The application of data analysis methods for surface electromyography in shot putting and sprinting

Róisín Marie Howard

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Supervisors: Dr. Richard Conway & Prof. Andrew J. Harrison

Department of Electronics and Computer Engineering

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Abstract

Title: The application of data analysis methods for surface electromyography in a shot putting and sprinting

Author: Róisín Marie Howard

Muscles are the key drivers in any human movement. Since the muscles generate the forces and consequently the impulses to move the athlete from one position to another, it can be useful to study the muscle activity during sports movements to help with optimisation of technique, injury prevention and performance enhancements. Due to recent advances in electromyography (EMG) technologies, muscle activity in sports movement such as shot putting and overground sprinting can now be acquired using wireless surface mount sensors. Previously the use of tethered devices restricted the movements which could be analysed. The aim of this research was to investigate data analysis methods for use with EMG. There is a need to develop an in depth understanding of what EMG data can convey by understanding muscle activations and patterns in various sports movements and techniques.

The research has been implemented by conducting a literature review, a survey and experimental studies to examine EMG signals on shot putting, sprinting and to understand cross-talk. There has been significant work done in understanding the biomechanics of sprinting, with emphasis on kinematics. The literature review on muscle activities in sprinting highlighted the need for wireless devices to allow testing of athletes in ecologically valid environments, rather than on a treadmill which offers little comparison with the environment of the sprinter, and proposed that there existed a bias on the muscles studied which may have been due to technology constraints of tethered systems. The survey of biomechanists gave an insight into the sensor devices utilised, the types of experimental studies being undertaken and the specifications desired in these devices. The study of muscle activations during the glide technique in shot put delivered meaningful activation patterns which coincided with key movements in the technique and augmented previously known kinematic data and anecdotal evidence. The study on muscle activations during maximal sprinting returned similar results, the 50% threshold provided information on the higher volume of muscle activity and these bursts of activity also coincided with key kinematic events. The use of independent component analysis (ICA) was examined to reduce cross-talk during sporting movements and recreating EMG signals due incorrectly positioned electrodes. Few studies have examined ICA with myoelectric signals. This research applies ICA to EMG signals during isometric contractions; small increases in correlation were found in some cases between the output signals and the ideal signals.

The data analysis methods used in this research along with the supporting studies may prove to be a vital aid in supporting practitioners, coaches and athletes in the analysis of shot putting and sprinting using muscle activations and patterns. The thresholding methods used in this work may be useful in future studies to distinguish between low and high volumes of EMG activity in sports movements. It is recommended that future studies examine the muscle activity of specific exercises and compare the activity to that of sports movements to determine which exercises are most suitable in training and for pre-activation. The ICA algorithm should be examined further, to analyse isotonic movements.
Declaration

I hereby declare that the work contained within this current thesis is my own and was completed with the council of my supervisors Dr. Richard Conway of the Department of Electronic and Computer Engineering, University of Limerick and Prof. Andrew Harrison of the Department of Physical Education and Sports Sciences, University of Limerick. The work has not been submitted to any other university or higher education institution or for any other academic award within this university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

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Róisín M. Howard

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Dr. Richard Conway

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Prof. Andrew J. Harrison

Date: _______________________
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# Nomenclature & Definitions

Abbreviations used for terminology throughout the thesis

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2D</td>
<td>Two Dimensional</td>
</tr>
<tr>
<td>3D</td>
<td>Three Dimensional</td>
</tr>
<tr>
<td>ADC</td>
<td>Analog-Digital Convertor</td>
</tr>
<tr>
<td>AEMG</td>
<td>Average EMG</td>
</tr>
<tr>
<td>AMER</td>
<td>Americas</td>
</tr>
<tr>
<td>APAC</td>
<td>Asia Pacific</td>
</tr>
<tr>
<td>BSS</td>
<td>Blind Source Separation</td>
</tr>
<tr>
<td>BF</td>
<td>Biceps Femoris</td>
</tr>
<tr>
<td>CMJ</td>
<td>Countermovement Jump</td>
</tr>
<tr>
<td>CMR</td>
<td>Common Mode Rejection</td>
</tr>
<tr>
<td>CMRR</td>
<td>Common Mode Rejection Ratio</td>
</tr>
<tr>
<td>CNS</td>
<td>Central Nervous System</td>
</tr>
<tr>
<td>CoM</td>
<td>Centre of Mass</td>
</tr>
<tr>
<td>CT</td>
<td>Contact Time</td>
</tr>
<tr>
<td>DJ</td>
<td>Drop Jump</td>
</tr>
<tr>
<td>DSP</td>
<td>Digital Signal Processing</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform</td>
</tr>
<tr>
<td>ECG</td>
<td>Electrocardiogram</td>
</tr>
<tr>
<td>LG</td>
<td>Lateral Gastrocnemius</td>
</tr>
<tr>
<td>EEMG</td>
<td>Electromyography</td>
</tr>
<tr>
<td>EMG</td>
<td>Electromyography</td>
</tr>
<tr>
<td>FP</td>
<td>Force Platform</td>
</tr>
<tr>
<td>GA</td>
<td>Gastrocnemius</td>
</tr>
<tr>
<td>GMAX</td>
<td>Gluteus Maximus</td>
</tr>
<tr>
<td>GMED</td>
<td>Gluteus Medialis</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning Unit</td>
</tr>
<tr>
<td>GRF</td>
<td>Ground Reaction Force</td>
</tr>
<tr>
<td>HS</td>
<td>High Speed</td>
</tr>
<tr>
<td>HJ</td>
<td>Height Jumped</td>
</tr>
<tr>
<td>IAAF</td>
<td>International Athletics Association</td>
</tr>
<tr>
<td>ICA</td>
<td>Independent Component Analysis</td>
</tr>
<tr>
<td>iEMG</td>
<td>Integrated EMG</td>
</tr>
<tr>
<td>IMU</td>
<td>Inertial Measurement Units</td>
</tr>
<tr>
<td>ISBS</td>
<td>International Society of Biomechanics in Sport</td>
</tr>
<tr>
<td>MEG</td>
<td>Magnetoencephalography</td>
</tr>
<tr>
<td>ISBS</td>
<td>International Society of Electromyography and Kinesiology</td>
</tr>
</tbody>
</table>
MG – Medial Gastrocnemius

SENIAM – Surface Electromyography for the non-invasive assessment of muscles

MU – Motor Unit

SM – Semimembranosus

MUAP – Motor Unit Action Potential

SNR – Signal to noise ratio

MUAPT – Motor Unit Action Potential Train

SOL – Soleus

MVC – Maximum Voluntary Contraction

SPSS – Statistical Package for the Social Sciences

PB – Personal Best

ST – Semitendinosus

PCA – Principal Component Analysis

TA – Tibialis Anterior

RF – Rectus Femoris

VL – Vastus Lateralis

sEMG – Surface EMG

VM – Vastus Medialis

Symbols used to represent variables in equations throughout the thesis

s – Speech signals

x – Mixture of signals, a weighted sum of speech signals

A – Matrix, \( a_{ij} \) are parameters that depend on the distance of the receiver from the speaker

\((a_{11} a_{12} a_{21} a_{22})\)

Symbols used to abbreviate statistical terminology throughout the thesis

d – Cohen’s D Effect Size

d – Cohen’s D Effect Size

RMS – Root mean square

p – Probability

SD – Standard deviation

r – Correlation Coefficient

\( \chi^2 \) – Chi Square

xiv
Definitions of key terms used throughout the thesis

Braking Phase – The early stance or absorption phase in running gait, when the leg in question becomes in contact with the ground and muscles are working in a stabilisation role until mid-stance.

Contact time – The time at which the foot remains in contact with the ground during a sprint for example.

Indwelling electrodes – These electrodes are inserted into the muscle under observation.

Nyquist rate – The minimum sampling rate required to recover the signal from its samples without introducing errors / aliasing.

Power Clean – An Olympic weight lifting exercise; the bar is quickly pulled from the floor to the front of the shoulders in one movement.

Pre-activation Phase – The late swing phase in running gait, the muscles tense prior to ground contact, pre-activation to brace for impact.

Propulsion Phase – The late stance phase in running gait, when the leg in question is no longer in the braking phase, the leg is moving from the mid-stance position and the muscles are now working in a driving / propulsive role to drive the body forward until the toe leaves the ground.

Recovery Phase – The early swing phase in running gait, the toe of the leg in question has left the ground.

Sampling Rate – The number times an analog signal is measured per second in order to be converted into digital form, measured in Hz.

Spectral Analysis – A spectrum of frequencies of the signal is analysed.
Submissions and publications arising from and related to the thesis

Peer-reviewed journal articles


Journal articles in review


Peer-reviewed magazine articles

Peer-reviewed international conference proceedings (4 page paper)


Peer-reviewed international conference proceedings (1 page paper)


Peer-reviewed national conference proceedings (6 page paper)


**Peer-reviewed national conference proceedings (1 page paper)**


Chapter 1: Introduction to the Thesis

“He who is not courageous enough to take risks will accomplish nothing in life”

Muhammad Ali
1.1 Introduction

This research outlines the application of sensor devices in sport, the signal processing and analysis methods which were used to enhance the data gathered using these devices and an outline of further work which can be done. The first three sections of this chapter outline the background and context of the research, and its purposes. The last section includes an outline of the remaining chapters of the thesis.

1.2 Thesis background

Devices which are used to measure the electrical impulses of the muscles during a contraction, Electromyography (EMG) systems, were in the past tethered devices. Advances with technology allowed these devices to become telemetric. However, there were still wires attached between the sensors and the transceiver pack which was attached to the participant, all of which restricted the types of movement and had extra interference from wires. In recent years, wireless technologies have been developed for many sensor devices; EMG is one such sensor device. With the advances in technology, acquiring the muscle activations from athletes in an ecologically valid environment was possible. There was an opportunity to research the muscle activations in track and field athletes, with an emphasis on sprinting and exploring ways to improve the results using signal processing techniques which were tried and tested in other disciplines such as image and audio processing.

A profile of the muscle activations in terms of timing and sequencing across an event was missing in some cases; this was mainly due to technology constraints. This was now possible with the wireless EMG devices. Information of this kind would be very beneficial to both the athlete and the coach. It would help with understanding the movement in terms of what the muscles are doing throughout, and how the impulses generated in the muscles cause all of the movements. The types of EMG sensor devices that are generally used for these high velocity
movements in track and field athletics are surface mount sensors which are less invasive and less cumbersome for participants. However, the disadvantages to these sensors are that they are limited to superficial muscles and are susceptible to cross-talk from adjacent muscles. There are recommendations for placements in each muscle which were designed to limit cross-talk and achieve the cleanest signals possible, but it is known that there will still be cross-talk with these ideal placements. By using signal processing techniques from other disciplines it may be possible to reduce the cross-talk from the acquired signal and possibly even recreate ideal signals which were gathered incorrectly due to misplaced electrodes.

1.3 Thesis context

In sport many sensor devices are utilised to characterise movement, improve performance and identify injury prevention techniques. As sport is very versatile and consists of rapid complex movements, sensor devices need to be small and cause little encumbrances. This research focuses on movements in track and field athletics with an emphasis on sprinting. Previously for the analysis of muscle activations in sprinting, data was acquired using tethered devices while the athlete ran on a treadmill. Treadmills have little ecologically validity compared to that of overground sprinting. Participants require non-invasive wireless sensor devices so their movement can be performed with ease in an ecologically valid environment, without wires and invasive electrodes impeding the movements. Practitioners also see the benefit to such sensors, it allows them to be used in the participants’ ecologically valid environment, therefore signals are more representative of the movements and set-up is quicker. However with these advantages there are still limitations to devices. Cross-talk is a common problem in surface mount electrodes. There is a need to deepen the knowledge of EMG signals in terms of muscle activations and make use of signal processing algorithms to separate the signals into their individual muscle contributions. A deeper understanding into the EMG signal across a range of movements and contraction types will help with the
analysis of muscle activity. Finding the correct way to separate signals without losing information will aid the practitioner and give them a greater insight into the workings of muscles throughout human movement.

1.4 Thesis purpose

The purpose of this research is to allow for a greater understanding of muscle activity in shot put and sprinting by utilising successful algorithms and data processing techniques from a range of disciplines. The aim of this research is to provide a novel contribution to the area of sports biomechanics in terms of EMG analysis and signal processing as follows:

1. Gathering information on the various muscles analysed during sprinting and understanding the important muscles for sprinting in terms of sequencing and timings of muscle activations.

2. Gathering information on the various EMG technologies and their key features used for sEMG during sprinting.

3. Gather information from a significant population of sports biomechanists on their use of sensor devices across a sporting application and on the features required of these devices.

4. Creating a profile of timings and sequencing of muscle activations of the legs in shot put during the glide technique to provide representative data on this event which was not previously available.

5. Creating a profile of timings and sequencing of muscle activations using wireless sEMG in overground sprinting to provide representative data on sprinting which was previously available using tethered devices.
Comparing and contrasting the data gathered using sEMG in overground sprinting to the data collated in the literature review.

The thesis objectives were set out to meet the aims as follows:

1. Complete an in depth review of the literature review on articles utilising sEMG during sprinting to examine the various muscles analysed during sprinting to highlight the important muscles for sprinting in terms of sequencing and timings of muscle activations, and to also understand the various technologies used and their key features.

2. Create and conduct a survey of biomechanists on their use of sensor devices to gather information on the best EMG systems and the specifications desired by researchers and to guide the selection of the EMG system used in experimental studies.

3. Gather a target population of athletes, who are at least national level in their chosen discipline, who will volunteer as participants in the all the experimental studies undertaken.

4. Create testing plans for the chosen disciplines in which participants will perform a standardised warm up and specific movements related to the event before the maximal trial of the event is tested.

5. Develop and test Matlab scripts and functions for offline analysis of all EMG data gathered in experimental studies.

6. Compare the muscle activation timings between data acquired from wireless sEMG devices and tethered sEMG device.
1.5 Thesis structure

This research contains a series of progressively linked studies and is structured as follows:

- Chapter 2 contains the background knowledge on biomechanics, muscle physiology, sprinting, EMG and other sensor devices, and signal processing. All of which was necessary knowledge to complete this research.

