtained from patients suffering from neurological disorders (26). The other major advantage of using this method of normalisation is that participants are not required to perform specific calibration trials to obtain peak activation, thereby reducing data collection time and potential risk of participant fatigue (26). Allison, Marshall and Singer showed that this method of normalisation removes the true biological variation within the signal (60). In contrast, Benoit et al. were able to detect the differences between the injured and non-injured leg when sEMG data recorded during walking trials were normalised to peak muscle activation obtained from walking trials (functional movement task) within the same experiment (54). It should be noted that the peak muscle activation values obtained from the functional trials does not provide any information on the degree of muscle activation required to execute a task as we do not have enough evidence to show that the peak obtained is the true maximal voluntary effort (MVE) of each individual muscle (26). However this limitation is associated with all normalisation methods which obtain peak muscle activation values through voluntary contractions. Another drawback of using functional trials for

normalisation is that athletes' may become more proficient at the functional movement trials assessed following intervention training (47), meaning pre to post changes in sEMG muscle activation may be compromised. It is unlikely an athlete will only become efficient at the movement used for normalisation and none of the others tested, although this still remains a possibility. The major drawback associated with this type of normalisation method is that it cannot be used to compare normalised muscle activation values between different trials such as walking and running (47).

Rudolph and colleagues (50,51) have utilised the peak obtained from a combination of MVIC and functional trials. A combination methodology was adopted by these researchers as it was not possible or feasible to elicit maximal muscle activation for all muscles from a single method. The rationale for the use of a combination method is to avoid normalised muscle activation levels exceeding 100% MVC. Other studies have used standardised functional trials such as a straight line running task (4,6). Despite its common use in the literature, this method of normalisation might not be the most suitable as it is not likely to obtain maximum muscle activation values of all the lower limb muscles from a single dynamic movement. To date, no study has investigated the effect of different normalisation methods on sEMG data during common clinical movement assessments like sidestepping and single leg landing. It is therefore unknown what influence a normalisation method may have on the clinical interpretation of these data.

2.7 Review of co-contraction ratio algorithms

In the context of clinical movement analysis for knee ligament injuries, it is possible to obtain clinical information from normalised sEMG data by calculating variables such as mean total muscle activation (TMA) and the co-contraction ratio of the agonist and antagonist muscles surrounding a joint (4,6,27). The formula to

calculate mean TMA has been standardised, however a number of researchers have developed their own algorithms to assess the co-contraction ratio of agonist and antagonist muscles crossing the knee joint during functional tasks (4,6,27,61). This makes comparison of results between studies arduous due to the seemingly vast combinations of muscles and algorithms that can make up a co-contraction ratio (62). It is apparent that with recommendations for the processing of sEMG data (38), research should be conducted to establish standards for the calculation of co-contraction ratios across different joints. To our knowledge, a direct comparison of co-contraction methods is not available in the literature. We aim to bridge this gap by comparing three different co-contraction algorithms currently documented in the literature (25,27,61). Detailed information on the mathematical formula and the muscles included are provided in the Appendix B.

2.8 Conclusion

After a thorough review of literature, it is evident that no study has examined the effect of using different filters and normalisation methods to process EMG data and its impact on the interpretation of results during common clinical movement assessments such as running and change of direction tasks. Therefore, we aim to compare the different filtering and normalisation procedures, assisting the development/evolution of recommendations detailing the use of filtering and normalisation techniques for the signal processing of EMG data. This research will also help in the development of recommendations regarding the use of a single algorithm to calculate co-contraction ratios across the knee joint during clinical movement assessments.

Reference list – Chapter two

1. Enoka RM. Neuromechanics of human movement. Human Kinetics; 2008.

2. Heckman CJ, Enoka RM. Physiology of the motor neuron and the motor unit [Internet]. Handbook of Clinical Neurophysiology. Elsevier B.V.; 2004. 119-147.

3. Rubenson J. More than Meat and a Motor: The Diverse Biomechanical Roles of Skeletal Muscle abd Their Place in "Semi-Living" Machines. Leonardo. 2015;0(0):176–7.

4. Besier TF, Lloyd DG, Ackland TR. Muscle activation strategies at the knee during running and cutting maneuvers. Med Sci Sports Exerc. 2003 Jan;35(1):119–27.

5. Donnelly CJ, Elliott BC, Ackland TR, Doyle TLA, Beiser F, Finch CF, et al. Research in Sports Medicine : An An Anterior Cruciate Ligament Injury Prevention Framework : Incorporating the Recent Evidence. 2012;(July):239–62.

6. Donnelly CJ, Elliott BC, Doyle TLA, Finch CF, Dempsey a R, Lloyd DG. Changes in muscle activation following balance and technique training and a season of Australian football. J Sci Med Sport. Sports Medicine Australia; 2014 May 14.

7. Morgan KD, Donnelly CJ, Reinbolt JA. Elevated gastrocnemius forces compensate for decreased hamstrings forces during the weight-acceptance phase of single-leg jump landing: implications for anterior cruciate ligament injury risk. J Biomech. Elsevier; 2014 Oct 17;47(13):3295–302.

8. Lloyd DG. Rationale for training programs to reduce anterior cruciate ligament injuries in Australian football. J Orthop Sports Phys Ther. 2001 Nov;31(11):645–54; 661.

9. Lloyd DG, Besier TF. An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo. J Biomech. 2003 Jun;36(6):765–76.

10. Widmaier EP, Raff H, Strang KT. Vander's human physiology: the mechanisms of body function. McGraw-Hill Higher Education; 2011.

11. Villareal M. Complete neuron cell diagram. 2007. Available from: commons.wikimedia.org/wiki/File:Complete_neuron_cell_diagram_en.svg

12. Magill RA. Motor learning and control. 8th ed. McGraw-Hill Higher Education; 2004.

13. Winter DA. Biomechanics and motor control of human movement. John Wiley & Sons.

14. Galvani L, Aldini G. De Viribus Electricitatis In Motu Musculari Comentarius Cum Joannis Aldini Dissertatione Et Notis; Accesserunt Epistolae ad animalis electricitatis theoriam pertinentes. Apud Societatem Typographicam; 1792.

15. Rasch PJ, Burke RK. Kinesiology and applied anatomy. Lea & Febiger; 1967.

16. Kleissen RF. Effects of electromyographic processing methods on computer-averaged surface electromyographic profiles for the gluteus medius muscle. Phys Ther. 1990 Nov;70(11):716–22.

17. Clarys JP. Electromyography in sports and occupational settings: an update of its limits and possibilities. Ergonomics. 2000 Oct;43(10):1750–62.

18. Basmajian JV, De Luca C. Muscles alive. 1985.

19. Parent A. Duchenne De Boulogne: a pioneer in neurology and medical photography. Can J Neurol Sci. 2005;32(3):369–77.

20. Kleissen RF, Buurke J, Harlaar J, Zilvold G. Electromyography in the biomechanical analysis of human movement and its clinical application. Gait Posture. 1998 Oct 1;8(2):143–58.

21. Inman V, Saunders M, Abbott L. Observations on the function of the shoulder joint. JB deC. 1944;1–30.

22. Quach JH. Surface Electromyography : Use , Design & Technological Overview. 2007;1–34.

23. De Luca CJ. The use of surface electromyography in biomechanics. J Appl Biomech. 1997;13:135–63.

24. Rosen J, Brand M, Fuchs MB, Arcan M. A myosignal-based powered exoskeleton system. IEEE Trans Syst Man, Cybern - Part A Syst Humans. 2001 May;31(3):210–22.

25. Lloyd DG, Buchanan TS. Strategies of muscular support of varus and valgus isometric loads at the human knee. J Biomech. 2001 Oct;34(10):1257–67.

26. Yang JF, Winter DA. Electromyographic amplitude normalization methods: improving their sensitivity as diagnostic tools in gait analysis. Arch Phys Med Rehabil. 1984;65(9):517–21.

27. Heiden TL, Lloyd DG, Ackland TR. Knee joint kinematics, kinetics and muscle co-contraction in knee osteoarthritis patient gait. Clin Biomech (Bristol, Avon). Elsevier Ltd; 2009 Dec;24(10):833–41.

28. De Luca CJ, Gilmore LD, Kuznetsov M, Roy SH. Filtering the surface EMG signal: Movement artifact and baseline noise contamination. J Biomech. Elsevier; 2010 May 28;43(8):1573–9.

29. Drake JDM, Callaghan JP. Elimination of electrocardiogram contamination from electromyogram signals : An evaluation of currently used removal techniques. 2006;16:175–87.

30. Hug F. Can muscle coordination be precisely studied by surface electromyography? J Electromyogr Kinesiol. 2011 Feb;21(1):1–12.

31. Smith SW. The Scientist and Engineer's Guide to Digital signal processing. IEEE Signal Processing Magazine. 1997.

32. Gottlieb G, Agarwal G. Filtering of electromyographic signals. Am J Phys Med Rehabil. 1970;49(2):142–6.

33. Halbertsma J, De Boer R. On the processing of electromyograms for computer analysis. J Biomech. 1981;14(6):431–5.

34. Kreifeldt JG. Signal versus noise characteristics of filtered EMG used as a control source. IEEE Trans Biomed Eng. 1971 Jan;18(1):16–22.

35. Arsenault A, Winter DA, Marteniuk R. Is there a "normal"profile of EMG activity in gait? Med Biol Eng Comput. 1986;24(4):337–43.

36. Winter DA, Yack H. EMG profiles during normal human walking: stride-to-stride and inter-subject variability. Electroencephalogr Clin Neurophysiol. 1987;67(5):402–11.

37. Winter DA, Sienko SE. Biomechanics of below-knee amputee gait. J Biomech. 1988;21(5):361–7.

38. International Society of Electrophysiology and Kinesiology. Standards for Reporting EMG Data. J Electromyogr Kinesiol. 2014 Oct [cited 2014 Oct 6];24(5):I – II.

39. Stegeman DF, Hermens HJ. Standards for surface electromyography : the European project " Surface EMG for non-invasive assessment of muscles (SENIAM)." 1999;108–12.

40. Robertson DGE, Dowling JJ. Design and responses of Butterworth and critically damped digital filters. J Electromyogr Kinesiol. 2003 Dec;13(6):569–73.

41. Pezzack J, Norman R, Winter DA. An assessment of derivative determining techniques used for motion analysis. J Biomech. 1977;10(5):377–82.

42. Murphy SD, Robertson DGE. Construction of a High-Pass Digital Filter From a Low-Pass Digital Filter. 1990;374–82.

43. Shiavi R, Frigo C, Pedotti a. Electromyographic signals during gait: Criteria for envelope filtering and number of strides. Med Biol Eng Comput. 1998;36(2):171–8.

44. Hug F, Turpin NA., Dorel S, Guével A. Smoothing of electromyographic signals can influence the number of extracted muscle synergies. Clin Neurophysiol. 2012;123(9):1895–6.

45. Ball N, Scurr JC. Efficacy of current and novel electromyographic normalization methods for lower limb high-speed muscle actions. 2011;11(November).

46. Burden A, Bartlett R. Normalisation of EMG amplitude: an evaluation and comparison of old and new methods. Med Eng Phys. 1999 May;21(4):247–57.

47. Burden A. How should we normalize electromyograms obtained from healthy participants? What we have learned from over 25 years of research. J Electromyogr Kinesiol. Elsevier Ltd; 2010 Dec;20(6):1023–35.

48. Dorel S, Guilhem G, Couturier A, Hug F. Adjustment of muscle coordination during an all-out sprint cycling task. Med Sci Sports Exerc. 2012;44(11):2154–64.

49. Rouffet DM, Hautier CA. EMG normalization to study muscle activation in cycling. J Electromyogr Kinesiol. 2008 Oct;18(5):866–78.

50. Rudolph KS, Axe MJ, Snyder-Mackler L. Dynamic stability after ACL injury: who can hop? Knee Surgery, Sport Traumatol Arthrosc. 2000 Jul 20;8(5):262–9.

51. Rudolph KS, Axe MJ, Buchanan TS, Scholz JP, Snyder-Mackler L. Dynamic stability in the anterior cruciate ligament deficient knee. Knee Surgery, Sport Traumatol Arthrosc. 2001 Feb 27;9(2):62–71.

52. Nishijima Y, Kato T, Yoshizawa M, Miyashita M, Iida H. Application of the segment weight dynamic movement method to the normalization of gait EMG amplitude. J Electromyogr Kinesiol. Elsevier Ltd; 2010 Jun;20(3):550–7.

53. Norcross MF, Blackburn JT, Goerger BM. Reliability and interpretation of single leg stance and maximum voluntary isometric contraction methods of electromyography normalization. J Electromyogr Kinesiol. Elsevier Ltd; 2010 Jun;20(3):420–5.