- Chapter 3 contains a comprehensive review of the literature on surface EMG in sprinting. Information on the muscles analysed, the timings and the activity level of the muscles across the phases of the running gait cycle and the technologies used are discussed. Due to technology constraints and tethered devices, previously most sprints were performed on treadmills which provided little ecologically validity; there is the option to now analyse overground sprinting using new wireless technologies.

- Chapter 4 examines the results from the conducted survey of biomechanists, focusing on current use of electromyography (EMG) device preferences. This chapter highlights the main findings of the survey that there is a need for a simple, low power, multi-channel device which incorporates the various sensors into one single device. It also emphasises the need to develop software analysis tools to accompany the multi-channel device; providing all the basic functions while maintaining compatibility with existing systems.

- Chapter 5 provides an analysis on the muscle activation sequencing of leg muscles during linear glide shot put technique utilising an EMG device identified in Chapter 4. There is an absence of previous research on the muscle activations of the legs during shot put. Since the muscles generate the impulse to move the athlete and project the shot into the air, there is a need for information on phasic muscle activity of the event to provide initial representative data and provide important technical information for
coaches. A comprehensive understanding of movement and muscle activation patterns for coaches is essential to facilitate optimal technique throughout each of the key phases of the event.

- Chapter 6 provides an analysis on the muscle activation sequencing of leg muscles during overground sprinting. The research design, implementation and data analysis from Chapter 5 are applied to similar data gathered during a maximal sprint to evaluate the use of the thresholding algorithm on different movements. A comparison between the muscle activations of previous research from Chapter 3 and the data in this chapter using wireless sensors was conducted.

- Chapter 7 contains the discussion, implications and conclusions of the research. The key findings of the research are summarised, the practical implications and the constraints of the research are identified. The future directions for research in this area are also identified.
Chapter 2: Background

“Biomechanics is the study of structure and function of biological systems by means of the methods of mechanics”

Hatze (1974)
2.1 Introduction

This chapter provides a review of the fundamental material necessary for this research. The purpose of this chapter was to provide an overview of biomechanics, including topics such as kinematics, kinetics, kinesiology and electromyography (EMG). The aim of this chapter was to provide detailed background on the musculoskeletal system, sensor devices and EMG acquisition and analysis methods which were used in the ensuing chapters.

2.2 Biomechanics

A simple definition for biomechanics is the “study of the effects of forces on living systems” (McGinnis, 2013a). The study of biomechanics of humans covers a broad range of topics. Biomechanics spans from the inner workings of a cell, the mechanical properties of soft and hard tissues, to the development and movement of the neuromusculoskeletal system of the body. Mechanical factors affect the form, performance and function of the musculoskeletal system. Human movement is a complex and highly coordinated mechanical interaction between bones, muscles, ligaments and joints within the musculoskeletal system under the control of the nervous system. Deviation from normal movement in motion analysis in terms of kinematic, kinetic or electromyography (EMG) patterns can be identified and used to evaluate neuromusculoskeletal conditions. The performer’s technique in a sporting setting is a combination of the internal and external forces acting on the human body. These forces determine how the various parts of the body move while the activity is being performed. Biomechanists seek to improve sporting performances by improvements in technique or developing new techniques. (Ethier & Simmons, 2007a; Hay, 1993a; Kamen, 2014a; McGinnis, 2013a; Winter, 2009)
2.2.1 Kinematics

Figure 2.1 The coordinate system for human movement analysis
The frontal plane divides the body into anterior (front) and posterior (rear) halves. The sagittal plane divides the body into left and right halves. The transverse plan divides the body into superior (top) to inferior (bottom) halves. The direction in which the body is progressing (principal horizontal direction of motion) is the X-axis, the vertical direction (orthogonal to the X-axis) is the Y-axis and the sideways direction (right perpendicular to the X-Y plane) is the Z-axis.

Kinematics examines the motion of bodies, it encompasses speed and time. It is divided into two parts: linear kinematics to deal with linear motion and angular kinematics to deal with angular motion. Kinematics is concerned with details on the movement itself, to ascertain how fast a body is moving, what distance it is moving and if it is moving at a constant speed or is it accelerating or decelerating. Displacement (distance), velocity and acceleration are the main parameters studied in kinematics. It can be studied in two-dimensions (2D) or three-dimensions (3D). The human body has a special coordinate system; it is divided into 3 planes which help describe the movement relative to the ground or the direction of gravity (see Figure 2.1). The main questions asked in the kinematics of sporting movements are: What athlete is moving faster? What are the various ranges of motion of the joints during this
sporting movement? And, how do the motion patterns of these athletes differ? (R. Bartlett, 2014b; Hay, 1993a; Robertson & Caldwell, 2014; Winter, 2009)

2.2.2 Kinetics

Kinetics is the branch of biomechanics which is concerned with causes of motion or tendency to move or change state of motion. It is primarily the recording of forces that affect motion. Internal forces are those which are internal to the system such as the movement of one limb causing the movement of another, and external forces are those which are external to the system such as the ground reaction force from a runner’s heel strikes. (Caldwell, Robertson, & Whittlesey, 2014; Hay, 1993a; Winter, 2009)

2.2.3 Electromyography

Electromyography (EMG) is a technique that is used to record and evaluate electrical activity which is produced within the skeletal muscles. An electromyograph is used to record changes in the electrical potential which is generated by the activated muscle cells. The EMG signals recorded are useful in detecting medical abnormalities, the activation level of a muscle or to analyse the biomechanics of movement in humans or animals. In the area of sports biomechanics the EMG signal is used to analyse athletic performance and to reduce the likelihood of sports injuries. More information on EMG can be found in Section 2.4.2. (Basmajian & De Luca, 1985; Criswell, 2011; Kamen, 2014b; Kamen & Gabriel, 2010a; McGinnis, 2013b; Weiss, Silver, & Weiss, 2004)

2.2.4 Sports Biomechanics

Sports biomechanists are movement analysts who study and analyse human movement patterns in sport (R. Bartlett, 2014b). Potential benefits within sport as a result of biomechanics include performance, technique, equipment, training, injury prevention and rehabilitation (McGinnis, 2013a). Ultimately the goal of sports biomechanics is to improve
performance during a particular sporting task. Injury prevention and rehabilitation are secondary goals; however there is a very close link between injury prevention and performance. If biomechanists can analyse human movement patterns and know what the optimum movement pattern is for the particular sport, then any deviations from the norm will be a sign of an impending injury. By noticing that an injury is likely to occur, training can be modified for the athlete, thus preventing the injury from occurring and allowing more technique and performance related training to take precedence. (McGinnis, 2013a)

2.3 Muscles

Muscles are required for movement of the body, such as locomotion – walking, running or sprinting, the muscular action is caused by the generation of force by the muscle tissue (Ethier & Simmons, 2007b). In the average person around 40 – 50% of gross body weight is skeletal muscle (R. Bartlett, 2014b; Ethier & Simmons, 2007b). The development of tension within the muscle is known as a contraction. There are three types of contractions muscles can undergo while exerting forces (R. Bartlett, 2014a; Zatsiorsky & Prilutsky, 2012):

- **Isometric (static) contraction**: The muscle maintains a constant length as tension develops

- **Isotonic (dynamic) contraction**: The muscle length changes as it develops tension
  
  o **Concentric (miometric) contraction**: The muscle develops tension with a shortening of the muscle length
  
  o **Eccentric (plyometric) contraction**: The muscle lengthens as tension develops

- **Isokinetic contraction**: The muscle develops tension at a constant speed while the muscle lengthens or shortens
Agonist muscles are the prime movers; they undergo a concentric contraction and cause movement. Antagonist muscles are opposing muscles, they relax when the agonists contract. Stabilisers are the muscles which undergo an isometric contraction; they fix one bone against the pull of the agonists to allow the bone at the other end to move freely. When agonists have more than one function the fixators prevent undesired actions of the agonists. (R. Bartlett, 2014a).

Figure 2.2 The macro and micro structure of muscles
The composition of muscle cells, muscle fascicles, muscle fibre, myofibril, myofilaments, sarcomere, thick and thin filaments. Source: Netter Anatomy Illustration Collection, © Elsevier, Inc. All Rights Reserved.
2.3.1 Muscle Physiology

Tendons are tough, flexible bands of fibrous connective tissue which connect muscles to bones. Muscles contain compartments of muscle fibres. Muscle fibres are 10 to 100 µm in diameter and up to 0.3 m in length. Perimysium is the name for the connective tissue that surrounds the bundles of muscle fibres. These bundles of muscle fibres are called muscle fascicles. The fibrous elastic tissue surrounding a muscle is called the epimysium. Each individual muscle fibre is enclosed by a layer of connective tissue called the endomysium. Muscle fibres can be broken down further into clusters of individual myofibrils. The muscle fibres are filled with a thick solution known as the sarcoplasm and enclosed in sarcolemma. Nuclei are located peripherally, under the sarcolemma and satellite cells are precursors to skeletal muscle cells found in mature muscles. The basement membrane is a layer of extracellular matrix material which coats muscle fibres and other cells; they attach layers of tissue in the body. The myofibrils are strands which are braided in light and dark bands; they consist of overlapping myosin and actin protein filaments from one Z line to the next Z line called sarcomeres, see Figure 2.2. The actin filament is a thin filament, and the myosin filament is the thick filament. Both filaments are negatively charged. The I bands contain only actin, the H bands contain only myosin and the A bands is where the myosin and actin fibres overlap. The cross-bridges are formed between actin and myosin filaments, this is responsible for the contraction of a muscle. The actin and myosin filaments are the contractile proteins. The muscle fibres shorten during a concentric contraction when the actin and myosin filaments slide over each other. When the contraction is finished the filaments return to their original positions. The number of cross-bridges formed relates to the tension of the contraction and the contraction of a whole muscle is the sum of the singular contraction events which occur within the sarcomeres. (R. Bartlett, 2014b; Criswell, 2011; Ethier &
There are more than 430 skeletal muscles in the human body (Triplett, 2016). Figure 2.3 shows the frontal and rear view of the musculoskeletal system. This research examines the lower limb muscles.

![Figure 2.3 Skeletal musculature](image)

**Figure 2.3 Skeletal musculature**
The frontal view (a) and rear view (b) of the musculoskeletal system (Triplett, 2016, p. 4).

### 2.3.2 Muscle Activity

Muscle tissue membranes are excitable. Electrical impulses can be conducted through the membranes of muscles. The resting voltage gradient across the muscle fibre membrane is about -90 mV, the concentration of Na+ is high outside the membrane and the concentration
of K+ is low outside the membrane, inside the fibre the Na+ is low and the K+ is high. The resting membrane potential varies from person to person; it depends on factors such as the slow twitch and fast twitch fibres and exercise training (Moss et al. 1983). An impulse from a motor neuron is received by the muscle fibres to produce a muscular force. The Central Nervous System (CNS) activates the motor neuron and an electrical impulse propagates down the motor neuron to each motor endplate. The endplate region is the anatomical structure where the nerve interfaces with the muscle (synapse). The electrical impulse reaches the endplate region where an ionic event occurs and a muscle fibre action potential (AP) is generated. Every segment of the muscle fibre is activated by this neural message. The AP occurs in two phases, the Na+ permeability of the muscle fibre increases and there is an influx of Na+ into the cell and the inside of the muscle fibre becomes positive, the second phase occurs when there is an outflow of K+ from the muscle fibre which restores the resting membrane potential, see Figure 2.4. (Kamen, 2014b; Kamen & Gabriel, 2010a)

Figure 2.4 The generation of the action potential (AP)
The changes in membrane permeability to Na+ and K+ ions describes the generation of the action potential (Kamen & Gabriel, 2010a, p. 6).
The Motor Unit (MU) is responsible for the recruitment of the muscle through the nervous system. A MU is one motor neuron and all the muscle fibres innervated by that motor neuron. The summed electrical activity of all muscle fibres activated within the MU is the Motor Unit Action Potential (MUAP). See Figure 2.5, the MUs are denoted as αA and αB, the AP from muscle fibres 1 – 5 can also be seen, \( \sum MUAP_A \) is the sum of the APs from the muscle fibres activated by αA (1, 4, 5) and \( \sum MUAP_B \) is the sum of the APs from the muscle fibres activated by αB (2, 3). Recruitment is the orderly addition of MUs to increase the force of a contraction. In a contraction the first motor units to fire tend to be the smallest, known as Type I motor units. The motor units are recruited by increasing size, as the contraction increases there is an orderly recruitment of the larger motor units. More force is added to the contraction as a result of the larger motor units beginning to fire. (Basmajian & De Luca, 1985; Kamen, 2014b; Kamen & Gabriel, 2010a; McGinnis, 2013b; Moritani, Stegemen, & Merletti, 2004; Weiss et al., 2004; Winter, 2009)

The strength of a contraction can be increased in two ways. If the MUs which are firing increase their rate of firing the force of a contraction will increase. The second way to increase the force of a contraction is if additional MUs commence firing. A sequence of
stimuli is sent from the CNS to maintain a muscle contraction, the MUs are repeatedly activated and a train of MUAP is produced. Myopathic Recruitment is when there is an increased number and early recruitment of motor unit action potentials for the strength of the contraction. (Kamen, 2014b; Kamen & Gabriel, 2010a; Moritani et al., 2004; Weiss et al., 2004)

2.4 Wireless Sensor Devices & Electromyography

Accelerometers, gyroscopes and inertial measurement units (IMU) are an important part of human movement analysis. In recent years, there has been a large emphasis on physical activity and health monitoring and the use of accelerometers for physical activity monitoring has become popular (Mathie, Coster, Lovell, & Celler, 2004; Yang & Hsu, 2010).