54. Benoit D., Lamontagne M, Cerulli G, Liti a. The clinical significance of electromyography normalisation techniques in subjects with anterior cruciate ligament injury during treadmill walking. Gait Posture. 2003 Oct;18(2):56–63.

55. Burden A, Trew M, Baltzopoulos V. Normalisation of gait EMGs: a re-examination. J Electromyogr Kinesiol. 2003 Dec;13(6):519–32.

56. Pieter Clarys J, Scafoglieri A, Tresignie J, Reilly T, Van Roy P. Critical appraisal and hazards of surface electromyography data acquisition in sport and exercise. Asian J Sports Med. 2010 Jun;1(2):69–80.

57. Dousset E, Jammes Y. Reliability of burst superimposed technique to assess central activation failure during fatiguing contraction. J Electromyogr Kinesiol. 2003 Apr;13(2):103–11.

58. Dowling JJ, Konert E, Andrews DM. Are humans able to elicit maximum muscle force? 1994;179(1):25–8.

59. Kellis E, Baltzopoulos V. Muscle activation differences between eccentric and concentric isokinetic exercise. Med Sci Sports Exerc. 1998;30:1616–23.

60. Allison GT, Marshall RN, Singer KP. EMG signal amplitude normalization technique in stretch-shortening cycle movements. J Electromyogr Kinesiol. 1993 Jan;3(4):236–44.

61. Hamstra-Wright KL, Swanik CB, Sitler MR, Swanik K a, Ferber R, Ridenour M, et al. Gender comparisons of dynamic restraint and motor skill in children. Clin J Sport Med. 2006 Jan;16(1):56–62.

62. Ford KR, van den Bogert AJ, Myer GD, Shapiro R, Hewett TE. The effects of age and skill level on knee musculature co-contraction during functional activities: a systematic review. Br J Sports Med. 2008 Jul;42(7):561–6.

CHAPTER THREE

THE INFLUENCE OF DIGITAL FILTER TYPE AND NORMALISATION METHOD ON SURFACE EMG DATA DURING DYNAMIC MOVEMENT TASKS

The influence of digital filter type and normalisation method on surface EMG data during dynamic movement tasks

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ABSTRACT

Throughout the literature, sEMG data is filtered and normalised using a variety of methods, making comparison between studies difficult. This study therefore aimed to determine the potential influence of digital filter and normalisation method selection on the clinical interpretation of results. Additionally, co-contraction ratios of the agonist /antagonist muscles crossing the knee joint were calculated via three well documented formulae. Twelve elite athletes completed a sidestepping protocol along with isokinetic dynamometry and dynamic calibration trials. sEMG data were processed using an underdamped Butterworth filter and independently normalised using the following three methods; peak muscle activation obtained from a combination of isokinetic dynamometry, functional movements trials and dynamic calibration trials (COMB), peak muscle activation obtained from a functional movement trial only (FUNC), and average peak muscle activation obtained from straight line running trials (SLRm). For each normalisation method, mean total muscle activation (TMA) and directed co-contraction ratio (DCCR) during the pre-contact (50ms prior to foot contact of the stance leg; PC50) and weight acceptance (WA) phases of a sidestep were determined (1). The COMB method presented as the most suitable normalisation procedure and was therefore used to obtain mean TMA and DCCR values (PC50 and WA) from a signal independently filtered using a second order zero-lag underdamped Butterworth and critically damped filter. Integrated EMG was obtained during the PC50 phase of all functional movements assessed using a second order zero-lag underdamped Butterworth and critically damped filter. Results indicate that the underdamped Butterworth filter is the most suitable to filter sEMG data due to an increased ability to attenuate noise. Furthermore, the COMB and DCCR methods are the most suitable normalisation and co-contraction ratio methods, respectively.

Keywords: underdamped Butterworth filter; critically damped filter; EMG; sEMG; normalisation, co-contraction ratio.

3.1 INTRODUCTION

Electromyography (EMG) is a common measurement technique that has been widely used in clinical and research settings to record the electrical activity of skeletal muscles during static and dynamic movement tasks (2). To attain clinically relevant information from these high frequency time varying signals (bandwidth 10 – 500 Hz) (3), digital filters are used extensively to remove sources of systematic noise (i.e. movement artefacts (4) and heart rate contamination (5)). The raw sEMG signal is band pass filtered (10 – 350 Hz), full wave rectified and then a low pass filter of a given time constant (50 – 250ms) is applied to smooth the rectified sEMG signal (6). Additionally, processed EMG signals are generally normalised to a muscle's peak activation for researchers to make intra-subject, inter-subject and intra-muscle comparisons. The International Society of Electrophysiology and Kinesiology (ISEK) and Surface ElectroMyoGraphy for the Non-invasive Assessment of Muscles (SENIAM) provide signal processing guidelines, detailing the steps involved in processing a raw EMG signal. Though it is widely acknowledged that digital filters possess unique filter characteristics that influence the time varying features of the filtered signal (i.e., minima and maxima), there are currently no standards for the type of digital filter used for the signal processing of an EMG signal. There are also no recommendations for the methods used to normalise the EMG signal.

There are many digital filters that can be used to process EMG signals, including Paynter filter (7), Bessel filter (8), moving average filter (9) and the critically damped filter (10). Though there are many choices available, the filter predominantly used in the field of biomechanics to process EMG data is the underdamped Butterworth filter (11). Though widely used in the field, it has been well documented that underdamped Butterworth filters are prone to undershoot or overshoot high frequency signals (i.e. step

response) when removing noise (9,12). As EMG are characterised as being high frequency signals, underdamped Butterworth filters may be adding unwanted artefact information to the processed signal. Unlike the underdamped Butterworth filters, critically damped filters do not undershoot or overshoot high frequency signals during processing. For this reason it would appear that critically damped filters may offer a logical alternative to the popular underdamped Butterworth (12). To the best of our knowledge, there have been very few published studies comparing the impact of different filtering approaches on the clinical interpretation of EMG data processed (13–15). However, the foci of those studies were to investigate the different approaches used to obtain linear envelopes and its impact on the properties of the EMG signals (13–15). Therefore, these studies did not directly compare the effect of using an underdamped and critically damped filter to process EMG and its impact on clinical interpretation of results.

Normalisation is another essential step involved in the processing of EMG data as it facilitates intra- and inter-subject comparisons, along with intra-muscle comparisons (16). It also reduces signal variability (intra-, inter-subject) and improves reliability of results (17). Within the standards for reporting EMG data (6), it is advised that EMG data should be normalised, however no recommendations have been published advocating the specific type of normalisation method to be used. This leaves a seemingly vast number of normalisation methods a researcher can choose from. Some of the commonly used normalisation methods are maximum voluntary isometric contraction (17), functional methods (i.e. maximum obtained during the functional movement assessed) (18), isokinetic dynamometry tasks (19), dynamic calibration trials (e.g. countermovement jump, all-out sprint cycling task) (16,20,21) or finally, a combination of these methods. Hence, it is unclear if the normalisation method used can

influence the clinical interpretation of common dependent variables used during clinical movement assessments.

Two prominent measures used by clinicians include mean total muscle activation (TMA) and co-contraction ratios (CCR) (1,22,23). CCR are generally used to estimate the magnitude of agonist versus antagonist muscles activation across a joint when a net joint moment is produced (24). These measurements can provide researchers with information on the relative mechanical efficiency of movement (24), and also information on joint stabilisation/support (along with mean TMA) during a functional movement task (22,1). The methods (e.g. included musculatures) and algorithms available to calculate co-contraction ratios vary extensively throughout the literature (22,25–27), making comparison of results between studies a difficult task (24). As with recommendations for the processing of sEMG data, research should focus on establishing standards for the calculation of co-contraction ratios across different joints.

The primary purpose of this study was therefore to investigate the effect of utilising different digital filtering methods and normalisation procedures to process sEMG data, and to subsequently assess the clinical information obtained from the different approaches. A secondary aim was to determine the most suitable algorithm for obtaining co-contraction ratio of agonist and antagonist muscles crossing the knee joint on the basis of clinical information provided.

3.2 METHODS

3.2.1 PARTICIPANTS

Sixteen athletes (22.2 ± 2.9 years. 167 ± 10 cm, 66.3 ± 6.7 kg) from the Australian National Women's Field Hockey Team participated in this study. Each participant read and signed the consent forms (Approval ID– RA/4/1/5713) approved by

the Human Research ethics committee at the University of Western Australia. Data for this study was collected as an addendum to a larger biomechanical analysis. Due to prior history of ACL injury, some athletes (n = 4) were unable to complete the dynamic calibration tasks, hence their data was unusable.

3.2.2 EXPERIMENTAL PROTOCOL

The participants performed planned straight running trials (PSLR), planned sidestepping (PSS) and unplanned sidestepping (UPSS) trials at $5ms^{-1}$ as per the UWA sidestepping protocol (1,22) along with dynamic calibration and isokinetic dynamometry trials. The dynamic calibration trials included in the protocol were single leg drop jump (SLDJ) where particiapnts were asked to jump off a 31 centimetre box onto a single limb and rebound for height immediately, counter movement jump (CMJ) and single leg squat (SLSQ). All trials performed in this study were adopted from previous work (1,28,29). It should be noted that isokinetic dynamometry trials were performed to elicit maximal muscle acitivation (within the experiment) of the knee flexor and extensor muscle groups only. All participants performed three sets of four repetitions of flexion-extension at 60°/second through a total range of 90°. Sets were performed at 50%, 75% and 100% of the participants maximum, where the third set was used for analysis.

3.2.3 KINEMATICS AND GROUND REACTION FORCE DATA

Whole body kinematics data were recorded using a 12-camera VICON MX motion capture system (VICON, Oxford Metrics Ltd., UK) at 250 Hz during the functional movement trials (PSLR, PSS and UPSS) and dynamic calibration trials (SLSQ, CMJ, SLDJ). Along with the motion capture data, ground reaction force (GRF) data (AMTI, Watertown, MA) were recorded synchronously with the kinematic data at 2000 Hz during the functional movement and dynamic calibration trials. Marker trajectories and GRF data were low pass filtered at 15 Hz cut off frequency to remove

artefacts. The low pass filter cut off frequency was determined using residual analysis (11). Following this, the pre-contact and weight acceptance phase were determined for PSLR, PSS and UPSS trials using custom software program in MATLAB (Matlab 2013a, The Math Works, inc., Natick, Massachusetts, USA). The pre-contact (PC50) phase was defined as the phase occurring 50 milliseconds prior to foot contact of the stance leg. The weight acceptance (WA) phase was defined as the phase in between heel contact and the first trough observed in the ground reaction force signal (22). The hip, knee and ankle joint angle recorded during the WA phase of all functional movement and dynamic calibration trials (refer to Appendix E).

3.2.4 sEMG DATA COLLECTION

sEMG data was recorded during all trials within the experiment using a 16 channel telemetry system (TeleMyo 2400 G2, Noraxon, Scottsdale, Arizona) at 2,000 Hz with a 16 bit A/D card (Power 1401, Cambridge Electronic Design, UK). Input impedance was > 100 MΩ; common mode rejection ratio (CMRR) was > 100 dB at 50 Hz and the amplifier gain was set at 100.

3.2.5 SKIN PREPARATION

Prior to electrode placement, the skin was prepared by shaving, exfoliating and then cleaning with alcohol. Bipolar disc shaped (diameter = 30mm) disposable surface electrodes (Cleartrace^{TM} Ag/Agcl, ConMed, Utica, NY), with an inter-electrode distance of 20 mm were placed over the muscle bellies of the following nine muscles;) *Semimembranosus* (SM), *long head of Biceps Femoris* (BF), *Vastus Lateralis* (VL), *Vastus Medialis* (VM), *Rectus Femoris* (RF), *Gluteus Maximus* (Gmax), *Gluteus Medius* (Gmed), *Medial Gastrocnemius* (MG) and *Lateral Gastrocnemius* (LG). These muscles were identified according to the methods published by Perotto & Delagi (30).