2.4.1 Wireless Sensor Devices

Accelerometers are very commonly used in gait measures to quantify physical activity. Accelerometers and gyroscopes have been utilised and validated in running gait analysis studies (Norris, Anderson, & Kenny, 2014). Such studies have derived both coach oriented and research oriented kinematic parameters. They can acquire data on the segment accelerations and whole body accelerations depending on sensor placement, however various methodologies have been utilised by previous researchers and further investigation of the methodologies are needed in the future (Norris et al., 2014). It is possible to calculate different kinematic parameters from accelerometer data such as joint angles at particular phases of a movement, speed and distance values (J. P. Alexander et al., 2016; Alonge, Cucco, D'Ippolito, & Pulizzotto, 2014; Djurić-Jovičić, Jovičić, & Popović, 2011; Higginson, 2009; Yang & Hsu, 2010). As with any activity it is not always guaranteed that the orientations of joints are consistent in the initial plane. Observing a high jump, for example, the legs are initially perpendicular to the ground, during the flight they move into a position
parallel to the ground. If the trace from an accelerometer placed on the shin of this athlete is observed the trace in one axis may not account for the true movement. A simple countermovement jump may provide a clearer picture. During this movement an accelerometer placed at the centre of gravity will measure the vertical component of the jump, however as the participant squats down to generate momentum to jump into the air they tilt their torso forward and the vertical axis in the accelerometer is no longer pointing in the vertical direction. When the orientations change the accelerometer no longer aligns with the global access (Howard, Conway, & Harrison, 2014; Howard, Healy, Conway, & Harrison, 2014). The resultant acceleration of all three axes can be calculated but it will not provide an accurate enough representation of the acceleration in the vertical axis (Howard, Conway, et al., 2014; Howard, Healy, et al., 2014); further analysis is needed in order to use the rotation values from the gyroscope to rotate the axes accordingly during the movement. The use of gyroscopes or magnetometers is thus used to understand the rotation of the device or its orientation in space. This added functionality can be used to re-orientate the signal to the global coordinate system. Their use in physical activity measure and in sports biomechanics increased in recent years (Howard, Conway, & Harrison, 2016). However, due to various collection and processing methods used with accelerometers between-study comparisons are not possible; limitations exist with their validity and comparability (Cain, Sallis, Conway, Van Dyck, & Calhoon, 2013; Pedisic & Bauman, 2014).

2.4.2 Electromyography

An overview of EMG was given in Section 2.2.3. An outline of the electrodes used for EMG analysis is given in this section. There are two types of electrodes which can be used to measure the muscle activity, surface mount electrodes and indwelling electrodes:
2.4.2.1 **Surface Electromyography**

SEMGs are a non-invasive form of measuring the electrical impulses during a muscle contraction. The electrodes are easy to apply and are placed on the surface of the skin over the muscle belly. Due to the non-invasive nature of SEMG, the encumbrance of the sensor for the subject being tested is reduced. The disadvantages however, are that the surface mount electrodes are limited to superficial muscles and are subject to cross-talk as it is difficult to isolate the individual muscle activity. (De Luca, Kuznetsov, Gilmore, & Roy, 2012; De Luca & Merletti, 1988; Howard, Conway, & Harrison, 2015; Kamen, 2014b; Kamen & Gabriel, 2010b; Winter, Fuglevand, & Archer, 1994)

2.4.2.2 **Preparation of skin & electrode placement**

Recommendations in Surface Electromyography for the non-invasive assessment of muscles (SENIAM) outline that the skin should be prepared in such a way as to increase the signal to noise ratio (SNR), and to create better EMG recordings (SENIAM, 2016). The impedance of the skin should be reduced to $< 50 \, \Omega$. The normal impedance across the skin surface is 50 k$\Omega$. Techniques for preparing the skin vary throughout the papers but the general approach is to shave any hair in the area and cleanse using an alcohol solution. Gels are used to create better conduction in some studies. SENIAM recommends pre-gelled surface electrodes with the wrist or ankle as the reference electrode point. The orientation of the sensors should be parallel to the muscle fibres. (R. Bartlett, 2014a; Basmajian & De Luca, 1985; Criswell, 2011; Hermens, 1999; Hermens, Freriks, Dissanhorst-Klug, & Rau, 2000; Kamen & Gabriel, 2010b; Merletti & Hermens, 2004)
2.4.2.3 Electrodes

Various materials can be used for the electrodes; Silver/Silver Chloride (Ag/AgCl) is the most commonly used electrode material due to its connectivity properties. The most common arrangement of electrodes is in a bipolar fashion (see Figure 2.6). This is also known as a single differential arrangement. A double differential arrangement has also become popular (see section 2.4.2.4). A signal electrode is known as mono-polar. The electrode shape can be square or oval, a 10 mm diameter for circular electrodes is recommended. Either a circular disk of diameter R or a square electrode with length of R will have roughly the same coverage area. An inter-electrode distance of 20 mm is recommended to reduce cross-talk. For smaller muscles the inter-electrode distance should not exceed ¼ of the muscle fibre length. The position at which the nerve enters the muscle is the motor point. The EMG signals at this point are not accurate. (Kamen, 2014b; Kamen & Gabriel, 2010b; Merletti & Hermens, 2004)
2.4.2.4 Parallel bar & double differential electrodes

Delsys sensors first came to the market in 1979 (see Figure 2.7). Extensive research and testing has been done on the sensor design and they are thought to achieve the best signal quality and also help reduce cross-talk (Basmajian & De Luca, 1985; De Luca, 1979; De Luca & Forrest, 1972; De Luca & Merletti, 1988; Roy, De Luca, & Schneider, 1986). Electrodes have been designed in the form of parallel bars (10 mm long and 1 mm wide) with an inter-electrode distance of 10 mm. Additional advantages to this type of electrode are that it is small and lightweight and thus is not obtrusive to the subject, and the spacing between the electrodes is large enough so that when skin sweats an electrical shortening path is not created (De Luca, 2003). There are single (see Figure 2.8 (a)) and double (see Figure 2.8 (b)) differential sensors. The double differential sensor differs to the single differential sensor by having three electrodes rather than two, each separated by 10 mm and performing a two-stage subtraction (Delsys, 2016).

**Figure 2.7 Timeline of sensor development**
Delsys EMG technologies and software solutions development timeline (http://www.delsys.com/about-delsys/innovation/)
2.4.2.5 Indwelling Electrodes

There are two types of indwelling electrodes, needle electrodes and fine-wire electrodes (see Figure 2.9), these electrodes are inserted into the muscle under observation. This form of EMG measurement is more precise in locating muscle activity; there is also the added benefit of getting access to deeper muscle tissue and thereby reducing cross-talk from other muscle responses. While there are benefits of fine-wire EMG measurements, it is still an invasive technique and poses minor discomfort for the subject. Due to this invasive nature of the electrodes it is less likely to obtain ethical approval for routine use and sEMG is more commonly found in studies on non-pathological subjects. The proficient use of indwelling electrodes requires significantly more training than that required for surface electrode use. It only offers a small detection area and cannot be repositioned once inserted. Accurate placement of these electrodes is more difficult than with surface electrodes. Indwelling electrodes also contain higher frequency content than the surface EMG electrodes; as the electric currents propagate through the muscle tissue the amplitude and frequency content are reduced, thus the surface electrodes record lower frequency content. (Kamen, 2014b; Kamen & Gabriel, 2010b; Moritani et al., 2004)
2.4.2.6 Recording the EMG signal

2.4.2.6.1 Sampling Frequency

To correctly reconstruct the signal, the sampling rate must be greater than twice the frequency of the highest component of the signal. According to SENIAM recommendations sampling should be between 1-2 kHz as the SEMG signal components are within the range of 10-500 Hz. Most studies use a 1 kHz sampling frequency with some cases using a smaller sampling frequency which could cause aliasing or distortion if the sampling frequency is too low (DeLuca, 2003; Lathi & Green, 2014). Aliasing occurs if signals are sampled below the Nyquist frequency. This causes a distortion in the signal. Samples are incorrectly detected as lower frequencies if they are above that of the sampling frequency and the signal cannot be reconstructed. Figure 2.10 shows three signals with different frequencies all sampled at the same rate. The first signal has a high sampling rate to allow reconstruction, the second has a just enough points to allow reconstruction and the sampling rate of the third signal is too low to allow correct reconstruction. The sampling frequency should be at least 1 kHz, if not 2 kHz, for any activity which involves such rapid movements like sprinting so as not to cause

Figure 2.10 An example of sampling
a) This signal has a good sampling rate to allow reconstruction
b) This signal has just enough points to allow a reconstruction
c) The sampling rate of this signal is too low to allow correct reconstruction

2.4.2.6.2 Amplifier

SEINAM recommends a 12-bit or a 16-bit analog-to-digital converter (ADC). The resolution is $2^n$ levels, n being the number of bits. Figure 2.11 outlines a 4-bit ADC; there are $2^4 = 16$ binary levels. A higher resolution increases the number of levels and decreases the quantisation error.

Figure 2.11 An example of a sine wave sampled by a 4-bit analog-to-digital converter
The resolution of the converter is 4-bits; if the number of bits was increased a smoother, more accurate digital waveform would be created. Adapted from Kamen and Gabriel (2010b)
The gain (the ratio of the output to input voltage) should be set with the intention that the amplitude of the signal is matched to the range of the ADC. Figure 2.12 shows an example where the gain is set too high and clipping of the signal occurs. A typical gain used is 1000. (R. Bartlett, 2014a; Criswell, 2011; Hermens, 1999; Kamen, 2014b; Kamen & Gabriel, 2010b; Merletti & Hermens, 2004; Winter, 2009)

Figure 2.12 An example of the input range of the ADC and the amplifier gain set too low
The amplifier gain is set too low for the resolution of the ADC, clipping will occur and some of the signal will be lost

A common technique, differential amplification, is used when signals are picked up from the body. Power line interference is a common unwanted signal. To eliminate this signal, which is known as a common mode signal, a differential amplifier is used to reject the common signal at the amplifiers inputs, detectable differences are then amplified. This is known as Common Mode Rejection (CMR). The Common Mode Rejection Ratio (CMRR) is the ability of an amplifier to amplify differential signals over common signal. A high CMRR (90 – 140dB) is typically considered adequate for suppressing extraneous electrical interference. Figure 2.6 shows the arrangement of amplifiers which is used to create the bipolar surface EMG and the output signals in monopolar- and in bipolar arrangement. (R. Bartlett, 2014a; Criswell, 2011; Kamen, 2014b; Kamen & Gabriel, 2010b; Merletti & Hermens, 2004; Winter, 2009)
2.4.2.6.3 Input Impedance of amplifier

A typical input impedance of $> 100 \, \text{M} \Omega$ is seen in the articles reviewed. According to the SENIAM recommendations, the impedance of the skin should be reduced to $< 50 \, \Omega$. Very high input impedance is necessary to reduce the loading at the skin-electrode contact point. When the electrodes are attached, a circuit is formed between the amplifier and the muscle. Due to the fact that the amplifier draws current, the potential difference between the recording electrodes is decreased. This means that the voltage recorded by the amplifier is less than the actual magnitude. High input impedance is critical to make sure the larger proportion of voltage drop is across the amplifier rather than the body. (R. Bartlett, 2014a; Criswell, 2011; Hermens, 1999; Kamen, 2014b; Kamen & Gabriel, 2010b; Merletti & Hermens, 2004; Winter, 2009)

2.5 Signal Processing

Signal processing is the enabling technology for the generation, transformation, and interpretation of information. With advances in digital hardware, digital signal processing (DSP) has grown exponentially since its emergence in the 1970s. Applications of these techniques are now prevalent in such diverse areas as biomedical engineering, acoustics, sonar, radar, seismology, speech communication, telephony, nuclear science, image processing and many others. (Lathi & Green, 2014)

2.5.1 Processing the EMG signal

The acquisition and analysis of the sEMG signal is very important in making sure that results are valid and reliable. Many standards have been developed in reporting sEMG signals. The SENIAM guidelines outline standards for reporting sEMG data during the acquisition stage. There are also standards for the data analysis stage outlined by the International Society of Electromyography and Kinesiology (ISEK). The data analysis of raw EMG signals is crucial.
2.5.1.1 Amplitude Analysis

2.5.1.1.1 Peak to Peak Amplitude

The peak-to-peak amplitude measurement is useful in measuring M-waves and H-reflex’s. The M-wave is the maximum amplitude of the EMG signal; it is the maximum EMG activity the muscle is capable of producing. It is measured from the negative to the positive peak. The H-reflex is a reflex action of the muscle after electrical stimulation; it is smaller in magnitude than the M-wave. When a low intensity electrical stimulus is applied to the peripheral motor nerve the H-reflex is evoked. (Kamen, 2014b)

![Sample Amplitude Analysis of EMG signal](image)

Figure 2.13 Sample Amplitude Analysis of EMG signal
The raw EMG signal is the unprocessed signal acquired from the EMG system, a DC offset is applied to the raw EMG signal and then it is full wave rectified, a 10Hz low pass Butterworth filter is applied then to achieve a linear envelope, finally the signal is integrated and the maximum value is the iEMG.

2.5.1.1.2 Rectification & Removal of DC offset

Full-wave rectification is a technique used to get the absolute value of all parts of the EMG signal; it is generally one of the first post-processing steps performed on the raw EMG signal,
see Figure 2.13. The polarity of the negative part is inverted so the signal is super imposed on the positive side. Half wave rectification removes the negative part of the signal completely and only keeps the positive values. The AP of a resting muscle tends to sit at -90 mV; another initial step in the post processing of the raw EMG signal is to remove the DC offset and return the EMG signal to the 0V level. (Kamen, 2014b; Winter, 2009)

2.5.1.1.3 Root Mean Square Amplitude

The Root Mean Square (RMS) Amplitude is calculated on the raw EMG signal; see equation 2.1. Since the raw EMG signal has both positive and negative values the average may yield a value of zero. To prevent this, the values are made positive by squaring each amplitude component. The next step is to take the square root of the average (mean) of the squared values.

\[
RMS\{EMG(t)\} = \sqrt{\frac{1}{T} \int_{t}^{t+T} EMG^2(t) dt}
\]  

2.1

The RMS amplitude applies to periodic signals like sinusoids as well as noise so it is a commonly accepted measure of amplitude. The RMS amplitude is useful for EMG signals as they are complex waveforms; unlike sinusoids they are non-repeating, the RMS offers an unambiguous measure of amplitude with physical significance. Some typical window sizes used are 20 ms, 50 ms and 100 ms. For this technique there is no need for rectification of the raw EMG signal. (Robertson et al. 2014b)

2.5.1.1.4 Filtering

There are a wide range of filters available when using signal processing to analyse different datasets. Commonly, for EMG analysis, a high pass filter is used to remove motion artefact and a low pass filter is used to create a linear envelope. Removing motion artefact is often performed using a band pass filter which is a combination of a low pass and high pass filter.
A low pass filter is used to reject high frequency components; it allows low-frequency components pass through and attenuates the high frequency components above that of the cut-off frequency, see Figure 2.14. The cut-off frequency of the low pass filter should be typically 500Hz, half that of the sampling frequency. In cases where indwelling electrodes are used higher frequency components are registered therefore the cut-off frequency is greater, roughly 1 kHz. A linear envelope is created using a low pass filter which has as an input a full-wave rectified EMG signal; see Figure 2.13. This is a type of moving average as it follows the trend of the EMG signal. It is used to measure the volume of the activity of the EMG signal. An anti-aliasing low pass filter is used to restrict the bandwidth of the signal to satisfy the sampling theorem. This filter is therefore used before the signal is sampled. (Kamen, 2014b; Kamen & Gabriel, 2010c; Winter, 2009)

![Low Pass Filter Diagram](image)

**Figure 2.14 Low Pass Filter**  
The pass band ranges from the lowest frequency component to the cut-off frequency; from here frequencies that are higher than the cut-off frequency will be attenuated. In the transition band some frequencies will get through and no high frequency components will pass through in the stop band.