3.2.6 DATA PROCESSING

The sEMG data was filtered separately using an 2nd order zero-lag underdamped Butterworth and critically damped filter according to the guidelines specified by SENIAM (3) and ISEK (6). The following steps were carried out to process the raw sEMG data : 1) removal of direct current (DC) offset; 2) band pass filtered between 30Hz (1,5,22,31) and 400 Hz (3); 3) full wave rectification; and then 4) linear envelope was created by low pass filtering at 6 Hz (1,32). To assess the effect of normalisation methods, the EMG data processed with an underdamped Butterworth filter was selected for further comparative analysis. The three different normalisation methods used in the current study are normalisation with the maximal muscle activation obtained from functional movements assessed (FUNC), average peak from PSLR trials (SLRm) and peak muscle activation obtained from a combination of functional movement task, dynamic calibration and isokinetic dynamometry trials (COMB). Mean Total Muscle Activation (TMA) was calculated for gluteals (GL) (n = 2), quadriceps (QUAD) (n = 3), hamstrings (HAM) (n = 2), gastrocnemius (GAS) musculature (n = 2) and the muscles crossing the knee joint (KJM) (n = 7) during the PC50 and WA phase of all functional movements assessed from sEMG data normalised in three separate ways. Similarly, directed co-contraction ratio (DCCR) (refer to Appendix B) was calculated according to the algorithm published by Heiden et al. (23) for all functional movement trials assessed.

After determining the most suitable normalisation method, the entire signal processing procedure stated above (DC offset removal, band pass filtering, full wave rectification and low pass filtering) was performed on raw sEMG data using a low and high pass critically damped filter (12,33). This step was performed to assess if any difference arise as a result of the filtering procedure. Integrated EMG (IEMG) was

calculated using the trapezoidal integrator function in MATLAB (Matlab 2013a, The Math Works, inc., Natick, Massachusetts, USA) for all nine muscles during the PC50 phase of PSLR, PSS and UPSS trials using an underdamped Butterworth and critically damped filter.

In order to compare and contrast the different co-contraction ratios reported in the literature, co-contraction ratios were also calculated according to the formulas devised by Lloyd and Buchanan (34) and Hamstra-Wright et al. (27). Detailed information outlining the input parameters and formulas for each of the three algorithms is provided in Appendix B. To assess the effect of normalisation methods, the EMG data processed with an underdamped Butterworth filter was selected for further comparative analysis. This choice was made in order to maintain consistency with the existing literature. Co-contraction ratios and mean TMA obtained during the PC50 and WA phase of EMG data normalised using three different normalisation methods were also compared. Foreshadowing the results section, for comparison between digital filtering approaches, the EMG data normalised with the peak muscle activation obtained from a combination of all three methods of normalisation was used.

3.2.7 STATISTICAL ANALYSIS

DCCR and mean TMA obtained from three different methods of normalisation using an underdamped Butterworth filter were compared using one-way repeated measures ANOVA. IEMG, TMA and DCCR obtained separately using a 2^{nd} order zero-lag underdamped Butterworth and critically damped filter during the EMG signal processing steps were compared using paired sample t-test (parametric data) and Wilcoxon signed rank test (non-parametric data). All statistical analysis was performed using SPSS for windows (Version 22.0; SPSS; Chicago, IL, USA). A significance level of $\alpha < 0.05$ (Sidak post hoc analysis) was used for one-way repeated measures ANOVA

and $\alpha < 0.05$ was used for paired sample t-test (parametric data) and Wilcoxon signed rank test (non-parametric data). In order to compare the co-contraction ratios obtained using the three different algorithms, descriptive statistical measures (mean and standard deviations) were used. Statistical tests (parametric or non-parametric) were not performed as the all three formulas provide a ratio whose limits vary from one another. For instance, the CCR provides a value in between 0 to 1; DCCR provides a ratio between -1 to +1 and the HW method can provide values ranging from 0 to 5. Hence, they measure the extent of co-contraction in different scales.

3.3 RESULTS

3.3.1 PEAK MUSCLE ACTIVATION

The majority of participants were able to elicit peak muscle activation within the experiment for gluteals (Gmax, Gmed), quadriceps (VL, VM) and gastrocnemius (MG, LG) muscles' by performing dynamic trials such as SLSQ, SLDJ and CMJ. Isokinetic dynamometry trials were most suitable to elicit peak muscle activation of the SM and BF muscles' (Table 3.1). A small number of subjects were able to elicit peak muscle activations for gluteals, quadriceps (except RF), hamstrings and gastrocnemius musculature from one of the functional trials (PSLR, PSS and UPSS) (Table 3.1).

Table 3.1: Number of participants who have elicited maximal muscle activation within the experiment during isokinetic dynamometer, dynamic calibration and functional trials for each of the lower limb muscles tested. It should be noted that the dynamometer trials were only used to attain maximal muscle activation from the quadriceps and hamstrings muscle groups only. N/A indicates not applicable.

Trial type	Gmax	Gmed	VM	RF	VL	SM	BF	MG	LG
Isokinetic Dynamom-etry	N/A	N/A	3	6	1	9	7	N/A	N/A
Dynamic calibration Trials	7	7	8	6	7	2	2	7	7
Functional Trials	5	5	1	0	4	1	3	5	5

3.3.2 COMPARISON BETWEEN NORMALISATION METHODS

As we had obtained peak muscle activation for the nine lower limb muscles from a variety of trials, we decided to normalise the EMG data from the peak muscle activation obtained from a combination of dynamic, functional and isokinetic dynamometry trials (COMB), functional movement trial assessed (FUNC) and peak average of PSLR trials (SLRm) respectively.

3.3.2.1 MEAN TOTAL MUSCLE ACTIVATION

A significant main effect was observed in the mean TMA estimates of the GL, QUAD, HAM, GAS and KJM muscle groups during the PC50 and WA phase of all functional movement trials assessed ($\alpha = 0.05$). Sidak *post-hoc* tests revealed that the COMB method of normalisation produced significantly lower estimates of mean TMA for all five muscle groups across both phases (PC50 and WA) and all three functional movement trials (PSLR, PSS and UPSS) assessed. The *p* values calculated were found to be in the range of $p = 0.016$ to $p < 0.001$ (Table 3.2).

During the PC50 phase of all three functional movement trials assessed, the FUNC method of normalisation produced significantly lower estimates of mean TMA

for the HAM and KJM muscle groups when compared with the SLRm method of normalisation. The *p* values were found to be in the range of $p = 0.015$ to $p < 0.001$ (See table 3.2). The FUNC method of normalisation also produced significantly lower estimates of mean TMA for GL, QUAD and GAS muscles when compared with the mean TMA estimates obtained from SLRm method of normalisation during the PC50 phase of PSS trials. The *p* values were found to be in the range of $p = 0.008$ to $p < 0.001$. During the PC50 phase of UPSS trials, the FUNC method of normalisation also produced significantly lower estimates of mean TMA for the QUAD muscle group when compared with the estimate obtained from SLRm method of normalisation ($p = 0.007$).

The FUNC method of normalisation produced significantly lower estimates of mean TMA for all muscle five groups across the weight acceptance phase of PSS trials when compared with the mean TMA estimates obtained from SLRm method of normalisation. The *p* values were found to be in the range of $p = 0.002$ to $p < 0.001$. During the WA phase of UPSS trials, the FUNC method of normalisation produced significantly lower estimates of mean TMA for the GL, QUAD, GAS and KJM muscle groups. The *p* values were found to be in the range of $p = 0.010$ to $p = 0.002$ (Table 3.2).

3.3.2.2 DIRECTED CO-CONTRACTION RATIO

A significant main effect was observed for SM/BF DCCR values obtained during the PC50 phase of PSLR trials between all three normalisation methods. However, the Sidak *post-hoc* test revealed that there was no significant difference between the three values obtained from the three different methods of normalisation. The *p* values were found to be in the range of $p = 0.056$ to $p = 0.624$ The COMB method of normalisation indicated that the BF muscle was more active when compared

with SM; yet, the SM/BF DCCR obtained from the FUNC and SLRm method indicated that the BF musculature were more active (refer to Table 3.3). These results suggest that the clinical interpretation of EMG data can vary as a result of the normalisation method employed (Table 3.3).

A significant main effect was also observed in the F/E DCCR value obtained during the PC50 phase of PSS trials from the COMB, FUNC and SLRm method of normalisation. However, Sidak *post-hoc* test revealed that there was no significant difference between the values obtained (Table 3.3).

In the WA phase of PSLR and PSS trials, the F/E DCCR obtained from all three normalisation methods were significantly different from each other. Sidak *post-hoc* tests revealed that the F/E DCCR values obtained from the COMB method of normalisation during PSLR trials were significantly different from the values obtained from the FUNC ($p = 0.005$) and SLRm ($p = 0.008$) methods of normalisation. During the WA phase of PSS trials, the COMB method produced significantly different F/E DCCR estimates when compared with the value obtained from the FUNC ($p = 0.015$) method of normalisation. In clinical terms, the COMB method would have suggested co-contraction would have been directed towards the flexor muscle groups during WA. However, the other two methods would have stated that there was maximum co-contraction between the flexor and extensor muscle groups (Table 3.3).

Table 3.2: Mean total muscle activation of GL, QUAD, HAM, GAS and KJM muscles obtained from EMG data normalised separately using COMB, FUNC and SLRm respectively. TMA was calculated during the PC50 and WA phase of PSLR, PSS and UPSS.

Mean total muscle activation (TMA)	**PSLR**			**PSS**			**UPSS**		
Phase: PC50									
	COMB	FUNC	SLRm	COMB	FUNC	SLRm	COMB	FUNC	SLRm
GL	$0.15 \pm 0.06^{\dagger,a}$	$0.24 \pm 0.12^{\dagger,b}$	$0.29 \pm 0.11^{\dagger,b}$	$0.49 \pm 0.20^{\dagger,a}$	$0.63 \pm 0.30^{\dagger,b}$	$1.01 \pm 0.59^{\dagger,c}$	$0.47 \pm 0.19^{\dagger,a}$	$0.57 \pm 0.23^{\dagger,b}$	$0.98 \pm 0.58^{\dagger,b}$
QUAD	$0.15 \pm 0.06^{\dagger,a}$	$0.26 \pm 0.09^{\dagger,b}$	$0.33 \pm 0.13^{\dagger,b}$	$0.23 \pm 0.05^{\dagger,a}$	$0.35 \pm 0.09^{\dagger,b}$	$0.52 \pm 0.18^{\dagger,c}$	$0.30 \pm 0.13^{\dagger,a}$	$0.41 \pm 0.17^{\dagger,b}$	$0.67 \pm 0.37^{\dagger,c}$
HAM	$0.63 \pm 0.29^{\dagger,a}$	$0.97 \pm 0.28^{\dagger,b}$	$1.25 \pm 0.46^{\dagger,c}$	$0.79 \pm 0.25^{\dagger,a}$	$1.10 \pm 0.20^{\dagger,b}$	$1.68 \pm 0.40^{\dagger,c}$	$0.66 \pm 0.20^{\dagger,a}$	$1.00 \pm 0.25^{\dagger,b}$	$1.40 \pm 0.40^{\dagger,c}$
GAS	$0.20 \pm 0.14^{\dagger,a}$	$0.26 \pm 0.17^{\dagger,b}$	$0.29 \pm 0.19^{\dagger,b}$	$0.47 \pm 0.27^{\dagger,a}$	$0.55 \pm 0.33^{\dagger,b}$	$0.68 \pm 0.35^{\dagger,b}$	$0.44 \pm 0.24^{\dagger,a}$	$0.53 \pm 0.31^{\dagger,a,b}$	$0.66 \pm 0.31^{\dagger,b}$
KJM	$0.98 \pm 0.42^{\dagger,a}$	$1.50 \pm 0.42^{\dagger,b}$	$1.87 \pm 0.63^{\dagger,c}$	$1.50 \pm 0.38^{\dagger,a}$	$2.00 \pm 0.42^{\dagger,b}$	$2.89 \pm 0.59^{\dagger,c}$	$1.40 \pm 0.36^{\dagger,a}$	$1.93 \pm 0.54^{\dagger,b}$	$2.73 \pm 0.89^{\dagger,c}$
Phase: WA									
	COMB	FUNC	SLRm	COMB	FUNC	SLRm	COMB	FUNC	SLRm
GL	$0.40 \pm 0.10^{\dagger,a}$	$0.61 \pm 0.14^{\dagger,b}$	$0.79 \pm 0.27^{\dagger,b}$	$0.72 \pm 0.15^{\dagger,a}$	$0.90 \pm 0.21^{\dagger,b}$	$1.48 \pm 0.61^{\dagger,c}$	$0.56 \pm 0.19^{\dagger,a}$	$0.68 \pm 0.23^{\dagger,b}$	$1.18 \pm 0.62^{\dagger,c}$
QUAD	$0.49 \pm 0.20^{\dagger,a}$	$0.86 \pm 0.28^{\dagger,b}$	$1.08 \pm 0.45^{\dagger,b}$	$0.67 \pm 0.12^{\dagger,a}$	$1.04 \pm 0.22^{\dagger,b}$	$1.55 \pm 0.47^{\dagger,c}$	$0.78 \pm 0.22^{\dagger,a}$	$1.08 \pm 0.22^{\dagger,b}$	$1.83 \pm 0.84^{\dagger,c}$
HAM	$0.31 \pm 0.16^{\dagger,a}$	$0.50 \pm 0.18^{\dagger,b}$	$0.63 \pm 0.26^{\dagger,b}$	$0.63 \pm 0.16^{\dagger,a}$	$0.88 \pm 0.17^{\dagger,b}$	$1.38 \pm 0.43^{\dagger,c}$	$0.50 \pm 0.15^{\dagger,a}$	$0.74 \pm 0.15^{\dagger,b}$	$1.06 \pm 0.31^{\dagger,b}$
GAS	$0.37 \pm 0.17^{\dagger,a}$	$0.46 \pm 0.19^{\dagger,b}$	$0.52 \pm 0.19^{\dagger,b}$	$0.60 \pm 0.23^{\dagger,a}$	$0.69 \pm 0.28^{\dagger,b}$	$0.88 \pm 0.31^{\dagger,c}$	$0.51 \pm 0.18^{\dagger,a}$	$0.61 \pm 0.23^{\dagger,b}$	$0.74 \pm 0.22^{\dagger,c}$
KJM	$1.18 \pm 0.41^{\dagger,a}$	$1.82 \pm 0.41^{\dagger,b}$	$2.23 \pm 0.64^{\dagger,b}$	$1.90 \pm 0.38^{\dagger,a}$	$2.61 \pm 0.52^{\dagger,b}$	$3.80 \pm 0.95^{\dagger,c}$	$1.78 \pm 0.33^{\dagger,a}$	$2.43 \pm 0.46^{\dagger,b}$	$3.62 \pm 1.03^{\dagger,c}$

† indicates significant main effect (difference between normalisation methods), ($p < 0.05$) ($n = 12$). a, b, c indicates significant Sidak adjusted post hoc difference between independent variables ($\alpha = 0.05$) ($n = 12$). If two dependent variables possess the same letter they are not significantly different from each other.

Table 3.3: Flexion/Extension (F/E), Medial/Lateral (M/L) and Semimembranosus/Biceps Femoris (SM/BF) DCCR obtained during the PC50 and WA phase of PSLR, PSS and UPSS trials from EMG data normalised separately using COMB, FUNC and SLRm.

Directed Co-contraction ratio (DCCR)									
	F/E DCCR			M/L DCCR			SM/BF DCCR		
Phase:PC50									
	COMB	FUNC	SLRm	COMB	FUNC	SLRm	COMB	FUNC	SLRm
PSLR	0.74 ± 0.10	0.71 ± 0.12	0.70 ± 0.11	- 0.01±0.34	0.09 ± 0.29	0.13 ± 0.19	- 0.12±0.40†	0.05 ± 0.36†	0.11 ± 0.22†
PSS	0.74 ± 0.08†	0.70 ± 0.09†	0.69 ± 0.08†	0.03 ± 0.26	0.09 ± 0.17	0.16 ± 0.12	- 0.06±0.28	0.07 ± 0.23	0.18 ± 0.17
UPSS	0.60 ± 0.24	0.60 ± 0.23	0.55 ± 0.20	0.03 ± 0.21	0.11 ± 0.16	0.13 ± 0.14	- 0.14±0.26	0.01 ± 0.21	0.09 ± 0.24
Phase: WA									
	COMB	FUNC	SLRm	COMB	FUNC	SLRm	COMB	FUNC	SLRm
PSLR	0.04 ± 0.31^{†,a}	- 0.10±0.31^{†,b}	- 0.12±0.30^{†,b}	0.05 ± 0.24	0.05 ± 0.20	0.07 ± 0.17	-0.14±0.36	0.02±0.36	0.07 ± 0.27
PSS	0.23 ± 0.15^{†,a}	0.01 ± 0.16^{†,b}	0.07 ± 0.19^{†,a,b}	0.04 ± 0.21	0.07 ± 0.11	0.10 ± 0.08	-0.18±0.27	-0.06±0.22	0.04 ± 0.24
UPSS	- 0.01±0.28	- 0.04±0.21	- 0.15±0.27	0.05 ± 0.18	0.11 ± 0.13	0.10 ± 0.07	-0.13±0.30	0.02±0.25	0.09 ± 0.20

† indicates significant main effect (difference between normalisation methods), ($p < 0.05$) ($n = 12$). a, b, c indicates significant Sidak adjusted post hoc difference between independent variables ($\alpha = 0.05$) ($n = 12$). If two dependent variables possess the same letter they are not significantly different from each other.

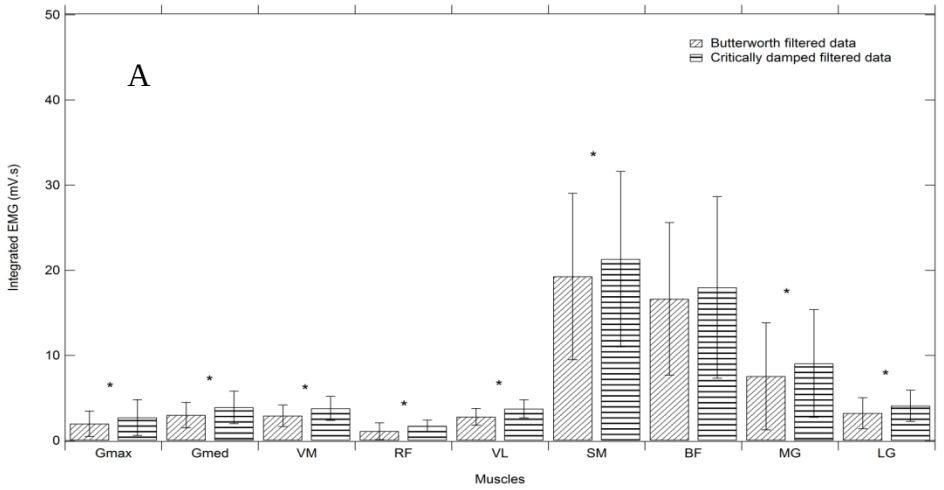
F/E DCCR – positive values indicates that the flexor muscles are more active, negative values indicate that the extensors are more active and values close to zero indicate maximum co-contraction between the flexors and extensors. M/L DCCR – positive values indicates that the medial muscles are more active, negative values indicate that the lateral muscles are more active and values close to zero indicate maximum co-contraction between the medial and lateral muscles. SM/BF DCCR – positive values indicates that the semimembranosus muscle is more active, negative values indicate that the biceps femoris muscle is more active and values close to zero indicate maximum co-contraction between semimembranosus and biceps femoris muscle.

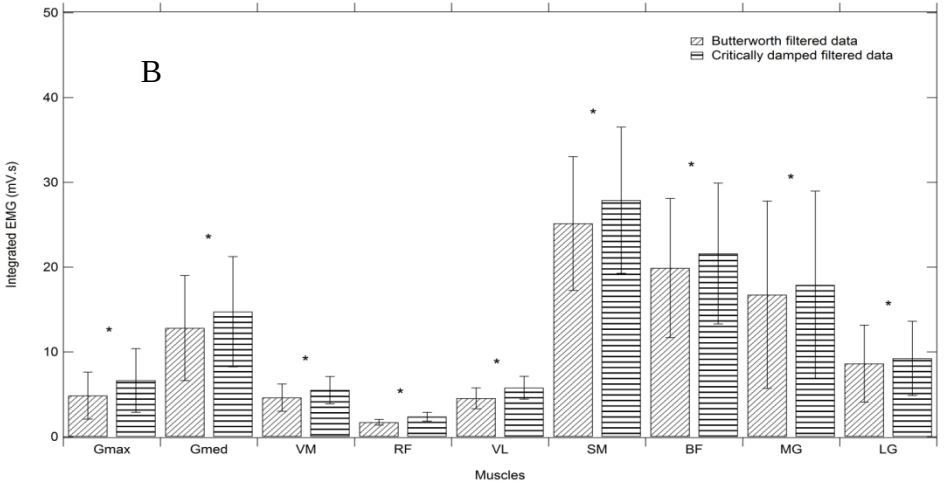
3.3.3 COMPARISON BETWEEN DIGITAL FILTERS

3.3.3.1 INTEGRATED EMG

During the PC50 phase of PSLR trials, the IEMG values obtained using an underdamped Butterworth filter were significantly lower than those of a critically damped filter for the following muscles; Gmax, Gmed, VM, VL, RF, SM, MG and LG. The *p* values were found to lie between $p = 0.03$ to $p < 0.001$ (Figure 3.1).

During the PC50 phase of PSS and UPSS trials, the underdamped Butterworth filter produced significantly lower estimates of IEMG for all muscles. The *p* values were found to lie between $p = 0.012$ to $p < 0.001$.





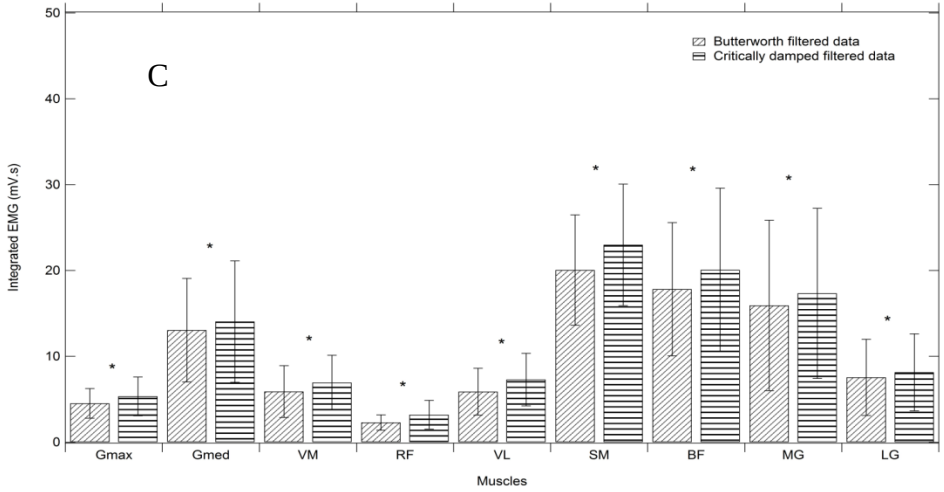


Figure 3.1 A, B and C: Integrated EMG(IEMG; mV.s) of nine lower limb muscles recorded during the PC50 phase of planned straight line running (PSLR), planned sidestepping (PSS) and unplanned sidestepping (UPSS) processed independently using a 2nd order zero-lag underdamped and critically damped filter. * indicates significant difference between CD and BW ($p << 0.05$)

3.3.3.2 MEAN TOTAL MUSCLE ACTIVATION

The critically damped filter produced higher estimates of mean TMA for the QUAD musculature during the PC50 phase of PSLR ($p = 0.004$), PSS ($p < 0.001$) and UPSS ($p < 0.001$). The critically damped filter also produced higher estimates of mean TMA for the GAS musculature ($p = 0.005$) during the PC50 phase of PSLR trials. The mean TMA of GL muscles during the WA phase of PSLR ($p < 0.001$), PSS ($p < 0.001$) and UPSS ($p = 0.005$) was also significantly different (Table 3.4).

Table 3.4: Mean total muscle activation (TMA) of the gluteals, quadriceps, hamstrings, gastrocnemius and all muscles crossing the knee joint during 50 ms pre-contact (PC50) and weight acceptance (WA) phase obtained using a 2nd order zero-lag underdamped Butterworth and critically damped filter during planned straight line running (PSLR), planned sidestepping (PSS) and unplanned sidestepping (UPSS).

Mean total muscle activation (TMA)						
	PSLR		**PSS**		**UPSS**	
Phase: PC50						
	BW	CD	BW	CD	BW	CD
GL	0.15±0.06	0.16±0.06	0.49±0.20	0.49 ±0.21	0.47 ± 0.19	0.46±0.19
QUAD	0.15±0.06	0.18±0.07*	0.23±0.05	0.26 ±0.05*	0.30 ± 0.13	0.34±0.13*
HAM	0.63±0.29	0.61 ± 0.29	0.79±0.25	0.7 ±0.26	0.66 ± 0.20	0.66 ± 0.20
GAS	0.20±0.14	0.23±0.15*	0.47±0.27	0.47±0.25	0.44 ± 0.24	0.44 ± 0.22
KJM	0.98±0.42	1.03 ± 0.43	1.50±0.38	1.51±0.40	1.40 ± 0.36	1.43 ± 0.34
Phase: WA						
	BW	CD	BW	CD	BW	CD
GL	0.40±0.10	0.37±0.09*	0.72 ± 0.15	0.66 ±0.16*	0.56 ± 0.19	0.52±0.18*
QUAD	0.49±0.20	0.50 ± 0.19	0.67 ± 0.12	0.68 ±0.11	0.78 ± 0.22	0.79 ± 0.24
HAM	0.31±0.16	0.32 ± 0.16	0.63 ± 0.16	0.62 ±0.14	0.50 ± 0.15	0.51 ± 0.14
GAS	0.37±0.17	0.37 ± 0.16	0.60 ± 0.23	0.60 ±0.22	0.51 ± 0.18	0.51 ± 0.17
KJM	1.18±0.41	1.19 ± 0.39	1.90 ± 0.38	1.90±0.36	1.78 ± 0.33	1.81 ± 0.34

*Indicates significant difference between CD and BW ($p<0.05$).