A high pass filter is used to reject low frequency components; it allows high-frequency components pass through and attenuates the low frequency components below that of the cut-off frequency, see Figure 2.15. Commonly a high pass filter with a cut-off frequency of 10 Hz should be used to remove unwanted low frequency components. However, often a cut-off
frequency between 10-20 Hz is used to remove frequency components due to movement artefacts.

Notch filters with cut-off frequencies between 50 – 60 Hz can be used; however a significant proportion of the EMG signal is eliminated in these cases. Notch filters are used to attenuate radio frequency activity from lights or other equipment which may affect the EMG signals. These filters are not being recommended. (Kamen, 2014b; Kamen & Gabriel, 2010c)

2.5.1.1.5 Integrated EMG

The integrated EMG (iEMG) is the area under the curve of the linear envelope of the EMG signal; see Figure 2.13. A sum of the total muscle activity over a period of time is calculated. This technique is useful for quantifying the amount of muscle activity or signal energy; it is important for quantitative EMG relationships such as EMG vs. muscular force. The iEMG can be calculated over the entire contraction performed; here the total iEMG value from the curve is used. It can also be performed whereby the signal is integrated and reset after a fixed time interval or after a particular voltage is reached (Kamen, 2014b). This can be useful in
analysing specific phases of a movement whereby the EMG vs force can be compared at different points in the movement. (Kamen, 2014b; Kamen & Gabriel, 2010c; Winter, 2009)

2.5.1.2 Frequency Analysis

Previous methods were computed in the time domain, where data are expressed as a sum of sinusoids when converted into the frequency domain. Many frequency analysis techniques have been used in the analysis of EMG signals to assess muscle fatigue. Both physiological and non-physiological information can be gathered, such as firing rates of MUs. It can also be used to removing noise. By computing the number of turning points in peaks per unit time or the number of times the signal crosses zero, an estimate of the frequency content of the EMG signal can be calculated. Fourier analysis methods can also be used to estimate the frequencies that make up the EMG signal. The Fourier series allows the representation of a signal in terms of sinusoids or complex exponentials (see equations 2.2 and 2.3). The DC component is represented by the component $A$, the amplitude of each cosine and sine term are represented by $B_n$ and $C_n$, and the frequency of each term is represented by $f_n$. (De Luca, 2003; Lathi & Green, 2014)

\[
x(t) = A + \sum_{n=1}^{\infty} [B_n \cos(f_n \cdot t) + C_n \sin(f_n \cdot t)]
\]

\[
x(t) = A + B_1 \cos(f_1 \cdot t) + C_1 \sin(f_1 \cdot t) + B_2 \cos(f_2 \cdot t) + C_2 \sin(f_2 \cdot t) + \cdots
\]

Taking an MUAP as an example signal, an infinite sum of sinusoids derived from the Fourier series can reconstruct the MUAP (see Figure 2.16). Only 10 sinusoids are shown here for illustrative purposes however the sum of these sinusoids provides a close to accurate reconstruction of the MUAP.
2.5.1.2.1 Fourier analysis

The Fourier Transform is used to calculate the frequency spectrum of the EMG signal, which is simply a histogram of the amplitudes of each sinusoid at each frequency. However, it requires a large amount of computations and processing power. The Fast Fourier Transform (FFT) was developed to reduce the processing time and number of computations. The original sequence is split into smaller segments and the number of additions and multiplications required is reduced, reducing the overall number of computations. Fourier analysis assumes that the signal is stationary, i.e. an isometric contraction performed while acquiring EMG data can undergo Fourier analysis. During isotonic contractions there are changes occurring such as muscle force, length and contraction speed. This is an issue for the FFT as it assumes that the frequency spectrum doesn’t vary over time.

A short-time Fourier Transform (STFT) is an option for isotonic contraction. The STFT needs the signal to be stationary within the running window, thus the spectral analysis for isotonic contractions are more effective using an STFT (Bigliassi et al., 2014). The power spectral density can be calculated from the frequency spectrum of EMG signal. It is the squared frequency spectrum; see Figure 2.17. Statistical variables such as mean and median can be applied to the power spectrum of the EMG signal to assess muscle fatigue and analyze MU recruitment. Wavelet based methods are another frequency domain analysis procedure which can be used with isotonic contractions. (De Luca, 2003; Lathi & Green, 2014)
Figure 2.16 An example of Fourier decomposition of a motor unit action potential (MUAP)
The original MUAP is shown in red. The blue superimposed signal is the mathematical sum of the
sinusoids shown above. To reconstruct the red signal exactly, an infinite number of sinusoids
would be required. (De Luca, 2003)

2.5.1.2.2 Mean & Median Frequency

Mean frequency (MNF) and median frequency (MDF) are traditional measures of the
frequency content of the EMG signal, Figure 2.17. The MNF is simply the average; it is
calculated by determining the frequency at which the average power of the power spectrum
exists. The MDF is calculated by determining the frequency that divides the power spectrum
in two regions having the same amount of power. They are the most popular frequency
domain features used in the assessment of fatigue. Typically in unfatigued muscles, the MNF or MDF in the spectrum is between 50 – 80 Hz. As muscles begin to fatigue the fast-twitch fibres drop out causing a shift in the frequency spectrum to the left. The MNF and MDF are thus lowered. There is less variability in the MNF as the SD of the MNF is lower than the SD of the MDF; therefore it is a better measure than the MDF. (Hermens, Vonbruggen, Baten, Rutten, & Boom, 1992; Kamen, 2014b; Kamen & Gabriel, 2010c)

![Figure 2.17 Power Spectrum of the EMG signal](image)

The bulk of the energy of the sEMG signal is between 10 – 500 Hz, the maximum frequency of the sample EMG signal is about 50 Hz, the median frequency is about 169 Hz and the mean frequency is about 188 Hz.

### 2.5.1.2.3 Normalisation

If comparisons are sought between EMG data with variability such as trials, muscle groups and participants, the EMG needs to be normalised. The most common technique is to calculate the EMG value during a maximum voluntary isometric contraction (MVIC); all other EMG values are then displayed as a percentage of the MVIC (Albertus-Kajee, Tucker, Derman, Lamberts, & I., 2011). However, the criticism of this technique is the fact that it is difficult to ensure the MVIC is truly maximal. Another technique is to use the maximum recorded value during an isotonic contraction and normalise the signal to this. An example of
this would be using the mean of a select few of the peak amplitudes recorded in the BF and RF during the fastest sprint, and normalising the corresponding BF datasets and RF datasets to these mean amplitudes. The EMG data recorded could then be represented as a percentage of the fastest sprint. It is also possible to normalise using the mean or peak EMG measured during a specific task; this is perfectly acceptable if inter-individual variability is the aim, but not when comparing between trials, individuals and different studies. (Albertus-Kajee et al., 2011; Ball & Scurr, 2008, 2011, 2013; Burden, 2010; Kamen, 2014b; Kamen & Gabriel, 2010c)

2.6 Cross-talk

The main disadvantage of sEMG is its limitation to use on superficial muscles and the effect of cross-talk. Cross-talk is the interference which is picked up by the EMG electrode from adjacent muscles. An example of how sEMG sensors may pick up cross-talk from adjacent muscles is shown in Figure 2.18. There are two main factors that contribute to the amount of cross-talk signal detected, the distance between the electrodes on the sEMG sensor and the position of the sensor on the muscle (De Luca et al., 2012). The amount of cross-talk also depends on the size of the muscle. In smaller muscles there are location constraints due to the size of the sensor in proportion to the size of the muscle to be analysed. The presence of cross-talk would therefore be more dominant in the smaller muscles as the sensors would be located near the adjacent muscles as a result of their size. During a movement where a greater force is output by the muscles the presence of cross-talk would be greater and have an effect on the EMG-force curves (Kuriki et al., 2012). As more MUs are contributing to the movement to provide a greater force not only will this be occurring in the muscle being analysed but also in the adjacent muscles which are also contributing to the movement.
Figure 2.18 SEMG sensors can pick up cross-talk from adjacent muscles
Muscle A and Muscle B are shown here. There are 5 EMG sensors located around the surface of the skin. EMG 2 will pick up the best signal from Muscle A, EMG1 and EMG3 would pick up cross-talk from adjacent muscles. Similarly EMG4 and EMG would pick up cross-talk from adjacent muscles but predominantly the signal from Muscle B. A better placement to acquire the signal from Muscle B would be a position between EMG 4 and EMG 5.

SENIAM recommends an inter-electrode distance of 20 mm (Hermens et al., 2000), however De Luca et al. (2012) observed reduced cross-talk using a 10 mm inter-electrode distance. It was found that the amplitudes of the sEMG signal using 10 mm, 20 mm, and 40 mm inter-electrode distances were not significantly different but as the inter-electrode distance increased, the amplitude of the cross-talk signal increased more than the signal from the muscle in question and the optimum inter-electrode distance to reduce cross-talk contamination was 10 mm (De Luca et al., 2012). It was observed that cross-talk is more affected by the inter-electrode distances when double differential systems are used (De Luca et al., 2012). Similarly, Farina, Merletti, Indino, Nazzaro, and Pozzo (2002) observed that the cross-talk signal increased as the inter-electrode distance increased. In single differential electrodes the differences in cross-talk across 10 mm to 40 mm inter-electrode distances showed a mean difference of about 2% (Farina et al., 2002). Cross-talk from double differential signals was much smaller than for single differential signals, however when the
inter-electrode distance increased from 10 mm to 20 mm the cross-talk almost doubled (Farina et al., 2002). Several articles have discovered that the best position to locate the sensor is in the middle of the muscle belly (Basmajian & De Luca, 1985; De Luca, 1997; De Luca, Gilmore, Kuznetsov, & Roy, 2010), like the position of EMG2 in Figure 2.18. Placing the sensor at the perimeter of the muscle surface will result in a greater detection of cross-talk from adjacent muscles rather than one placed in the centre of the muscle surface (Basmajian & De Luca, 1985; De Luca, 1997; De Luca et al., 2010; De Luca et al., 2012). The amplitude and frequency content of signals gathered using large inter-electrode distances for single differential systems are less affected by the electrode location (Farina et al., 2002).

2.7 Locomotion

The human musculoskeletal system (locomotor system) gives the human body the ability to move using its skeletal systems and muscles. Locomotion is also known as gait: it is the biphasic forward propulsion of the human body’s centre of gravity through the alternate movements of different segments of the body. Gait patterns are characterised by differences in limb movement patterns, speed, forces and changes in the foot ground contact. Walking is the slowest form of gait naturally occurring to humans. Due to the fact that a gait cycle is repetitive and cyclical, analysis can be done on a number of different gait cycles. (R. Bartlett, 2014b; Ethier & Simmons, 2007c)

2.7.1 Walking

Walking is a fundamental skill whereby the movement advances by lifting and setting down each foot in turn. While walking there is a single-support phase: one foot remains in contact with the ground, and a double-support phase: both feet will be in contact with the ground at the same time. The walking gait cycle can be defined as touch down or initial contact (IC) of one foot to the subsequent IC of the same foot or, the toe-off (TO) of one foot to the next TO
of the same foot. The walking gait can be divided into two phases: the stance phase and the swing phase. The stance phase begins at touchdown and ends at TO for one foot. The stance phase accounts for greater than 50% of the gait cycle, due to the double-support phase which occurs once at the beginning of the stance phase and once at the end of the stance phase (Novacheck, 1998). The mid-stance phase occurs when the foot is flat on the ground. The swing phase begins from the point the toe leaves the ground and ends at the subsequent touchdown; the foot will not be in contact with the ground during the swing phase. The double-support phase occurs at touchdown of one foot and just before TO of the opposite foot. (R. Bartlett, 2014b; Ethier & Simmons, 2007c)

The gait cycle can be described as follows from left foot touchdown to subsequent left foot touchdown (see Figure 2.19):

- left foot IC
- right foot TO
- left foot mid-stance
- right foot IC
- left foot TO
- right foot mid-stance
- left foot IC
2.7.2 Running

Running is a fundamental skill like walking; it is also a cyclical activity where each running stride follows the previous in a continuous pattern. The gait cycle, which is similar to walking, generally starts and finishes at the IC of the same leg or at the TO of the same leg. Running is faster than walking and unlike the walking gait cycle both feet will not be in contact with the ground at the same time (double support phase), instead twice during the gait cycle both feet will be airborne (Novacheck, 1998). This is known as the double float and occurs once at the beginning and once at the end of the swing phase. There are two phases, stance and swing, like walking. The phases can be broken down further into the braking phase (early stance), the propulsion phase (late stance), the recovery phase (early swing) and the pre-activation phase (late swing). The stance phase accounts for less than 50% of the gait cycle in running, the time at which TO occurs depends on the speed, less time is spent in stance as the speed increases (Novacheck, 1998). Figure 2.20 shows the various phases across the running gait cycle. (R. Bartlett, 2014b; Ethier & Simmons, 2007c)
Figure 2.20 The phases of the running gait cycle
The phases have been defined with respect to the right leg of the figure. The cycle begins and ends with the initial contact (IC) of the right leg. The stance phase is defined as the first IC until the toe-off (TO). The swing phase is defined as the TO until the next IC.