The underdamped Butterworth filter produced higher estimates of the mean TMA of GL muscles during the WA phase of PSLR ($p < 0.001$), PSS ($p < 0.001$) and UPSS ($p = 0.005$) trials (Table 3.4).

3.3.3.3 DIRECTED CO-CONTRACTION RATIO

A significant difference was observed in the F/E DCCR of PSLR ($p = 0.04$); PSS ($p = 0.01$) and UPSS ($p < 0.001$) recorded during the PC50 phase. However, the values obtained from the two different filters did not differ in the clinical information provided in terms of direction of co-contraction of the flexors and extensors muscle group. No significant differences in M/L DCCR, SM/BF DCCR or F/E DCCR were observed within the WA phase for the PSLR, PSS and UPSS trials (Table 3.5). Both the filters provided the same information in terms of directionality of muscle activation.

Table 3.5: Co-contraction ratios recorded during 50ms pre-contact (PC50) and weight acceptance (WA) phase of planned straight line running (PSLR), planned sidestepping (PSS) and unplanned sidestepping (UPSS) processed with a 2nd order zero-lag underdamped Butterworth and critically damped filter.

	F/E DCCR		M/L DCCR		SM/BF DCCR	
Phase: PC50						
	BW	CD	BW	CD	BW	CD
PSLR	0.74 ± 0.10	0.68 ±0.13*	-0.01±0.34	0.02 ± 0.30	-0.12±0.40	-0.08 ± 0.36
PSS	0.74 ± 0.08	0.70 ±0.08*	0.03 ±0.26	0.02 ± 0.25	-0.06±0.28	-0.03 ± 0.24
UPSS	0.60 ± 0.24	0.54 ±0.25*	0.03 ±0.21	0.02 ± 0.19	-0.14±0.26	-0.13 ± 0.21
Phase: WA						
	BW	CD	BW	CD	BW	CD
PSLR	0.04 ± 0.31	0.04 ±0.32	0.05 ±0.24	0.06 ± 0.22	-0.14±0.36	-0.11± 0.35
PSS	0.23 ± 0.15	0.22±0.17	0.04 ±0.21	0.05 ± 0.21	-0.18 ±0.27	-0.13 ± 0.24
UPSS	-0.01 ± 0.28	-0.01±0.28	0.05 ±0.18	0.05 ± 0.17	-0.13±0.30	-0.10 ± 0.25

*Indicates significant difference between CD and BW ($p < 0.05$)

3.3.4 COMPARISON BETWEEN CO-CONTRACTION RATIO METHODS

The formula devised by Lloyd and Buchanan (34) (CCR) provided information about the extent of co-contraction between the agonist and antagonist muscles; however, it did not provide the directionality of muscle activation (Table 3.6). In contrast, the co-contraction ratio formulas devised by Heiden et al. (23) and Hamstra-Wright et al. (27) provided information about both the magnitude and direction of co-contraction between the agonist and antagonist muscles. However, the information provided in terms of direction of co-contraction varied in some instances (Table 3.6).

Table 3.6: Co-contraction ratios calculated according to the formulas developed by Heiden et al. (23), Lloyd and Buchanan (34) and Hamstra-Wright et al. (27) during the 50 ms pre-contact (PC50) and weight acceptance (WA) phase of planned straight line running (PSLR), planned sidestepping (PSS) and unplanned sidestepping (UPSS) trials.

	Flexion/Extension			Medial/Lateral			Hamstrings		
Phase:PC50									
	F/E DCCR	F/E CCR	F/E HW	M/LDCCR	M/L CCR	M/L HW	SM/BF DCCR	SM/BF CCR	SM/BF HW
PSLR	0.74 ± 0.10	0.26 ± 0.10	4.90 ± 2.40	- 0.01±0.34	0.68 ± 0.16	1.11±0.52	- 0.12±0.40	0.61 ± 0.21	0.99 ± 0.60
PSS	0.74 ± 0.08	0.26 ± 0.08	4.55 ± 1.18	0.03 ± 0.26	0.76 ± 0.14	1.13±0.43	- 0.06±0.28	0.72 ± 0.12	1.02 ± 0.41
UPSS	0.60 ± 0.24	0.37 ± 0.18	3.56 ± 1.79	0.03 ± 0.21	0.77 ±0.063	1.10±0.28	- 0.14±0.26	0.68 ± 0.12	0.91 ± 0.32
Phase: WA									
	F/E DCCR	F/E CCR	F/E HW	M/LDCCR	M/L CCR	M/L HW	SM/BFDCCR	SM/BFCCR	SM/BF HW
PSLR	0.04 ± 0.31	0.71 ± 0.13	1.19 ± 0.53	0.05 ± 0.24	0.77 ± 0.11	1.12±0.32	-0.14 ±0.36	0.64 ± 0.22	0.93 ± 0.46
PSS	0.23 ± 0.15	0.70 ± 0.10	1.45 ± 0.33	0.04 ± 0.21	0.80 ± 0.10	1.11±0.32	-0.18 ±0.27	0.67 ± 0.14	0.86 ± 0.33
UPSS	-0.01±0.28	0.72 ± 0.14	1.11 ± 0.41	0.05 ± 0.18	0.82 ± 0.08	1.10±0.24	- 0.13±0.30	0.62 ± 0.11	0.96 ± 0.38

3.4 DISCUSSION

This study reviewed the established guidelines for the signal processing of sEMG data. In particular, the focus was to determine if the choice of normalisation method or digital filter type influenced the clinical interpretation of common clinically relevant dependent variables such as mean TMA and co-contraction ratios. We also investigated if the choice of co-contraction ratio algorithm influenced the clinical interpretation of an individual's muscle activation directionality during a clinical movement assessment. Three types of trials were considered in order to obtain peak muscle activation for normalising sEMG data. These included isokinetic dynamometry, dynamic calibration (SLSQ, CMJ, SLDJ) and functional (PSLR, PSS, UPSS) trials. Results (Table 3.1) showed that peak muscle activation values for the nine lower limb muscles were obtained from different combinations of the normalisation approaches used in the present study. Results also showed that for the same muscle, peak muscle activation was obtained from one of the three normalisation trials tested. Together, these results show that it is beneficial to have participants perform a variety of normalisation tasks within the same experiment to increase the probability of obtaining maximal muscle activation values of all muscles tested among seemingly homogenous test populations. Interestingly, we also found that that majority of the participants were able to elicit peak muscle activation values when conducting the dynamic calibration trials (SLSQ, CMJ, and SLDJ). In contrast, peak muscle activation values for the hamstring muscles were almost exclusively obtained from the isokinetic dynamometry normalisation trials. The likely reason why peak muscle activation for the hamstrings was observed during the isokinetic dynamometry trial is attributed to the fact that none of the dynamic or functional trials predominantly targeted the hamstring musculature. Future research is recommended to determine if an additional dynamic normalisation task (i.e., Nordic hamstring curls (35)) , which is focused on eliciting the maximal

activation of the hamstrings might be used in place of isokinetic dynamometry normalisation trials, with the primary benefit being to reduce the duration of the experimental protocol.

The choice of normalisation method (COMB, FUNC and SLRm) influenced the clinical interpretation of TMA during PSLR, PSS and UPSS movement assessments. The COMB method, which identified the peak muscle activation from a combination of dynamic calibration, functional movements assessed and isokinetic dynamometry trials, always returned muscle activation values within each running and sidestepping trial below 100% MVC. For this reason, the COMB method reported significantly lower TMA values relative to the FUNC and SLRm normalisation approaches. These results in part have been supported by Rudolph and colleagues, who have shown that isolated maximal voluntary isometric contraction normalisation methods consistently fail to report muscle activation values below 100% during dynamics movement trials (26). Though results show that COMB normalisation is the preferred method for identifying peak muscle activation among a group of homogeneous athletes, the SLRm normalisation methods have, and currently remains the normalisation method of choice among researchers assessing knee ligament injury risk among athletic populations (1,22). This is an important consideration for researches comparing data between studies, as results from this study have clearly shown that the support offered by the muscles crossing the knee can vary significantly as a function of the normalisation method employed. With results from this study showing the SLRm approach consistently produces the highest TMA values when compared with the other two methods, it would be deemed the least preferred method for the normalisation of muscle activation data for clinical movement assessments. Visual analysis of SLRm normalised data indicated that the muscle activation values exceeded 100% MVC for all participants executing PSS and UPSS trials.

In general, the interpretation of DCCR did not significantly vary from one another as a result of the normalisation method used. However, in some instances, the clinical information provided was not consistent across all three normalisation methods tested. For example, the COMB and FUNC method of normalisation indicated that there was maximal co-contraction between the flexors and extensors during the WA phase of UPSS; however, the SLRm method indicated that the extensors were more active relative to the flexors. Similarly, the COMB method of normalisation indicated that BF was more active when compared with SM during the PC50 and WA phase of all three functional movement trials assessed, whereas the other two methods suggested that SM muscle was more active. It is therefore recommended that comparison of DCCR data between studies are conducted with some caution as the normalisation method used, in some circumstances can influence the clinical interpretation of data.

The results from this investigation clearly show that the COMB method of normalisation is recommended for the normalisation of sEMG data during clinical movement assessments of athletic populations. However, we do understand that for the clinical movement assessment of pathological populations, performing maximum effort dynamic calibration tasks like a counter movement jump may not be possible. In these scenarios, we recommend the FUNC normalisation approach as these trials were most suitable in identifying maximum muscle activity without the need for these populations to perform additional clinical trials (i.e., isokinetic dynamometry, manual muscle testing). Of further benefit for healthy populations, for common movement assessments (walking gait, stair ascent, stair descent etc.), an effective EMG reference clinical movement template for FUNC normalisation is effectively embedded within the testing protocol itself (10).

An alternative application of sEMG data is within the field of EMG driven muscle modelling. EMG driven muscle models make use of the muscle physiological cross sectional area, force-length/force-velocity properties and normalised muscle activation (i.e., EMG) data to predict muscle forces (36). Our results show that the normalisation method used can significantly influence the magnitude of the muscle activation data used to drive these models. Differences in muscle activation values as a function of normalisation method have the potential for these models to produce varied force estimates across participants, artificially elevating inter-subject variability. The normalisation methods used could therefore add much variability to the assessment of toque production and/or the support offered by muscles crossing a joint during functional movements assessed among these populations.

Our second research question was to determine if the choice of digital filter (underdamped Butterworth vs. critically damped) during the sEMG signal processing steps impacted the clinical interpretation of IEMG, TMA and DCCR dependent variables. Currently, the ISEK and SENIAM make recommendations for steps involved in the processing of sEMG data (3,6), with no mention of the type of digital filter used to carry out the filtering portions of these signal processing steps. This has led to the use of different filter types for the high and low pass filtering of sEMG data (refer to Appendix A).

Results showed IEMG values obtained using an underdamped Butterworth filter were, in general, significantly lower to those derived using a critically damped filter during the PC50 phase across all three running and sidestepping tasks analysed. The results were initially surprising as underdamped Butterworth filters possess a damping ratio of $\zeta = 0.707$, meaning they have propensity to 'undershoot' and 'overshoot' step response signals (i.e., high frequency signal) when removing noise (9,12). Unlike the

underdamped Butterworth filter, the critically damped filters did not undershoot or overshoot when applied to a step response signal. Though the EMG signal is recognised as a high frequency biological signal (bandwidth 10-500 Hz), it is also continuous and time varying. Therefore, the response of an underdamped Butterworth and critically damped filter to an artificial step response signal (∞ Hz) may not be directly applicable to a continuously time varying EMG signal. On further analysis, it was observed that the high pass critically damped filter was not as efficient (i.e., roll-off) as the underdamped Butterworth filter in removing noise below 30 Hz. For the same number of passes (filter order) Robertson and Dowling have also shown that the low pass critically damped filters were not as effective as underdamped Butterworth filters in removing high frequency noise from a step response (12). This suggests that critically damped filters, with the same filter order and/or number of passes are likely to allow more low frequency noise into the processed EMG signal prior to full wave rectification, partially explaining why IEMG estimated using critically damped filters during the signal processing steps were greater than those derived with underdamped Butterworth filters. From a clinical perspective, IEMG under submaximal contractions have been used as a surrogate estimates of an individual's rate of oxygen consumption and average energy expenditure when muscular work is done during dynamic movements (37). They are also directly proportional to the force and tension of a muscle during isometric contractions (38). With our results showing that IEMG magnitudes are dependent on the type of filter used, caution should be used by researchers comparing between study data if different filter types are employed. For mean TMA estimates and DCCR's, there were little or few meaningful differences between data processed using critically damped and underdamped Butterworth digital filters. In the context of clinical interpretation, these results suggest that if data is normalised using a similar method, it is unlikely to have a significant difference in the clinical interpretation of results.

Simply stated, normalisation of EMG data is an important processing step towards mitigating the potential for differences in TMA and DCCR from being observed between studies using different digital filters (critically damped vs. underdamped Butterworth).

Our third research question was to compare the clinical interpretation of three different co-contraction ratio algorithms commonly used in the literature. These included co-contraction ratio's published by Heiden et al. (23), Lloyd and Buchanan (34) and Hamstra-Wright et al. (27). It should be noted that the input parameters (signal processing steps /normalisation methods and individual muscles) were the same for all three algorithms. The goal of these comparisons was to assess the clinical application of these algorithms for assessing the direction and relative magnitude of the co-contraction between agonist and antagonist muscle activation. The method which appeared to provide the most clinically relevant information was the algorithm developed by Heiden and colleagues (23). This method not only provided information on the directionality, it provided a relative magnitude estimate within a defined range (-1 to +1). In contract, the formula developed by Hamstra-Wright et al. provides information on directionality, however the relative range was not bounded (+0.80 to +4.90) making it difficult to objectively identify what was considered a large, moderate or low (27). The method devised by Lloyd and Buchanan appeared to be the least useful algorithm, as it only provided the relative magnitude of generalised co-contraction (0 to +1), with no information associated with the directionality (34).

During the development of the low-pass critically damped filter used for this study, there was an observed mismatch between the recommended sampling rates for surface and fine-wire EMG and the ISEK/SENIAM low-pass frequency cut-off recommendations (ISEK : surface EMG: 350 Hz; fine-wire EMG: 450Hz , SENIAM :

surface EMG: 500 Hz; fine-wire EMG: 1,000Hz) during the signal processing of the EMG signal. To satisfy Nyquist theorem, SENIAM and ISEK recommend that sEMG data is sampled at, or greater than twice the highest cut-off frequency selected. Using these recommendations, sEMG data for this study was sampled at 2,000 Hz (which is well above the Nyquist theorem requirements). As common place in the EMG literature, 4^{th} order zero-lag filters are commonly used during the sEMG signal processing steps (1,4). If using an underdamped Butterworth, a 4^{th} order zero-lag low-pass filter can be used to remove frequencies above 500 Hz as per the SENIAM recommendations with a sample frequency greater than 1,000 Hz. However, if a 4^{th} order zero-lag low-pass critically damped filter is used to remove frequencies above 500 Hz, when data is sampled at 2,000 Hz, the data cannot be processed due to violation of Nyquist theorem. The corrected cut-off frequency of a 4^{th} order zero-lag low-pass critically damped filter is greater than 1,660 Hz (refer to equations 1 and 2 of section 3.1.1) meaning a sample rate greater than 3,400 Hz (3,500 Hz recommended) would need to be used to abide by the SENIAM guidelines (sampling frequency greater than twice the highest frequency within the signal). In the case of ISEK guidelines, a 4^{th} order zero-lag low pass critically damped filter can be applied at a cut off frequency of 350 Hz (corrected cut off frequency is 1162 Hz, meaning a sampling rate greater than 2324 Hz would work if data is sampled at 2500 Hz). However, if fine-wire EMG were used, which possesses a bandwidth between of 10 – 1500 Hz (6), researchers would need to increase their sampling rate to 3,000 Hz and above if a 4^{th} order zero-lag low-pass critically damped filter at 450 Hz can be applied as per the ISEK signal processing guidelines (refer to equations 1 and 2 in Appendix D). These findings suggest that ISEK should either explicitly state that an underdamped Butterworth filter should be used to filter EMG data so their proposed signal processing steps align with their sampling rate

recommendations or reconsider the sampling rate recommendations for both fine wire and surface EMG if different filter types are used.

3.5 CONCLUSION

When possible, it is recommended that a variety of sEMG normalisation tasks are performed within an experiment to make sure that normalised muscle activation values of the functional movement trial are below 100% MVC. The choice of normalisation method will influence the clinical interpretation of mean TMA and to lesser extent co-contraction ratios obtained during clinical movement assessments.

The type of filter (underdamped Butterworth vs. critically damped) impacted the clinical interpretation of IEMG data during clinical movement assessments. Filter type did not influence the clinical interpretation of TMA and DCCR obtained during clinical movement assessments, as the data was processed using the same normalisation procedure.

Different co-contraction ratio algorithms produce different clinical interpretations. The DCCR algorithm proposed by Heiden et al. was deemed the most clinically useful as it provided information on directionality and the relative magnitude within a defined range (-1 to +1).

Reference list – Chapter three

1. Donnelly CJ, Elliott BC, Doyle TLA, Finch CF, Dempsey AR, Lloyd DG. Changes in muscle activation following balance and technique training and a season of Australian football. J Sci Med Sport. Sports Medicine Australia; 2014 May 14 .

2. Basmajian JV, De Luca CJ. (1985) Muscles alive. *Proceedings of the Royal Society of Medicine, 278, 126.*

3. Stegeman DF, Hermens HJ. Standards for surface electromyography : the European project " Surface EMG for non-invasive assessment of muscles (SENIAM)." 1999;108–12.

4. De Luca CJ, Gilmore LD, Kuznetsov M, Roy SH. Filtering the surface EMG signal: Movement artifact and baseline noise contamination. J Biomech. Elsevier; 2010 May 28;43(8):1573–9.

5. Drake JDM, Callaghan JP. Elimination of electrocardiogram contamination from electromyogram signals : An evaluation of currently used removal techniques. 2006;16:175–87.

6. International Society of Electrophysiology and Kinesiology. Standards for Reporting EMG Data. J Electromyogr Kinesiol. 2014 Oct;24(5):I – II.

7. Gottlieb G, Agarwal G. Filtering of electromyographic signals. Am J Phys Med Rehabil. 1970;49(2):142–6.

8. Halbertsma J, De Boer R. On the processing of electromyograms for computer analysis. J Biomech. 1981;14(6):431–5.

9. Kreifeldt JG. Signal versus noise characteristics of filtered EMG used as a control source. IEEE Trans Biomed Eng. 1971 Jan;18(1):16–22.

10. Winter DA, Yack H. EMG profiles during normal human walking: stride-to-stride and inter-subject variability. Electroencephalogr Clin Neurophysiol. 1987 Nov;67(5):402–11.

11. Winter DA (2009). Biomechanics and motor control of human movement. John Wiley and Sons.

12. Robertson DGE, Dowling JJ. Design and responses of Butterworth and critically damped digital filters. J Electromyogr Kinesiol. 2003 Dec;13(6):569–73.

13. Kleissen RF. Effects of electromyographic processing methods on computer-averaged surface electromyographic profiles for the gluteus medius muscle. Phys Ther. 1990 Nov;70(11):716–22.

14. Shiavi R, Frigo C, Pedotti A. Electromyographic signals during gait: Criteria for envelope filtering and number of strides. Med Biol Eng Comput. 1998;36(2):171–8.

15. Hug F, Turpin NA., Dorel S, Guével A. Smoothing of electromyographic signals can influence the number of extracted muscle synergies. Clin Neurophysiol. 2012;123(9):1895–6.

16. Ball N, Scurr JC. Efficacy of current and novel electromyographic normalization methods for lower limb high-speed muscle actions. 2011;11(November).

17. Burden A. How should we normalize electromyograms obtained from healthy participants? What we have learned from over 25 years of research. J Electromyogr Kinesiol. Elsevier Ltd; 2010 Dec;20(6):1023–35.

18. Yang JF, Winter DA. Electromyographic amplitude normalization methods: improving their sensitivity as diagnostic tools in gait analysis. Arch Phys Med Rehabil. 1984;65(9):517–21.

19. Kellis E, Baltzopoulos V. Muscle activation differences between eccentric and concentric isokinetic exercise. Med Sci Sports Exerc. 1998;30:1616–23.

20. Dorel S, Guilhem G, Couturier A, Hug F. Adjustment of muscle coordination during an all-out sprint cycling task. Med Sci Sports Exerc. 2012;44(11):2154–64.

21. Rouffet DM, Hautier CA. EMG normalization to study muscle activation in cycling. J Electromyogr Kinesiol. 2008 Oct;18(5):866–78.

22. Besier TF, Lloyd DG, Ackland TR. Muscle activation strategies at the knee during running and cutting maneuvers. Med Sci Sports Exerc. 2003 Jan;35(1):119–27.

23. Heiden TL, Lloyd DG, Ackland TR. Knee joint kinematics, kinetics and muscle co-contraction in knee osteoarthritis patient gait. Clin Biomech (Bristol, Avon). Elsevier Ltd; 2009 Dec;24(10):833–41.

24. Ford KR, van den Bogert AJ, Myer GD, Shapiro R, Hewett TE. The effects of age and skill level on knee musculature co-contraction during functional activities: a systematic review. Br J Sports Med. 2008 Jul;42(7):561–6.

25. O'Connor JJ. Can muscle co-contraction protect knee ligaments after injury or repair? J Bone Joint Surg. Br. 1993; 75(1).

26. Rudolph KS, Axe MJ, Snyder-Mackler L. Dynamic stability after ACL injury: who can hop? Knee Surgery, Sport Traumatol Arthrosc. 2000 Jul 20;8(5):262–9.

27. Hamstra-Wright KL, Swanik CB, Sitler MR, Swanik K a, Ferber R, Ridenour M, et al. Gender comparisons of dynamic restraint and motor skill in children. Clin J Sport Med [Internet]. 2006 Jan;16(1):56–62.

28. Donnelly CJ, Elliott BC, Doyle TLA, Finch CF, Dempsey AR, Lloyd DG. Changes in knee joint biomechanics following balance and technique training and a season of Australian football. Br J Sports Med. 2012 Oct;46(13):917–22.

29. Weir, G.J., Cantwell, D., Alderson, J.A., Elliott, B.C., Donnelly C. Changes in support moment and muscle activation following hip and trunk neuromuscular training: The hip and ACL injury .International Society of Biomechanics in Sports (ISBS) Annual Conference. 2014. p. 373–6.

30. Perotto A, Delagi EF. Anatomical guide for the electromyographer: the limbs and trunk. Charles C Thomas Publisher; 2005.

31. Potvin JR, Brown SHM. Less is more: high pass filtering, to remove up to 99% of the surface EMG signal power, improves EMG-based biceps brachii muscle force estimates. J Electromyogr Kinesiol. 2004 Jun;14(3):389–99.

32. Sartori M, Reggiani M, Farina D, Lloyd DG. EMG-driven forward-dynamic estimation of muscle force and joint moment about multiple degrees of freedom in the human lower extremity. PLoS One. 2012 Jan;7(12):e52618.

33. Murphy SD, Robertson DGE. Construction of a High-Pass Digital Filter From a Low-Pass Digital Filter. 1990;374–82.

34. Lloyd DG, Buchanan TS. Strategies of muscular support of varus and valgus isometric loads at the human knee. J Biomech. 2001 Oct;34(10):1257–67.

35. Van der Horst N, Smits D, Peterson J, Goedhart E, Backx F. The Preventive Effect of the Nordic Hamstring Exercise on Hamstring Injuries in Amateur Soccer Players: A Randomized Controlled Trial. Br J Sports Med. 2014;48(7):609–10.

36. Lloyd DG, Besier TF. An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo. J Biomech. 2003 Jun;36(6):765–76.

37. Bigland-Ritche B, Woods JJ. Integrated dynamic EMG and oxygen of human uptake during contractions muscles. J Appl Physiol. 1974;36(4):475–9.

38. Inman VT, Ralston HJ, De C.M. Saunders JB, Bertram Feinstein MB, Wright EW. Relation of human electromyogram to muscular tension. Electroencephalogr Clin Neurophysiol. 1952 May;4(2):187–94.

CHAPTER FOUR

EXTENDED METHODS

4.1 Extended Methods Section

In the present chapter, the design and testing of the low and high pass critically damped filter have been presented. This chapter contains additional information which was not provided in the manuscript prepared for submission.