The gait cycle can be described as follows:

- right foot IC
- right foot mid-stance
- right foot TO
- left foot IC
- left foot mid-stance
- left foot TO
- right foot IC

2.7.3 Sprinting
Sprinting is a high velocity cyclical activity, an extreme form of running. Generally as speed increases, running becomes sprinting and the IC changes from the heel to the ball of the foot (Novacheck, 1998). The running gait cycle defined above also applies to sprinting, and again the time in stance phase is reduced. World class sprinters could TO around 22% of the gait
cycle (Novacheck, 1998). Sprinting in Track and Field Athletics ranges from the 60 m (indoors) sprint to the 400 m sprint. There are four stages associated with a sprint, the drive (the athlete is driving low out of the blocks and accelerating), the transition (the athlete is accelerating and moving into an upright body position), the maximal velocity (the athlete has reached maximum velocity and is running in an upright body position) and the maintenance (the athlete is maintaining maximum velocity in an upright body position through to the finish line).

Muscle activations and their patterns are useful to consider during sprinting. With the advances in technology the analysis during sprinting has been simplified and proved more accurate, with less interference due to wired data logging systems. However, limitations still arise when measuring the electrical impulses during sprinting, this movement can produce considerable skin artefact and electrode movement, particularly during specific phases of the gait cycle when the skin is stretched (Kamen, 2014b). EMG can be used for normal muscle function studies, muscle activity in complex sports, rehabilitation movements, fatigue studies and many more. Patterns of muscle activity across the running gait cycle can be identified using EMG; see Figure 2.21, this type of figure may be useful in comparing variations across muscle activity in the running gait cycle and in other sporting techniques to enable speciality of training.
Figure 2.21 Muscle activity across the running gait cycle
The timing of muscle activity across the running gait cycle for various lower limb muscles, image adapted from Kamen and Gabriel (2010d)
2.8 Conclusion

This chapter provided detailed background on various areas of biomechanics with an emphasis on sports biomechanics, sensor devices and EMG. With the wide range of sensors available to practitioners there is an opportunity to examine the culture around various sensor devices, their use amongst the sports biomechanics community and their applications in sport biomechanics. With the recent advances in technology especially into wireless sensor devices there is also an opportunity to examine further EMG during sprinting. A comprehensive review of current literature and expectations of future research is necessary to highlight the use of EMG in sprinting. These recent advances into wireless EMG will also be useful in other sporting activities to provide analysis and a profile of muscle activity where previously due to technology constraints this was not possible. Finally the main limitation of sEMG is cross-talk; this is an area where more analysis needs to be undertaken to discover if it is possible to minimise cross-talk using advanced signal separation methods.
Chapter 3: Literature Review - Muscle Actions in Sprinting

“The more that you read, the more things you will know.

The more that you learn, the more places you’ll go.”

Dr. Seuss


3.1 Introduction

In sports biomechanics, EMG analysis provides important information on muscle activity which may be useful in optimising performance or reducing the likelihood of sports injuries (Ditroilo et al., 2011; Nummela, Rusko, & Mero, 1994; Paul & Wood, 2002). This is crucial for athletes such as sprinters, as speed increases the likelihood of injury are greatly increased (Higashihara, Ono, Kubota, Okuwaki, & Fukubayashi, 2010; Schache, Dorn, Blanch, Brown, & Pandy, 2012; Yu et al., 2008). Sports performance monitoring for injury prevention is very important for athletes and their coaches as potentially the risk of injury may be increased with an increase in speed and due to muscle fatigue. Identification of the specific effects of fatigue on muscle activation may provide important insights about specific injury mechanisms in sprinting (Thelen, Chumanov, Best, Swanson, & Heiderscheit, 2005; Yu et al., 2008). Utilising EMG to provide information on muscle activity can be useful in examining changes across increases in speed or muscle fatigue. Many features of the EMG signal have been associated with fatigue or speed, especially the amplitude of the EMG signal. Of particular importance are the average EMG (AEMG): the average amplitude of the rectified EMG signal and the integrated EMG (iEMG): the total accumulated activity of the muscle. An increase in either the AEMG or iEMG has been reported to be associated with an increase in muscular fatigue (Nummela et al., 1994; Nummela, Vuorimaa, & Rusko, 1992), while also having a positive association with increasing running speeds (Chumanov, Heiderscheit, & Thelen, 2007; Higashihara et al., 2010).

While many studies have examined applications of EMG in gait, relatively few have examined muscle activity in sprinting. This could be due to the many challenges associated with gathering accurate EMG data in sprinting. The demands of sprinting require EMG data to be acquired in an unobtrusive way, therefore the EMG sensor design needs to minimise encumbrances on the athlete during sprinting. Any change in the way in which an athlete
normally performs a sprint could result in unreliable data being gathered. To reduce discomfort and avoid invasive procedures, the majority of isotonic movements are analysed using sEMG. With advances in technology, sEMG measurements have evolved from tethered systems to data loggers (wireless telemetry) and more recently, to fully wireless systems. For the analysis of sprinting, wireless systems are particularly useful since they do not constrain the movement and facilitate ecologically valid data capture, such as the athlete sprinting on a track rather than on a treadmill in a laboratory setting (Baur, Hirschmuller, Muller, Gollhofer, & Mayer, 2007; Savelberg, Vorstenbosch, Kamman, van de Weijer, & Schambardt, 1998; Van Caekenberghe, Segers, Willems, et al., 2013).

To advance technical knowledge of coaches and athletes, there is a need to understand muscle activation sequences and timing in sprinting, and wireless EMG data could augment understanding of sprinting together with the existing kinematics and kinetic analyses of sprinting derived from many studies. Since the muscles generate the forces required for running there is a particular need to gain knowledge of the timings and sequencing of muscle activity in unrestricted sprinting across the phases of the running gait cycle. With the advent of wireless technology, an increase in studies using sEMG in overground sprinting is predicted. Therefore a review of existing knowledge of EMG in sprinting is necessary to determine the patterns of muscle activations during sprinting as it is vitally important to understand the muscles involved and how they act to produce an effective sprint running action since a full understanding of the biomechanics of sprinting requires analysis of movement, force generation and muscle action. A review of sEMG technologies and their applications in sprint analysis is also important and could highlight how the current knowledge base can be used most effectively in new sEMG studies of sprinting to identify specific areas for future research. Consequently, the primary aim of this study was to examine the various muscles analysed during sprinting, highlighting which muscles were
predominantly analysed, which muscles are important for sprinting in terms of sequencing and timings of activations and the changes in muscle activity levels as a function of running speed. The secondary aim was to understand the various technologies used for sEMG in sprinting, to identify the key features of these systems and examine their relative merits and limitations in the analysis of sprinting.

3.2 Methods

This review was limited to articles where sEMG data was collected on participants performing maximal sprint trials. Sprinting was defined as any distance up to and including 400 m, with only the maximal velocity part of sprinting being included in analysis (speeds above 7 m/s). Scopus, ScienceDirect, and Web of Science were searched to identify studies which utilised surface Electromyography in sprinting. The following keywords/ combinations were used in searches: (1) ‘Electromyography’ OR ‘EMG’ AND (2) ‘running’ OR ‘sprinting’. After the initial search results returned over 1200 citations the advanced search option was used. The inclusion criteria was defined as (1) articles written in English, (2) the source types were journals with books and conference proceedings being excluded, (3) the articles were published in the period from January 2000 to December 2014 and (4) the paper type was an article (review papers were excluded). A final search of ‘surface EMG’ was performed on the results and this identified 418 articles. The titles of the articles were subsequently reviewed with the inclusion criteria: (1) surface EMG measurements were acquired, (2) sprinting was performed and, (3) participants were human. Duplicates acquired from multiple databases were also excluded resulting in 36 articles. The reference lists of these articles were examined to identify any important articles not found in the previous search (28 extra articles were identified) and finally the full papers were examined of all remaining articles. Articles needed to include surface EMG measurements on participants while they were performing maximal sprints, those which did not meet the inclusion criteria
were excluded. Articles on the sprint start were excluded because these articles focused only on the start and acceleration phases and therefore the athletes would not have been sprinting at maximum velocity. On completion of this process, a total of 18 articles were identified which met all inclusion criteria. Additional databases such as Google Scholar, PubMed and Research Gate were examined under the same search criteria. The first 50 results were examined and no new papers satisfying the above criteria were found. A flow chart outlining selection and exclusion of articles is provided in Figure 3.1.

The key phases of the running gait cycle, adapted from (Novacheck, 1998; Nummela et al., 1994; Pinniger, Steele, & Groeller, 2000; Yu et al., 2008) are defined as follows for this study as shown in Figure 2.20 (page 43):

- The Early Stance (Braking) Phase: This phase begins as the foot makes initial contact (IC) and ends at the mid-stance phase, estimated at 0 – 15% of the cycle.

- The Late Stance (Propulsion) Phase: This phase begins at the mid-stance phase and ends at the toe off (TO), estimated at 15 – 30% of the cycle.

- The Early & Middle Swing (Recovery) Phase: This phase begins at TO and ends roughly two third of the way through the swing phase, estimated at 30 – 77% of the cycle.

- The Late Swing (Pre-activation) Phase: This phase begins roughly two third of the way through the swing phase and ends at the IC, estimated at 77 – 100% of the cycle.
Figure 3.1 The Selection Criteria Flow Chart
This chart outlines the databases searched, the inclusion criteria, the number of articles excluded and the final number of articles chosen.
The 18 articles were examined under two headings: (1) Muscle activations and timings in sprinting (2) EMG systems and specifications. The muscle activation timings were compared across the phases of running gait defined above. The review papers were analysed to compare and contrast the timings (Chumanov et al., 2007; Higashihara et al., 2010; Kuitunen, Komi, & Kyrolainen, 2002; Kyrolainen, Avela, & Komi, 2005; Mero & Komi, 1987; Pinniger et al., 2000; Thelen et al., 2005; Yu et al., 2008), EMG timings from the review paper on the biomechanics of running were also included to provide more detailed results on timings of muscle activation. Ensemble means of the muscle activation timings were derived and these were used to create a profile of the phasic muscle activity across the running gait cycle. Muscle groups included in the profile were based on the muscle groups where clear data was given in the papers reviewed and only muscles which had timings across the entire gait cycle were included.

3.3 Results

3.3.1 Study design and sample

Within the 18 selected articles, 204 participants (73 sprinters, 47 distance runners, 26 recreational runners, 12 footballers and 46 mixed sports or unknown) were tested with 11 ±5 participants per study. On average 5 ±3 trials of EMG data gathered during sprinting were performed by each participant in each study, with a total of 60 ±55 sprinting trials completed by all the participants in each study. A total of 1107 trials were examined over all studies. The mean maximum sprint velocity across all articles was 8.50 ± 0.89 m/s. Table 3.1 provides a complete summary of these data. Further information on the purpose and outcomes of each of the studies is outlined in Table 3.2.
Table 3.1. Participant information from the selected 18 review papers

The distribution of male and female participants is given along with their sport and the number of trials per participant and the total number of trials in the studies is also outlined.

<table>
<thead>
<tr>
<th>Participants per study</th>
<th>Trials per participant</th>
<th>Trials per study</th>
<th>Sprint speed (m/s)</th>
<th>Participants' sport</th>
</tr>
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<tr>
<td>Male</td>
<td>Female</td>
<td>Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Albertus-Kajee et al.(2011)</td>
<td>12*</td>
<td>2</td>
<td>24</td>
<td>NS(^1)</td>
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<td>Ball et al.(2011)</td>
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<td>16</td>
<td>48</td>
<td>NS(^1)</td>
</tr>
<tr>
<td>Ball et al.(2008)</td>
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<td>48</td>
<td>NS(^1)</td>
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<td>5</td>
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<td>50</td>
</tr>
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<td>5</td>
<td>25</td>
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<td>Yu et al.(2008)</td>
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<td>7</td>
<td>140</td>
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| 164  | 23  | 204  | 89  | 1077  | 8.50 ±0.89 |

*Gender of participants not disclosed.
\(^1\)Not specified by authors (NS).
<table>
<thead>
<tr>
<th>Participant</th>
<th>EMG characteristics</th>
<th>Purpose of study</th>
<th>Sprint trial description</th>
<th>Outcome measures</th>
<th>Results of study</th>
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<td>Albertus-Kajee et al. (2011)</td>
<td>EMG of right leg</td>
<td>Normalisation methods</td>
<td>(3 Days) 2 x 20 m max sprint: 140 m indoor track*</td>
<td>RMS and peak EMG</td>
<td>Sprint and MVC most repeatable methods</td>
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<td>Ball et al. (2011)</td>
<td>EMG of dominant leg</td>
<td>Normalisation methods for 20 m sprint</td>
<td>(3 Days) 3 x 20 m max sprint: indoor sports hall*</td>
<td>RMS &amp; peak EMG</td>
<td>Normalise to peak in sprint or squat jump</td>
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<td>Ball et al. (2008)</td>
<td>Unilateral EMG measures</td>
<td>Reliability and standardisation of normalisation methods</td>
<td>(3 Days) 3 x 20 m max sprint: indoor sports hall*</td>
<td>RMS and peak EMG</td>
<td>Sprint and squat jump methods</td>
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<td>Bartlett et al. (2013)</td>
<td>EMG of right leg</td>
<td>Activity of gluteal muscles in walk, run, sprint &amp; climb</td>
<td>5 x 30 m max sprint: 30 m runway*</td>
<td>RMS &amp; peak EMG</td>
<td>Gluteal activity changes with increased speed</td>
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<td>Chumanov et al. (2007)</td>
<td>EMG of right leg</td>
<td>Effects of speed on hamstring muscle mechanics</td>
<td>80%, 85%, 90%, 95% &amp; 100% of max velocity: treadmill</td>
<td>Linear Envelope</td>
<td>Increase in peak hamstring activity with increase in speed</td>
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<td>Higashihara et al. (2010)</td>
<td>Unilateral EMG measures</td>
<td>Hamstring muscle activity at different running speeds</td>
<td>50%, 75%, 85% &amp; 95% of max velocity: high speed treadmill</td>
<td>RMS &amp; peak time of maximum activity</td>
<td>Significant difference in activation patterns as speed increases</td>
</tr>
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<td>Kuitunen et al. (2002)</td>
<td>EMG of right leg muscles</td>
<td>Examine ankle and knee joint stiffness during sprinting</td>
<td>70% - 100% (4 sprints) of max velocity, accelerate to photocells (10 m apart)</td>
<td>Smoothed EMG (15 point average) &amp; Average EMG</td>
<td>Ankle stiffness remained constant, knee joint stiffness increased with running speed</td>
</tr>
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<td>Kyröläinen et al. (2005)</td>
<td>Unilateral EMG measures</td>
<td>Changes in muscle activations as speed increases</td>
<td>5 submaximal sprints &amp; 3 x 30 m max: 200 m indoor track*</td>
<td>Average EMG</td>
<td>Increase in activity of all muscles with increase in speed</td>
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<td>Mastalerz et al. (2012)</td>
<td>EMG of right &amp; left legs</td>
<td>Represent fatigue in EMG profile across different run intensities</td>
<td>4 x 400 m (90 s, 70 s, 60 s &amp; max): tartan athletics track</td>
<td>MPF &amp; FFT</td>
<td>Greater fatigue in left leg compared to right</td>
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<tr>
<td>Mero et</td>
<td>Unilateral EMG</td>
<td>Find relationship</td>
<td>2 runs x 5 speeds: indoor hall*</td>
<td>iEMG &amp; peak</td>
<td>Peak activity was shown in all</td>
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<td>Reference</td>
<td>Measures</td>
<td>Between EMG and Contact Forces in Sprinting</td>
<td>EMG Activities</td>
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<td>al.(1987)</td>
<td>EMG of right leg</td>
<td>Neural activation changes across speed in 400 m sprint (iEMG)</td>
<td>EMG activities in fatigued and non-fatigued sprinting</td>
<td>Fatigue in 400 m running is mainly due to skeletal muscles rather than the central nervous system</td>
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<td>EMG of right leg</td>
<td>(2 Days) 20 m max sprint &amp; 400 m &amp; 200 m (Day 1) &amp; 100 m &amp; 300 m (Day 2): indoor running track (flying start for all runs)*</td>
<td>(2 Days) 20 m max sprint (40 m flying start) &amp; 400 m time trial (Day 1) &amp; 3/4 submaximal 20 m (Day 2): outdoor running track</td>
<td>The increased neural activation was due to muscular fatigue</td>
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<td>Average EMG</td>
<td>Average EMG</td>
<td>Fatigue in 5km running at maximum effort was related to sprint performance</td>
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<td>Effects of hamstring fatigue induced by maximum effort during maximum sprint</td>
<td>Average EMG</td>
<td>Increased duration of hamstring activity and earlier offset of RF during swing phase</td>
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<td>Pinniger et al.(2000)</td>
<td>Unilateral EMG measures</td>
<td>3 x 40 m max sprint (non-fatigued); 10 maximal 40 m sprints hamstring fatigue task; 3 x40 m max sprint (fatigued)*</td>
<td>Linear Envelope</td>
<td>Peak musculotendon force and strain for the hamstrings occurred around the same time as terminal swing, this may be when hamstrings are at greatest risk of injury</td>
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<td>Schache et al.(2011)</td>
<td>Unilateral EMG measures</td>
<td>Differences in each hamstring muscle during sprint</td>
<td>Average EMG</td>
<td>A lower velocity in the inclined sprinting results in a decrease in hamstring activity</td>
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<td>Slawinski et al.(2008)</td>
<td>Unilateral EMG measures</td>
<td>Muscle activity during inclined and level training</td>
<td>RMS &amp; iEMG</td>
<td>Increase in excitation of BF at 70 – 80% of running gait cycle until the end of the swing phase</td>
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<td>Thelen et al.(2005)</td>
<td>Unilateral EMG measures</td>
<td>Mechanics of hamstring during swing phase of sprinting</td>
<td>Linear Envelope</td>
<td>Hamstrings were active during entire running cycle, maximum activations occurred during the early stance phase and late swing phase.</td>
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<td>Yu et al.(2008)</td>
<td>EMG of dominant leg</td>
<td>Mechanics of hamstring muscle strain injuries during overground sprinting</td>
<td>Linear envelope across running gait cycle</td>
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3.3.2 Muscle activations and timings in sprinting

3.3.2.1 Muscles analysed in sprinting

The analysis of the articles identified in this review demonstrated a focus on the hamstrings and quadriceps muscle groups as seen Table 3.3. 14 of the 18 articles analysed the biceps femoris (BF), seven analysed the medial hamstrings. 12 of the 18 articles analysed the rectus femoris (RF), 10 analysed the vastus lateralis (VL) and five analysed the vastus medialis (VM). Two of the 18 articles analysed the gastrocnemius (GA), 10 analysed specifically the medial gastrocnemius (MG) and three analysed the lateral gastrocnemius (LG). Of the 18 articles, five analysed the gluteus maximus (GMAX) and one analysed the gluteus medialis (GMED). Four of the 18 articles analysed the soleus (SOL) and the tibialis anterior (TA). 77 muscles were analysed in total across all the articles reviewed. Of these, 35% of the 77 muscles analysed were quadriceps; 27% were hamstrings, 25% were calves, 8% were gluteal muscles and 5% were TA. Over 70% of the 77 muscles analysed were the upper leg muscles with less than 30% of those analysed being from the lower leg muscles.
Table 3.3 Muscles Analysed using Electromyography during Sprinting
This table outlines the frequency of which muscles analysed using Electromyography for sprinting studies

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3.3.2.2 Muscle activation timings

The muscle activation timings of the lower limbs are presented in Figure 3.2. The periods of muscle activity were identified using the timings gathered from the review papers which gave timing details (Chumanov et al., 2007; Higashihara et al., 2010; Kuitunen et al., 2002; Kyrolainen et al., 2005; Mero & Komi, 1987; Pinniger et al., 2000; Thelen et al., 2005; Yu et al., 2008) and the biomechanics of running paper by (Novacheck, 1998). The mean and standard deviation of the timings of the muscle activity were calculated to produce this figure. The light grey areas represent periods where there is muscle activity. The error bars in the plot represent the SD of the mean onset and termination times which were gathered.

3.3.2.3 Muscle activation timings in the stance phase

It can be seen from Figure 3.2 that the hamstrings were active through the stance phase (Higashihara et al., 2010; Pinniger et al., 2000; Yu et al., 2008). An earlier peak activation of the BF than the ST during the stance phase was found (Higashihara et al., 2010). The quadriceps muscle group were also active in the stance phase (see Figure 3.2), which was consistent with Pinniger et al. (2000). Peak activity of the gluteus maximus (GMAX) was at foot strike, with activity in the early stance phase as seen in Figure 3.2 (J. L. Bartlett, Sumner, Ellis, & Kram, 2014; Kyrolainen et al., 2005). It can also be observed in Figure 3.2 that the GA was active during the stance phase (Kuitunen et al., 2002; Kyrolainen et al., 2005; Mero & Komi, 1987; Pinniger et al., 2000) and the SOL was active in the braking (early stance) phase, with the peak activity 50 ms after the initial contact (Kuitunen et al., 2002). The TA also showed activity in the early stance phase in Figure 3.2 (Kuitunen et al., 2002; Kyrolainen et al., 2005; Mero & Komi, 1987).

3.3.2.4 Muscle activation timings in the swing phase

Figure 3.2 also shows the hamstrings are active in the late swing phase (Chumanov et al., 2007; Higashihara et al., 2010; Pinniger et al., 2000; Thelen et al., 2005; Yu et al., 2008). It
can be seen from Figure 3.2 that the RF had two bursts of activity, in the early swing phase and late swing phase, and the VL was also active in the late swing phase (Pinniger et al., 2000). Muscle activity was observed in the GMAX in the late swing phase (Kyrolainen et al., 2005) and as outlined in Figure 3.2. The GA and the SOL were active in the pre-activation (late swing) phase (Kuitunen et al., 2002; Kyrolainen et al., 2005; Mero & Komi, 1987). Figure 3.2 showed activity beginning in the mid-swing phase for the TA (Kuitunen et al., 2002; Kyrolainen et al., 2005; Mero & Komi, 1987).

3.3.2.5 Muscle activity levels

Seven articles found an increase in muscle activity with an increase in speed (Albertus-Kajee et al., 2011; J. L. Bartlett et al., 2014; Higashihara et al., 2010; Kuitunen et al., 2002; Kyrolainen et al., 2005; Mastalerz, Gwarek, Sadowski, & Szczepanski, 2012; Nummela et al., 1994). The maximum activations of the BF and semimembranosus (SM) were found in the late swing and early stance phases, with the activation in the late swing phase being two to three times greater than the late stance and early swing (Yu et al., 2008). Similarly Kuitunen et al. (2002) found the highest EMG activity of the BF in the pre-activation (late swing) phase. The ST showed greater activity than the BF during the mid-swing phase, with the earlier peak activation of the ST than the BF during the late swing phase (Higashihara et al., 2010). In an inclined sprint, the root mean square (RMS) of the BF and ST was decreased compared to level sprinting during the early stance phase (Slawinski et al., 2008). Slawinski et al. (2008) found the RMS of the VL and the SOL was also lower in inclined sprinting compared to level sprinting. Ball and Scurr (2011) showed higher RMS EMG in Medial Gastrocnemius (MG) and SOL compared to Lateral Gastrocnemius (LG). Mastalerz et al. (2012) found greater fatigue in the left BF to the right BF on bend running.
Figure 3.2 Muscle activity of the lower limbs during sprinting
The muscle activity was gathered from the papers reviewed and the mean and standard deviation of the timings of the muscle activity were calculated to produce this figure. The light grey areas represent periods where there is muscle activity. The error bars in the plot represent the SD of the mean onset and termination times which were gathered.
3.3.3 EMG systems and specifications

3.3.3.1 EMG Electrodes

In all 18 articles reviewed Ag/AgCl bipolar surface mount electrodes were used. The most commonly used electrodes are the Beckman type electrodes and Blue Sensor electrodes, each of which were used in four of the reviewed articles. All of the electrodes used in the review are summarised in Table 3.4.

Table 3.4 EMG Electrode Types
Various EMG Electrode types used in sprinting studies

<table>
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<tr>
<th>EMG electrodes</th>
<th>Beckman type (Ag/AgCl)</th>
<th>Biometrics SX230 active (Ag/AgCl)</th>
<th>Biovision (Ag/AgCl)</th>
<th>Blue Sensor (Ag/AgCl)</th>
<th>DE-2.1 DelSys (Ag/AgCl)</th>
<th>Red Dot Infant (Ag/AgCl)</th>
<th>Nicolet Biomedical (Ag/AgCl)</th>
<th>Unknown Ag/AgCl Brand</th>
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The electrode shape used was either disk or bar shaped in all the articles reviewed. A 10 mm diameter for circular electrodes is recommended and 11 out of the 18 articles used the 10 mm diameter shape. An inter-electrode distance of 20 mm was most common, with nine of the
articles reviewed using this distance. Table 3.5 outlines some of the specifications of the EMG electrodes used in the review papers.

Table 3.5 EMG Electrode Specifications
An outline of the features associated with each surface mount electrode

<table>
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<tr>
<th>Surface Electrode Specifications</th>
<th>Inter electrode Distance (mm)</th>
<th>Pre-amplified</th>
<th>Diameter (mm)</th>
<th>Self-adhesive</th>
<th>High Impedance</th>
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3.3.3.2 EMG Systems

The range of EMG systems used within the papers is outlined in Table 3.6. Of the 18 articles reviewed, 14 used telemetry (of which four were also data logging), two used data logging systems and two used wired systems. Four of the articles mentioned the use of transmitter devices attached to the participants back, either strapped (Albertus-Kajee et al., 2011; Pinniger et al., 2000) or attached to a belt (Nummela et al., 2008; Nummela et al., 1994; Nummela et al., 1992). Two articles mention taping cables back to avoid motion artefacts.
The EMG system from Noraxon was the most commonly used; five of the 18 articles recorded the EMG signals with these devices. There are two models of the Mega Electronics EMG systems mentioned in this review; four of the articles used either of these two models. The DelSys EMG systems, the Biometrics EMG system and the Medinik EMG system have each been used to record EMG signals in two of the 18 articles reviewed. The EMG systems used in the articles reviewed appear to be among the most commonly used EMG systems in the analysis of data during sprinting.