4.1.1 Critically damped filter

The use of digital filters for the signal processing of sEMG signals is imperative as the biological signal of interest can contain multiple sources of noise such as movement artefact, heart rate contamination, power line noise and the adipose tissue (layer of fat) covering the muscle (spatial filtering). The guidelines provided by SENIAM (1) and ISEK (2) provide very clear signal processing steps to remove unwanted noise from the recorded sEMG biological signal. Though clear filtering steps have been recommended, they do not advocate towards the use of a particular type of digital filter for the signal processing steps. As it is known that each filter type contains unique filter characteristics, it is unclear if the choice of the digital filter used has any effect on the clinical interpretation of results. In order to answer this question, we implemented a low pass critically damped (3) and high pass critically damped filter (4) to process the sEMG data captured. The sEMG data processed with a critically damped filter was compared with the data processed by an underdamped Butterworth filter where the findings were used to provide recommendations for the signal processing of sEMG data.

4.1.1.1 Critically damped low pass filter

Low pass filters are generally used to remove high frequency noise. For sEMG data, a low pass filter is first applied at 350 – 500 Hz to capture muscle activity and remove high frequency noise from the signal. It is again applied at 6 – 8 Hz to the full

wave rectified signal in order to create a linear envelope. For this purpose, we constructed a low pass filter based on the guidelines provided by Robertson and Dowling (3).

In the field of biomechanics; data is generally filtered once in the forward and backward direction, to remove phase shifts or time delays that can be introduced when applied to time varying signals. Therefore, a correction factor needs to be introduced in order to maintain the correct cut off frequency when multiple passes of the filter are applied to the data.

The variables and coefficients used in the design of critically damped filters are:

$$C_{crit} = 1/(\sqrt{2}^{1/2*n} - 1) \quad (1)$$

$$F_{crit} = F_{cut} * C_{crit} \quad (2)$$

$$\omega_c = \tan(\pi * F_{crit}/F_{sr}) \quad (3)$$

C_{crit} is the correction factor used to maintain the required cut off frequency when applying multiple passes. For every pass, C_{crit} is then multiplied with F_{crit} in order to maintain the required cut off frequency. ω_c is the corrected angular cut off frequency and F_{sr} is the sampling frequency in Hz.

The coefficients of the critically damped filter according to Dowling and Robertson (3) are:

$$K_1 = 2\,\omega_c;\ K_2 = \omega_c\text{^}2 \quad (4)$$

$$Ao = A2 = K_2/(1 + K_1 + K_2);\ A1 = 2\,Ao; \quad (5)$$

$$B1 = 2\,Ao\,((1/K_2) - 1);\ B2 = 1 - (Ao + A1 + A2 + B1); \quad (6)$$

Unlike the underdamped Butterworth filter, the critically damped filter does not undershoot or overshoot data. The damping ratio (ζ) of the critically damped filter is 1 and that of an underdamped filter is 0.707. This makes the underdamped filter susceptible to undershoot or overshoot. For the purpose of this study, we have made use of the "*filtfilt*" function in Matlab (Matlab 2013a, The Mathworks, Inc., Natick, MA, USA). This function enables the digital filter to process the data in both the forward and backward direction; thereby maintaining zero-phase lag or eliminating phase delays from being introduced to the filtered signal.

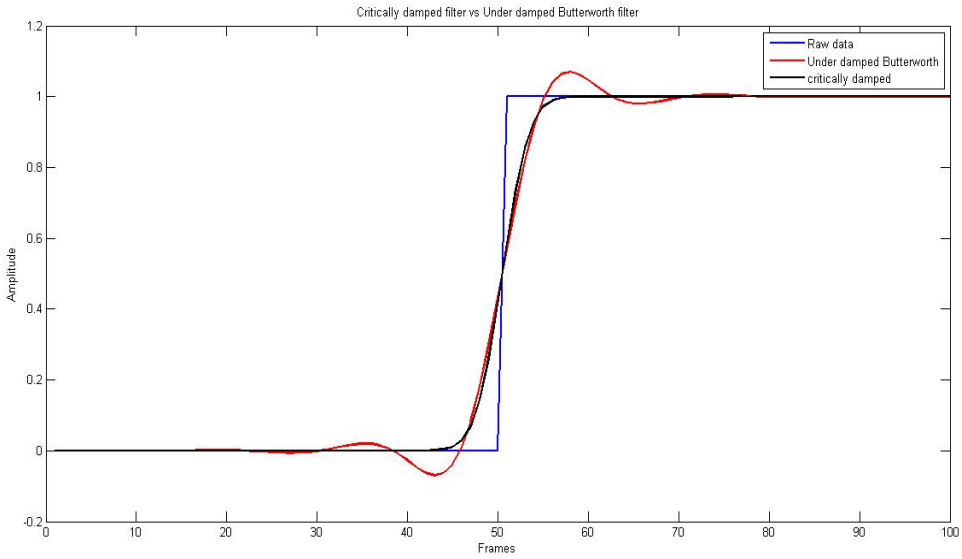


Figure 4.1: Response of a fourth order low pass zero-lag underdamped and critically damped filter to a step response signal when filtered at 10 Hz.

Robertson and Dowling have shown that the underdamped Butterworth filter is more efficient at removing noise from the signal of interest due to its high roll off. Unlike the underdamped Butterworth filter, the critically damped, with the same filter order is less efficient at removing noise. The critically damped filter will require additional number of passes only if the data that has time derivatives (differentiated)

that need to be filtered (3). The Matlab function used to implement the critically damped filter has been presented in Appendix D.

4.1.1.2 Critically damped high pass filter

High pass filters has been used to remove low frequency noise which tends to affect the biological signal of interest. For sEMG data; the major sources of low frequency noise are movement artefacts (10 – 30 Hz), heart rate contamination (30Hz) and adipose tissue covering the muscle. A critically damped high pass filter was constructed according to the guidelines specified by Murphy and Robertson (4).

The equations used in the design of a critically damped high pass filter from the coefficients of a critically damped low pass filter are:

Recursive equation of a second order zero-lag low pass filter is

$$y_n = a_o x_o + a_1 x_{n-1} + a_2 x_{n-2} + b_1 y_{n-1} + b_2 y_{n-2} \quad (7)$$

In order to construct a high pass filter from a low pass filter, we use the following equation

$$H_{lp}(Z^{-1}) = \frac{A_o + A_1 Z^{-1} + A_2 Z^{-2}}{1 - B_1 Z^{-1} - B_2 Z^{-2}} \quad (8)$$

A high pass filter can be constructed by using the following equation

$$Z^{-1} = -\frac{(Z^{-1} + \alpha)}{1 + \alpha Z^{-1}} \quad (9)$$

Where

$$\alpha = \frac{\cos(\theta\_lp * T + \omega\_hp * T)/2}{\cos(\theta\_lp * T - \omega\_hp * T)/2} \quad (10)$$

$$\omega\_hp = 2 * \pi * F_{crit\_hp}; \quad (11)$$

ω_hp is the angular velocity of the high pass filter in rad/s

$$\theta\_lp = 2*\pi*F_{crit\_lp}; \quad (12)$$

θ_lp is the angular velocity of the low pass filter in rad/s

$$T = \frac{1}{F_{sp}} \quad (13)$$

T is the sampling time and F_{sp} is the sampling frequency

$$\delta = 1+B_1*\alpha - B_2*\alpha^2; \quad (14)$$

$$ao = \frac{Ao - A1*\alpha + A2*\alpha^2}{\delta}; \quad (15)$$

$$a1 = \frac{Ao*2*\alpha - A1*(1+\alpha^2) + A2*2*\alpha}{\delta} \quad (16)$$

$$c2 = \frac{Ao*\alpha^2*2 - A1*\alpha + A2}{\delta} \quad (17)$$

$$b1 = \frac{(-2*\alpha - B1*(1+\alpha^2) + B2*2*\alpha)}{\delta} \quad (18)$$

$$b2 = \frac{(-\alpha^2 - B1*\alpha + B2)}{\delta} \quad (19)$$

Equations 13 -19 represent the coefficients of a high pass filter which was derived from the coefficients of a low pass filter.

$$C_{crit\_hp} = \sqrt{}(2\text{^}(1/(2*N))-1) \quad (20)$$

C_{crit_hp} is the correction factor used when filtering the forward and reverse direction in order to have zero-phase lag.

$$F_{crit\_hp} = F_{crit}*C_{crit\_hp} \quad (21)$$

F_{crit_hp} is the corrected cut off frequency of the critically damped high pass filter.

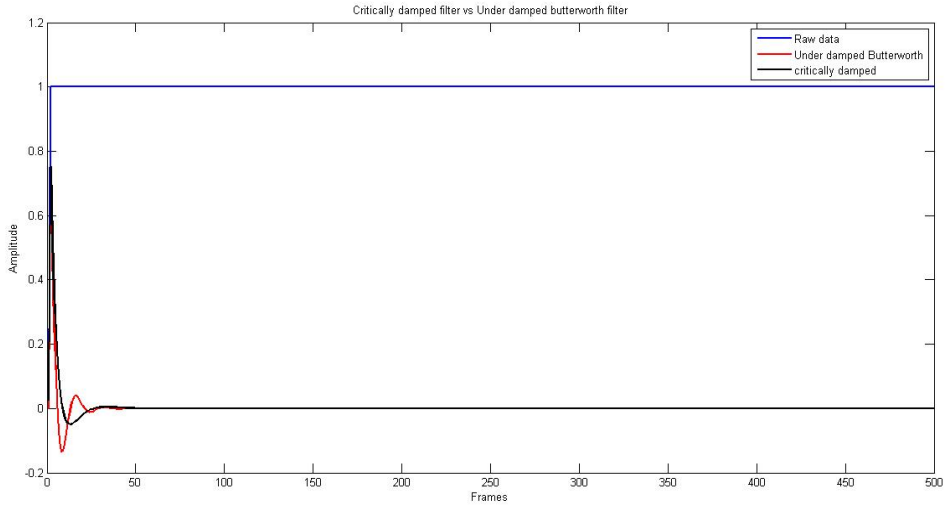


Figure 4.2: Response of a fourth order zero-lag high pass underdamped and critically damped filter to a step response signal when filtered at 10 Hz.

For the purpose of this study, we have used the critically damped high pass and low pass filters presented above to filter sEMG data. Despite the tendency of an underdamped filter to undershoot or overshoot data, it has been predominantly used to filter sEMG data. The main reason for this is its optimal stability in the band pass region and increased ability to attenuate noise. In the case of sEMG data; Robertson and Dowling have identified that the critically damped filter will require the same number of passes as that of the underdamped Butterworth filter to remove noise (3). Consequently, we implemented a 4^{th} order underdamped zero-lag Butterworth and critically damped filter to process the sEMG data.

Reference list – Chapter four

1. Stegeman DF, Hermens HJ. Standards for surface electromyography : the European project " Surface EMG for non-invasive assessment of muscles (SENIAM)." 1999;108–12.

2. International Society of Electropgysiology and Kinesiology. Standards for Reporting EMG Data. J Electromyogr Kinesiol [Internet]. 2014 Oct 24(5):I – II.

3. Robertson DGE, Dowling JJ. Design and responses of Butterworth and critically damped digital filters. J Electromyogr Kinesiol [Internet]. 2003 Dec 13(6):569–73.

4. Murphy SD, Robertson DGE. Construction of a High-Pass Digital Filter From a Low-Pass Digital Filter. 1990;374–82.

APPENDIX A

DIGITAL FILTERS USED TO PROCESS sEMG DATA

Table A: The different types of digital filters used in the last few decades to process sEMG data. The purpose of the current section is to highlight the usage of different signal processing methods for sEMG, highlighting the point, 'comparison of results between studies is an arduous task'.

Author	Aim	Methods	Results & Discussion	Drawback/Conclusion
Gottlieb and Agarwal - (1)	To process sEMG signal without obscuring any important information such as activation/deactivation timing and average sEMG amplitude.	3rd order Paynter filter with T = 10 milliseconds is used to filter the raw sEMG data obtained from the triceps surae and anterior tibial muscles obtained during voluntary contraction.	Paynter filter is able to restore the signal dynamics i.e. activation timing and amplitude unlike the moving average filter which tends to obscure the signal dynamics.	The drawback of Paynter filter is that it is very difficult to manipulate the time constants and is also susceptible to obscure short term detail (2).
Kreifeldt - (3)	To show the invariant nature of the signal to noise ratio (SNR) of the processed EMG and recommend a filter which produces the highest SNR ratio.	Simple RC filter, 1st order and 3rd order Butterworth filters were used to filter step response signals and also sEMG obtained from extensor digitorum muscles during MVC tasks.	In terms of SNR; moving average filters performed better than the 1st order and 3rd order Butterworth filters. The underdamped Butterworth filters tend to overshoot; thereby making it unsuitable for use in delicate control situations.	The moving average filter performs poorly in terms of separating one frequency from another i.e., its stop band attenuation is very poor and the roll off is very slow.