Table 3.6 EMG Systems
The frequency of use of various EMG systems in sprinting studies

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<th>EMG system</th>
<th>Bangoli-16 DeSys</th>
<th>Biometrics Datalog EMG System</th>
<th>Glommer Biomes 2000</th>
<th>ME3000 Mega Electronics</th>
<th>ME6000 Mega Electronics</th>
<th>Tekmyo EMG System Noraxon</th>
<th>Medinik AB (IC-600-G)</th>
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<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
3.3.3.3 Recording the EMG signal

Similar specifications were seen across the various EMG systems (see Table 3.7). Of the articles reviewed 10 operated with a sampling frequency of 1 kHz. The next most common sampling rate was 2 kHz, which five of the articles sample at. One article samples below the recommended rate at 833 Hz, while another samples above the recommended at 2.4 kHz. The final article sampled at 1.5 kHz, taking the mid-point of the recommended sampling range. Typically a 12 – 16 bit Analog to Digital Converter, and a gain of 500 – 1000 was used. The bandwidth of the systems was generally from 10 to 500 Hz and the input impedance was set below 100 MΩ. Five articles also mentioned the use of a ground or reference electrode attached to the wrist (Ball & Scurr, 2008, 2011; Thelen et al., 2005) or the tibia (Pinniger et al., 2000; Schache et al., 2012; Yu et al., 2008)
### Table 3.7 Specifications of EMG Systems
An outline of the features associated with the EMG systems used in the sprinting studies

<table>
<thead>
<tr>
<th>EMG devices specifications</th>
<th>Sampling Rate</th>
<th>Analog to Digital Converter (ADC)</th>
<th>Common Mode Rejection Ratio (CMRR)</th>
<th>Input Impedance</th>
<th>Gain</th>
<th>Bandwidth (BW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bartlett et al.(2013)</td>
<td>1 kHz</td>
<td>16-bit</td>
<td>&gt;100 dB</td>
<td>&gt;100 MΩ</td>
<td>1700</td>
<td>2 - 500 Hz</td>
</tr>
<tr>
<td>Mastalerz et al.(2012)</td>
<td>1 kHz</td>
<td>14-bit</td>
<td>&gt;130 dB</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Albertus-Kajee et al.(2011)</td>
<td>2 kHz</td>
<td>16-bit</td>
<td>&gt;100 dB</td>
<td>&gt;100 MΩ</td>
<td>1000</td>
<td>10 - 500 Hz</td>
</tr>
<tr>
<td>Ball et al.(2011, 2008)</td>
<td>1 kHz</td>
<td>&gt;96 dB @ 60 Hz</td>
<td>&gt; 100 MΩ</td>
<td></td>
<td>1000</td>
<td>20 - 450 Hz</td>
</tr>
<tr>
<td>Schache et al.(2011)</td>
<td>1.5 kHz</td>
<td>16-bit</td>
<td>&gt;100 dB</td>
<td>&gt;100 MΩ</td>
<td>500</td>
<td></td>
</tr>
<tr>
<td>Higashihara et al.(2010)</td>
<td>2 kHz</td>
<td>16-bit</td>
<td></td>
<td></td>
<td></td>
<td>50 - 500 Hz</td>
</tr>
<tr>
<td>Nummela et al.(2008, 1994, 1992)</td>
<td>1 kHz</td>
<td></td>
<td></td>
<td></td>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>Slawinski et al.(2008)</td>
<td>1 kHz</td>
<td>16-bit</td>
<td>&gt;100 dB</td>
<td>&gt;100 MΩ</td>
<td>375</td>
<td>8 - 500 Hz</td>
</tr>
<tr>
<td>Yu et al.(2008)</td>
<td>2.4 kHz</td>
<td>16-bit</td>
<td>&gt;84 dB @ 60 Hz</td>
<td>&gt;100 MΩ</td>
<td>1000</td>
<td>10 - 800 Hz</td>
</tr>
<tr>
<td>Chumanov et al.(2007)</td>
<td>2 kHz</td>
<td>12-bit</td>
<td>&gt;84 dB @ 60 Hz</td>
<td>&gt;100 MΩ</td>
<td>500</td>
<td>20 - 450 Hz</td>
</tr>
<tr>
<td>Kyröläinen et al.(2005)</td>
<td>1 kHz</td>
<td></td>
<td></td>
<td></td>
<td>500</td>
<td>0 - 360 Hz</td>
</tr>
<tr>
<td>Thelen et al.(2005)</td>
<td>2 kHz</td>
<td>12-bit</td>
<td>&gt;84 dB @ 60 Hz</td>
<td>&gt;100 MΩ</td>
<td>1000</td>
<td>20 - 450 Hz</td>
</tr>
<tr>
<td>Kuitunen et al.(2002)</td>
<td>833 Hz</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pinniger et al.(2000)</td>
<td>1 kHz</td>
<td>16-bit</td>
<td>&gt;100 dB</td>
<td>&gt;100 MΩ</td>
<td>1000</td>
<td>0 - 340 Hz</td>
</tr>
<tr>
<td>Mero et al.(1987)</td>
<td>1 kHz</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 3.3.3.4 Data Analysis

Table 3.8 highlights the various cut-off frequencies of the filters used in the papers. Typically for creating a linear envelope an 8 – 20 Hz cut-off is used, four articles used a cut-off of 20 Hz. In the elimination of motion artefact a 450 – 500 Hz cut-off is used, only two studies used this type of filtering. One study used a notch filter of 50 Hz (Albertus-Kajee et al., 2011) and a TKEO filter is used in one study also (Schache et al., 2012).
**Table 3.8 Data Analysis Steps: Filtering**  
An outline of the various steps applied to the raw EMG signal

<table>
<thead>
<tr>
<th>Filtering Specifications</th>
<th>Notch Filter (interference from external sources)</th>
<th>Low Pass Filter (linear envelope)</th>
<th>High Pass Filter (eliminate motion artefact)</th>
<th>Other Filters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bartlett et al.(2013)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Mastalerz et al.(2012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Albertus-Kajee et al.(2011)</td>
<td>50 Hz</td>
<td>15 Hz</td>
<td>500 Hz</td>
<td>TKEO filter</td>
</tr>
<tr>
<td>Ball et al.(2011, 2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Schache et al.(2011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higashihara et al.(2010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slawinski et al.(2008)</td>
<td></td>
<td></td>
<td>20 Hz</td>
<td></td>
</tr>
<tr>
<td>Yu et al.(2008)</td>
<td></td>
<td></td>
<td>20 Hz</td>
<td></td>
</tr>
<tr>
<td>Chumanov et al.(2007)</td>
<td></td>
<td></td>
<td>20 Hz</td>
<td></td>
</tr>
<tr>
<td>Kyröläinen et al.(2005)</td>
<td></td>
<td></td>
<td>12 Hz</td>
<td></td>
</tr>
<tr>
<td>Thelen et al.(2005)</td>
<td></td>
<td></td>
<td>20 Hz</td>
<td></td>
</tr>
<tr>
<td>Kuitunen et al.(2002)</td>
<td></td>
<td></td>
<td>20 Hz</td>
<td></td>
</tr>
<tr>
<td>Pinniger et al.(2000)</td>
<td>20 Hz</td>
<td></td>
<td>20 Hz</td>
<td></td>
</tr>
<tr>
<td>Mero et al.(1987)</td>
<td></td>
<td></td>
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</tbody>
</table>

The various amplitude analysis procedures used by the articles reviewed are outlined in Table 3.9. Full wave rectification is used in 10 of the articles. Six articles used various normalisation methods, three of which used the MVC method (Albertus-Kajee et al., 2011; Higashihara et al., 2010; Kyrolainen et al., 2005). Typical windows sizes were 20 – 100 ms for the RMS Amplitude. One study calculated an Average EMG (Kuitunen et al., 2002) and four calculated the integrated EMG (Mero & Komi, 1987; Nummela et al., 2008; Nummela et al., 1994; Nummela et al., 1992).
**Table 3.9 Data Analysis: Amplitude Analysis**
The use of different data conditioning techniques on the raw EMG signal

<table>
<thead>
<tr>
<th>Data Conditioning</th>
<th>Full wave Rectification</th>
<th>Root Mean Square (RMS)</th>
<th>Averaged EMG (AEMG)</th>
<th>Normalising</th>
<th>Integrated EMG (iEMG)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bartlett et al.(2013)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>100 ms window</td>
</tr>
<tr>
<td>Mastalerz et al.(2012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Albertus-Kajee et al.(2011)</td>
<td></td>
<td>50 ms moving average</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ball et al.(2011, 2008)</td>
<td></td>
<td>20 ms window</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Schache et al.(2011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higashihara et al.(2010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>MVC</td>
</tr>
<tr>
<td>Slawinski et al.(2008)</td>
<td></td>
<td>20 ms window</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yu et al.(2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Chumanov et al.(2007)</td>
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<td></td>
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</tr>
<tr>
<td>Kyröläinen et al.(2005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>VC</td>
</tr>
<tr>
<td>Thelen et al.(2005)</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Kuitunen et al.(2002)</td>
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<td></td>
<td></td>
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<tr>
<td>Pinniger et al.(2000)</td>
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<td></td>
</tr>
<tr>
<td>Mero et al.(1987)</td>
<td></td>
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</tr>
</tbody>
</table>

**3.4 Discussion**

The primary aim of this review was to examine the various muscles analysed during sprinting, highlighting where the focus has been, which muscles were important for sprinting in sequencing and timings of activations and the changes in muscle activity levels as a function of running speed. Analysis of the hamstring muscle mechanics and fatigue during sprinting were two of the most common themes emerging from this review. This focus on hamstring muscle sEMG is reasonable given the important role that the hamstrings play in generating forward ground reaction forces during the propulsive part of stance in sprinting. This muscle group is also the most commonly injured during sprinting (Chumanov et al., 2007; Thelen et al., 2005) which emphasises the importance of evaluating the hamstring
muscle activity during sprinting. Yu et al. (2008) examined the kinematics and activations of the hamstrings during over-ground sprinting using sEMG wireless telemetry. Differences in running biomechanics and onset times of muscle activations have been noted between treadmill and overground running (Baur et al., 2007; Wank, Frick, & Schmidtbleicher, 1998), since treadmills have limited ecological validity analysis of over-ground sprinting is more appropriate and valid (Van Caekenberghe, Segers, Willems, et al., 2013).

Higashihara et al. (2010) and (Schache et al., 2012) analysed the BF and ST and compared their muscle activity over trials of increased running speed. A potentially greater risk of hamstring strain as sprint speed increased was proposed. However it must be noted that although the authors suggest an increased risk it was not directly observed or measured. Understanding the specific muscle activations of the hamstring and gluteal muscle groups is useful for coaches and practitioners as this knowledge may provide vital insights on injury risk factors and muscle loadings during the various phases of the sprint action. Hamstring strain injuries are likely to occur at the muscle belly during the late swing phase (Best, McElhaney, Garrett, & Myers, 1995; Yu et al., 2008). Yu et al. (2008) observed that the peak eccentric contraction speeds of the hamstring muscle were significantly greater during the late swing phase than the late stance phase, which could explain why 90% of hamstring strain injuries occur in the muscle belly (Askling, Tengvar, Saartok, & Thorstensson, 2007; Koulouris, Connell, Brukner, & Schneider-Kolsky, 2007). Early identification of injury risks in athletes will highlight the possibility of muscle imbalances or incorrect running biomechanics. This in turn, may help prevent the risk of a more serious injury or reoccurrence due to non-optimal running biomechanics or training methods.

The effects of fatigue on muscle activation can also provide vital insights about specific injuries during sprinting (Thelen et al., 2005; Yu et al., 2008). These studies noted that there was increased muscle activation due to muscle fatigue in submaximal conditions. Fatigue in
the muscles was also correlated with an increase in the duration of the muscle activation, an increase in the AEMG or an increase in the iEMG. For coaches and practitioners it is crucial to be able to recognise the onset of fatigue. Recognising the onset of fatigue during EMG monitoring of sprinting may help to prevent the injury occurring by preventing the athlete from sprinting while fatigued.

Pinniger et al. (2000) noted that in a fatigued sprint, the duration of the muscle activation in the ST muscle increased significantly with an earlier onset and a later termination of the activation. Similarly there was a difference in the RF in the fatigued condition: the first burst of activity terminated significantly earlier and the second burst turned on significantly earlier (Pinniger et al., 2000). The authors also observed that fatigue measured during the 20 m sprints and during the maximum voluntary contraction (MVC) were not related to the fatigue which caused the decrease in velocity during the endurance task. Longer endurance sprints, such as the 400 m, were performed in some studies to consider the effects of fatigue (Mastalerz et al., 2012; Nummela et al., 1994; Nummela et al., 1992; Slawinski et al., 2008). These studies observed that EMG activity increased as the sprint progressed. Increased contact times in the latter half of the run could be as a result of the increasing number of slow-twitch fibres involved as the fast-twitch fibres fatigued (Nummela et al., 1992). The left limb had a greater fatigue compared to the right limb due to a considerable load on the BF of the inner leg, which could be caused by the curve on the track (Mastalerz et al., 2012). Understanding the differences in fatigue between long and short sprinters is very important to allow coaches observe the signs of fatigue in their athletes during speed or endurance specific training session.

Several studies observed changes in the EMG data across various running speeds, which showed that the activity of the muscles increased with an increase in speed (Albertus-Kajee et al., 2011; J. L. Bartlett et al., 2014; Higashihara et al., 2010; Kuitunen et al., 2002;
Kyrolainen et al., 2005; Mastalerz et al., 2012; Nummela et al., 1994). Nummela et al.
(1994) observed a significant difference in the RF in the braking (early stance) phase; this
was most likely due to the important role the RF plays in tolerating impact loads. Kuitunen et
al. (2002) examined a variety of speeds as a percentage of maximum speed which showed
that there was an increase in muscle activation of the plantar flexors (TA) and the knee
extensors (RF) in the pre-activation (late swing) phase as the speed increased. The VM
showed earlier peak activation in the late swing phase in higher speeds and there was
significant differences were found in the BF with increased speeds. Another study found a
dramatic increase in EMG amplitude in sprinting compared to the walking condition. The
RMS mean normalised to walking showed a significant difference of four to seven times
greater during sprinting (J. L. Bartlett et al., 2014). The greatest changes in muscle activity
were found in the BF and RF as speed increased (Albertus-Kajee et al., 2011). Kyrolainen et
al. (2005) found that the MVC is not a good indicator of the activation potential, certain
muscles recorded amplitudes greater than the MVC recorded.

The timings of muscle activations provide a greater insight into the functions the muscles
perform throughout the gait running cycle. Figure 3.2 shows that during specific phases,
agonist and antagonist muscles co-contract allowing stabilisation for example in the braking
(early stance) phase. It can be seen from Figure 3.2 that the activation of one muscle
continues while the other ceases activity and begins functioning in a propulsive role, for
example the calves and the hamstrings in the propulsion (late stance) phase. Once the foot
leaves the ground and the knee is in a flexed position no activity is observed in the
hamstrings and the calves. Figure 3.2 shows RF is active in the early swing phase and
contracts eccentrically for hip extension and knee flexion. There is no activation of the RF
during the concentric contraction in the forward flexion of the thigh. However in the late
swing phase there is activation in the RF as the leg extends in preparation for the ground
contact (see Figure 3.2). Mero and Komi (1987) concluded that the RF had a more important role as a hip flexor than a knee extensor. The TA is also active earlier in the swing phase to keep the foot in a dorsiflexed position throughout mid swing to late swing phase. It is then activating in preparation for the ground contact when it takes on a stabilisation role alongside the calf muscle group in the braking phase. All of the muscle groups are active in the late swing phase in preparation for ground contact and then in the early stance phase in a stabilisation role (see Figure 3.2).