Halbertsma and De Boer - (4)	To focus on the processing of electromyograms for computer analysis	Raw sEMG data was high pass filtered; full wave rectified and low pass filtered to create a linear envelope. The processed signal was digitised and stored in the computer for further analysis.	The authors suggested that the use of a 5^{th} order low pass Bessel filter resulted in timing errors. However, it was also shown that the timing errors could be adjusted by increasing the cut off and sampling frequency.	Timing errors are a big disadvantage when processing sEMG data as muscle activation/deactivation timings provide useful insight about muscle function.
Kleissen - (5)	The purpose of the study was to demonstrate the use of different filters to create linear envelope (sEMG) and its impact on EMG profiles	A 3^{rd} order Butterworth filter with cut off frequency of 25 Hz and a critically damped filter with cut off frequency of 3Hz were used to filter sEMG data obtained from gluteus medius muscle.	The filter with low cut off (3 Hz) frequency produced smoother sEMG profiles. The authors reported that the use of a critically damped filter resulted in a time lag of 50 milliseconds	The study compared the effects of using different filters to produce linear envelopes of sEMG data and more emphasis was laid on the choice of cut off frequency. The authors have reported a time lag for critically damped filters; however the time lag can be removed by filtering in the forward and backward direction.

Winter and Scott - (6)	To record the sEMG data of six lower limb muscles and also measure muscle length and shortening/lengthening velocity to evaluate the role of a muscle as a generator or absorber of energy.	A 2^{nd} order critically damped filter was used to process the sEMG data. Changes in muscle length and velocity were calculated using a data which could estimate the muscle /tendon length.	The role of a muscle in generation/absorption of energy can be better understood by combing the joint angle data with the processed linear envelope.	This study was included to show that the use of a critically damped filter does not induce a time lag. Hence, would be able to provide accurate estimates of muscle activation and deactivation.
Masse, Lamontagne' and O'riain - (7)	To determine the ideal seating positon for wheel chair racing.	A 1^{st} order critically damped filter was used to process sEMG data of the upper body.	The lowest backward position was found to be the most ideal position for wheel chair racing as it resulted in lower IEMG values and also in the smooth movement of joints.	This study was included to show that the use of a critically damped filter does not induce a time lag.

Reference list – Appendix A

1. Gottlieb G, Agarwal G. Filtering of electromyographic signals. Am J Phys Med Rehabil. 1970;49(2):142–6.

2. Loeb GE, Gans C. Electromyography for experimentalists. University of Chicago Press; 1986.

3. Kreifeldt JG. Signal versus noise characteristics of filtered EMG used as a control source. IEEE Trans Biomed Eng. 1971 Jan;18(1):16–22.

4. Halbertsma J, De Boer R. On the processing of electromyograms for computer analysis. J Biomech. 1981;14(6):431–5.

5. Kleissen RF. Effects of electromyographic processing methods on computer-averaged surface electromyographic profiles for the gluteus medius muscle. Phys Ther. 1990 Nov;70(11):716–22.

6. Winter D a, Scott SH. Technique for interpretation of electromyography for concentric and eccentric contractions in gait. J Electromyogr Kinesiol. 1991 Dec;1(4):263–9.

7. Masse LC, Lamontagne M, O'Riain MD. Biomechanical analysis of wheelchair propulsion for various seating positions. J Rehabil Res Dev. 1992;29(3):12.

APPENDIX B

CO-CONTRACTION RATIO ALGORITHMS

Table B: Co-contraction ratio of the agonist and antagonist muscles crossing the knee joint according to Heiden et al. (1), Lloyd and Buchanan (2) and Hamstra-Wright et al. (3) during dynamic events.

Author	Co-contraction ratio formula	Muscles included
Heiden et al. (1)	DCCR = (1 – antagonist mean EMG)/agonist mean EMG ; if (agonist > antagonist)	M/L DCCR – Medial (SM, VM, MG); Lateral (BF, VL, LG)
	DCCR = agonist mean EMG/(antagonist mean EMG-1); if(antagonist>agonist)	F/E DCCR – Flexors (SM, BF, MG, LG); Extensors (VL, VM, RF)
		SM/BF DCCR – SM, BF
Lloyd and Buchanan (2)	CCR = average flexor activation/average extensor activation; if (extensor activation >flexor activation)	M/L CCR – Medial (SM, VM, MG); Lateral (BF, VL, LG)
	CCR = average extensor activation / average flexor activation; if(flexor activation > extensor activation)	
	CCI = CCR*(extensor activation + flexor activation)	Input parameter same as Heiden et al. (1)
Hamstra-Wright et al. (3)	Co-activation = Area of flexors / Area of extensors;	Input parameter same as Heiden et al. (1)

Reference list – Appendix B

1. Heiden TL, Lloyd DG, Ackland TR. Knee joint kinematics, kinetics and muscle co-contraction in knee osteoarthritis patient gait. Clin Biomech. Elsevier Ltd; 2009 Dec;24(10):833–41.

2. Lloyd DG, Buchanan TS. Strategies of muscular support of varus and valgus isometric loads at the human knee. J Biomech. 2001 Oct;34(10):1257–67.

3. Hamstra-Wright KL, Swanik CB, Sitler MR, Swanik K a, Ferber R, Ridenour M, et al. Gender comparisons of dynamic restraint and motor skill in children. Clin J Sport Med. 2006 Jan;16(1):56–62.

APPENDIX C

CLASSIFICATION OF MUCSLES CROSSING THE KNEE JOINT ACCORDING TO THEIR ABILITY TO SUPPORT

Table C: Muscles grouped according to ability to produce or support knee moments during flexion, extension, varus, valgus, internal and external rotation degree-of-freedom from 20 to 50 degrees of knee flexion (Besier et al. (1) , Buford et al. (2); Lloyd and Buchanan (3), Lloyd and Besier (4), Lloyd et al. (5)).

Flexion	Extension	Varus	Valgus	Int. Rotation	Ext. Rotation
SM	VM	SM	BF	SM	BF
BF	VL	MG	LG		
MG	RF	VM	VL		
LG					

SM (Semimembranosus), BF (Biceps femoris), MG (Medial Gastrocnemius), LG (Lateral Gastrocnemius), VM (Vastus medialis), VL (Vastus lateralis), RF (Rectus femoris).

Reference list – Appendix C

1. Besier, T.F., Lloyd, D.G., Ackland, T.R., 2003. Muscle activation strategies at the knee during running and cutting maneuvers. Med Sci Sports Exerc. 35(1), 119-27.

2. Buford, W.L. Jr., Ivey, F.M. Jr., Nakamura, T., Patterson, R.M., Nquyen, D.K., 2001. Internal/external rotation moment arms of muscles at the knee: moment arms for the normal knee and the ACL-deficient knee. Knee. 8, 293-303.

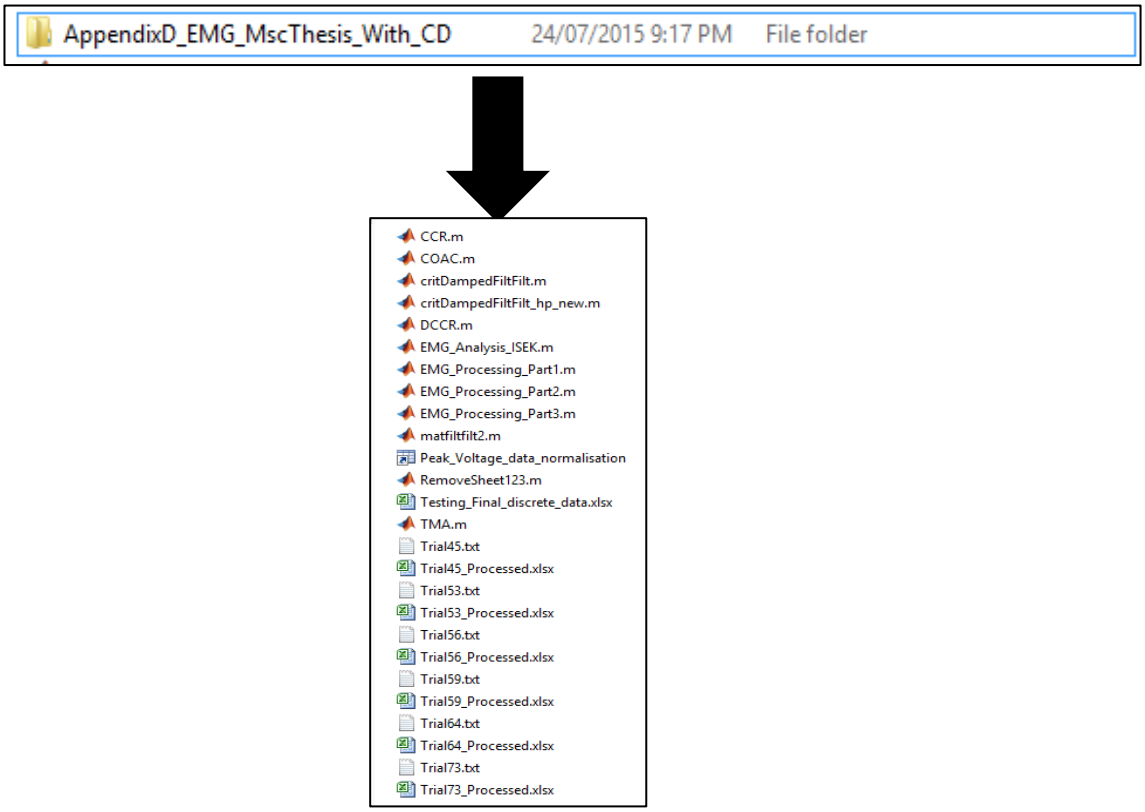
3. Lloyd, D.G., Buchanan, T.S., 2001. Strategies of muscular support of varus and valgus isometric loads at the human knee. J Biomech. 34, 1257-67.

4. Lloyd, D.G., Besier, T.F., 2003. An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo. J Biomech. 36, 765-76.

5. Lloyd, D.G., Buchanan, T.S., Besier, T.F., 2005. Neuromuscular biomechanical modeling to understand knee ligament loading. Med Sci Sports Exerc. 37, 1939-47.

APPENDIX D

MATLAB PROGRAMS



A digital copy of the surface electromyography software used to calculate the co-contraction ratio's and total muscle activation using an underdamped and critically damped Butterworth filter in chapter three can be found on the disk attached with this thesis. Sample input and output data have also been provided for future reference.

APPENDIX E

JOINT ANGLE DATA RECORDED DURING FUNCTIONAL MOVEMENT TRIALS

Table D: 3D kinematics hip, knee and ankle joint angle recorded during the WA phase of PSLR, PSS, UPSS, CMJ, SLDJ and SLSQ respectively.

		Hip Flexion/extension (°)	Knee Flexion/extension (°)	Ankle plantar /dorsiflexion (°)
PSLR	Heel contact	45 ± 4.5	14 ± 1.4	-17 ± 1.7
	Peak Angle	48 ± 4.8	31 ± 3.1	9 ± 0.9
	RoM	3 ± 0.3	17 ± 1.7	26 ± 2.6
PSS	Heel contact	50 ± 5	19 ± 1.9	-25 ± 2.5
	Peak Angle	55 ± 5.5	44 ± 4.4	14 ± 1.4
	RoM	5 ± 0.5	25 ± 2.5	39 ± 3.9
UPSS	Heel contact	58 ± 5.8	15 ± 1.5	-18 ± 1.8
	Peak Angle	70 ± 7	51 ± 5.1	2 ± 0.2
	RoM	12 ± 1.2	36 ± 3.6	20 ± 2
CMJ	Heel contact	30 ± 3	10 ± 1	-25 ± 2.5
	Peak Angle	60 ± 6	50 ± 5	25 ± 2.5
	RoM	30 ± 3	40 ± 4	50 ± 5
SLDJ	Heel contact	50 ± 5	13 ± 1.3	-30 ± 3
	Peak Angle	70 ± 7	60 ± 6	22 ± 2.2
	RoM	20 ± 2	47 ± 4.7	52 ± 5.2
SLSQ	Start descent	36 ± 3.6	22 ± 2.2	11 ± 1.1
	Peak Angle	106 ± 10.6	90 ± 9	30 ± 3
	RoM	70 ± 7	68 ± 6.8	19 ± 1.9

RoM – range of motion, ° denotes angle in degrees. Positive values denote flexion and negative values denote extension for the knee and hip joints. Positive value denotes dorsiflexion and negative values plantar flexion for the ankle joint.