The secondary aim of this research was to understand the various technologies used for sEMG in sprinting, to identify the key features of these systems and examine their relative merits and limitations in the analysis of sprinting. Examinations of EMG systems and their specifications in sprinting show that the main issues were with the data transmission rather than the specification of the acquisition features. System specifications were very similar across the devices, with data acquisition and analysis steps performed to similar standards. Many of the systems used were data logger technologies, which required long wires when evaluating sEMG on distal body segments was required. The quadriceps and hamstring muscles are prime movers in sprinting. Logically the majority of papers analysed these muscles, however the convenience in measuring the upper leg muscles during sprinting (see Table 3.3) may have also been a factor. Results show over 70% of the muscles analysed were the upper leg muscles. Less emphasis has been placed on the analysis of the lower leg muscles which may be due to technology constraints. Longer wires would cause increased noise artefact or movement encumbrance if the data logger was mounted on the distal segment. Clearly, there is a bias on the muscles analysed which may be a consideration due to the limitations of devices. The use of fully wireless sEMG systems could facilitate the effective analysis of a wider range of muscles used in sprinting (Howard, 2016; Howard et al., 2016).
There appears to be a historic trend which dominates sEMG measurements. Several studies in this review reported the use of a tethered sEMG system for analysing gait and running performance. However, these studies all involved the athlete running or walking on a treadmill (Chumanov et al., 2007; Higashihara et al., 2010; Thelen et al., 2005). Very few treadmills allow athletes to reach maximum sprint speed and this limits the ecological validity of treadmill running since sprinting or jogging on a treadmill is not identical with overground sprinting or jogging (Baur et al., 2007; Van Caekenberghe, Segers, Willems, et al., 2013; Wank et al., 1998). There may also be potential changes in the muscle activation timings and magnitudes as motorised treadmills also contribute to hip extension, as the belt moves the foot of the participant backwards (Van Caekenberghe, Segers, Aerts, Willems, & De Clercq, 2013). As a result a tethered sEMG system is likely to cause the athlete to moderate the way they run due to the fact sprints need to be performed on a treadmill. The use of data loggers and telemetry also required the participants to wear a transceiver pack connected via wires to the electrodes while sprinting which could cause changes in the sprint movement pattern.

For coaches monitoring sports performance, it is important that the results accurately reflect the activity in an ecologically valid environment. Technologies were initially quite bulky and limited the amount of data that could be captured. The majority of sampling rates of the systems in the papers reviewed were 1 kHz which is an appropriate sampling rate (SENIAM). More recently higher sampling rates are being used (Albertus-Kajee et al., 2011; Higashihara et al., 2010; Schache et al., 2012; Thelen et al., 2005; Yu et al., 2008). The issues associated with tethered systems highlight the need for wireless based sEMG devices. This will allow for EMG analysis of overground sprinting rather than simulating overground sprinting on a treadmill. The system selected for analysis of sprinting needs to ensure many system specifications such as high sampling rates and ACDs, while also allowing real time data
streaming. By exploiting wireless technology, the data gathering process will be simplified for the practitioner (Howard et al., 2016). Advances in technology have facilitated smaller wireless devices which can sample at higher rates and stream large data sets wirelessly across a long distance. Companies have invested in low power wireless technology with a huge emphasis on wearable wireless sensor technologies. Utilising such technologies will help improve the EMG systems. The analysis of sprint performance for both the coach and practitioner will be simplified.

3.5 Conclusion

This review presented information on muscle activations during maximal sprinting such as timings and activity levels across the running gait cycle. The overview of timings from previous research created a composite profile of the muscle activity timings across the running gait cycle and may be an aid and comparative tool to future researchers. Identification that an increase in muscle activation was correlated with fatigue provided important insights about specific injury mechanisms in sprinting, since injury risk was shown to increase during fatigue in sprinting. There is an opportunity to conduct more research in the area of injury prevention utilising data from muscle activations during sprinting, to allow a greater insight into the causes of injury and the times at which athletes are at a greater risk. This will aid coaches and facilitate more analysis in the area of sports performance for practitioners. This review also highlights the current technologies used in the analysis of sEMG in sprinting and will provide a useful reference for future studies. A review of the current EMG technologies, the specifications of the systems and the data analysis techniques used may be useful to conduct to discover which technologies are the best on the market to provide practitioners with such knowledge. Due to the limitations of sEMG devices, there are relatively few articles on sprinting using sEMG. EMG systems used throughout these studies tended to be tethered or data logging systems, creating a bias in the muscles analysed.
and the way in which sprints were performed. There is an opportunity at this point to utilise wireless technology to facilitate the analysis of all lower limb muscles during sprinting and allow practitioners to perform the analysis in an ecologically valid environment.
Chapter 4:  A Survey of Sensor Devices and their use in Sports Biomechanics

“Before anything else, preparation is the key to success”

Alexander Graham Bell

4.1 Introduction

An examination of current literature on biomechanics of accelerometers, gyroscopes and inertial measurement units (IMU) shows these devices are frequently used in human movement analysis (Fong & Chan, 2010; Patel, Park, Bonato, Chan, & Rodgers, 2012). In recent years, there has been a large emphasis on the monitoring of sport performance, physical activity and health using IMUs (Fong & Chan, 2010; Yang & Hsu, 2010). Recent advances in wireless electromyography (EMG) technologies have enabled its more widespread use, such as analysis in track and field athletics to obtain data on muscle activations (Chimera, Swanik, Swanik, & Straub, 2004). Using sensor devices, it is possible to gather information on muscle fatigue, performance, rehabilitation and injury prevention by analysing the EMG signal (Ditroilo et al., 2011; Nummela et al., 1994; Paul & Wood, 2002). The analysis of specific muscles can be extremely useful in prevention of injury (Yu et al., 2008). Identifying when the muscles are most active during a movement can provide insights on why in certain sports, specific muscles are prone to injury (De Luca, 1997; Kumar, 2001).

The evolution of sensor devices in sports biomechanics has been a critical element for the development of the discipline (Kanoun & Trankler, 2004). The initial devices were designed as tethered systems in which long wires connected the sensors to the receiver device (Kamen & Gabriel, 2010b). This was problematic as wires can cause interference and restrict the types of movement and muscles being analysed (Kamen, 2014b). Data loggers were the next step in the evolution, but most of these systems still retained wires. These technologies are generally radio frequency devices which need both a receiver and transmitter. The transmitter is connected to the EMG electrodes via wires, again restricting the placement of electrodes and the types of movement that can be monitored. More recently, data loggers in which an SD card is used to log the data have been developed and this can reduce the mass of
the technology, however there are limitations on the data being acquired due to memory restrictions.

Ideally in sports monitoring, complete freedom of movement is necessary, however for non-maximal speed running, treadmills have been used successfully in laboratory situations together with tethered EMG systems. In sprinting, the data collection process is more challenging with tethered and data logging systems, due to wires and data loggers causing encumbrances. Furthermore the use of a treadmill especially when sprinting is likely to cause changes in the way the athlete will run (Baur et al., 2007; Savelberg et al., 1998; Wank et al., 1998). Consequently, sprint monitoring of muscle activations and performance would be better achieved in an ecologically valid environment such as the track rather than a laboratory setting (Baur et al., 2007; Van Caekenberghe, Segers, Willems, et al., 2013).

Given the evolution of EMG devices, there is an opportunity for new knowledge on the current status of sensor technologies and their use in sports biomechanics applications. Inspection of the literature to date shows that no research on sports biomechanists’ and their use of sensor technologies has been previously published. There is also a lack of research on sports biomechanists expectations of technologies or to what extent they are operating old and/or modern devices. This suggests there may be a gap in knowledge of multi-sensor devices, wireless technologies and the expectations of users. This paper presents new information on sports biomechanists’ expectations, awareness and use of sensors of and their needs in relation to sensor technologies. Consequently, the rationale for this survey was to gather information from sports biomechanists about the current technologies used, to highlight the most suitable EMG devices and features required by practitioners and to provide information for sensor developers and users alike. Since many devices are available, researchers need to be able to distinguish which devices have the features they require and whether a single device with all the features is available. Information on fields of expertise
of the biomechanists and how long they have been working with sensor technologies does not exist. Neither is there any demographical data available to demonstrate how the use of various methods and technologies vary geographically or by discipline or level of experience.

The main purpose of this survey was therefore to gather information about the range of sensor expertise of sports biomechanists and to obtain specific information on: (i) the systems used: (ii) the numbers of researchers using EMG and other sensor devices, (iii) the EMG devices used and, (iv) the features and specifications required for EMG devices. In the absence of data on trends of use, the data were inspected for relative differences across geographical areas and for gender related changes that may affect the types of human movement studies or use of sensor devices. With the advances in technology it was useful to examine data on the differences in use of devices across the years of experience of the researchers.

4.2 Methods

A total of 68 participants, 55 male (age 42.7 ±12.3 years, mean ±SD) and 12 female (age 41.5 ±13.4 years, mean ±SD), took part in this survey (see Appendix B). Ethical approval was granted by the University of Limerick Faculty of Science and Engineering Research Ethics Committee (see Appendix A), with implied consent given if the survey was taken. This study utilised the ‘SurveyMonkey’ online survey tool (SurveyMonkey Inc., 2015). The inclusion criteria required that participants: (i) were involved in biomechanics research or teaching, (ii) used sensor devices to measure human movement, (iii) had knowledge of EMG and/or used EMG.

Various professional groups of sports biomechanists were considered to find the ideal population for this survey. Following careful consideration, it was decided that the International Society of Biomechanics in Sport (ISBS) would be the target community as it
had a huge diversity in members and had the largest database of sports biomechanists from around the world. To avoid overlap and duplication of participants, the survey was not sent to other groups in which sports biomechanists were members. ISBS members were the appropriate population for a web based survey given their computer literacy, their experience as a web based community and also because all members could be contacted via email (van Gelder, Bretveld, & Roeleveld, 2010). Since the official language of the society is English, the survey was published in English. A pilot test was completed within a local biomechanics research group to confirm there was no misinterpretation of the questions. Permission was sought from ISBS to send a survey via their mailing list. Once confirmed the survey was published online, the link embedded in an email and sent out to the mailing list. This gave participants the option to participate or ignore the request.

The survey was structured in four parts: (i) general information about the expertise of the participant: the number of years of experience, their current location and aspects of human movement measured, (ii) general information about the frequency of use of various types of sensors and devices, (iii) specific information about the use of EMG: various technologies and specifications of the devices and (iv) specific questions about acquisition and analysis features required.

4.2.1 Statistical Analysis

Analysis of the responses was conducted offline using SPSS version 22.0 for Windows (IBM, Armonk, NY, USA). Frequency analysis was conducted on each question with results presented as absolute frequency counts and percentages of total population. Given that the data was predominately rank order nature, all of the parametric requirements were not satisfied. Non-parametric tests were performed on the data. Cross tabulations using the years of experience, geographical region and expertise were performed against the specific
questions on sensor devices, human movement measures and data analysis techniques to identify trends. Chi-Square tests were performed to deduce if: (i) gender depends on geographical region or the years in sports biomechanics research, (ii) geographical region depends on years in sports biomechanics research, (iii) the frequency of use of sensor devices depends on the sub-discipline of expertise, (iv) the Likert scale on sensor specifications depends on the frequency of use of sensor devices and, (v) the awareness or use of EMG devices depends on the geographical region of participants. When the sample size was too small for this test to be valid, Fisher’s Exact Test was used for relatedness and Cramer’s V to measure the relationship strength.

4.3 Results
4.3.1 Participant Specific Demographics

**Number of years in Biomechanics**

![Bar chart showing the distribution of years in biomechanics research](image)

*Figure 4.1 Years in Biomechanics*

The number of years participants were involved in biomechanics related research

Figure 4.1 identifies the number of years of experience the participants have in biomechanics research. See Figure 4.2 for the proportions of researchers from different countries.
Countries were categorised into three geographical regions: The Americas (AMER), Europe, Middle East & Africa (EMEA) and Asia Pacific (APAC).

![Demographics]

**Figure 4.2: Locations of researchers**
The various countries each researcher associates themselves with

Table 4.1 outlines the cross tabulation of the number of years researchers have been involved in biomechanists, of gender and of the geographical region. It can be identified that in recent years there are more females in sports biomechanics research. Despite no significance and a weak relationship between categories, there are still more males in each geographical region: APAC (88.9%), EMEA (83.9%) and AMER (72.2%), due to biomechanics skewed as a male dominated discipline.
Table 4.1 Cross tabulation of Gender, Geographical Region and Years’ Experience
The number of years of experience divided by gender and geographical region, and the geographical region divided by gender.

<table>
<thead>
<tr>
<th>Years in Sports Biomechanics*</th>
<th>Gender*</th>
<th>Geographical Region*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male</td>
<td>Female</td>
</tr>
<tr>
<td>0 – 4 years</td>
<td>7 (12.7%)</td>
<td>4 (33.3%)</td>
</tr>
<tr>
<td>5 – 9 years</td>
<td>8 (14.5%)</td>
<td>2 (16.7%)</td>
</tr>
<tr>
<td>10 – 19 years</td>
<td>19 (34.5%)</td>
<td>3 (25.0%)</td>
</tr>
<tr>
<td>20 – 29 years</td>
<td>13 (23.6%)</td>
<td>1 (8.3%)</td>
</tr>
<tr>
<td>30 + years</td>
<td>8 (14.5%)</td>
<td>2 (16.7%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Geographical Region*</th>
<th>AMER</th>
<th>EMEA</th>
<th>APAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMER</td>
<td>13 (72.2%)</td>
<td>5 (27.8%)</td>
<td>-</td>
</tr>
<tr>
<td>EMEA</td>
<td>26 (83.9%)</td>
<td>5 (16.1%)</td>
<td>-</td>
</tr>
<tr>
<td>APAC</td>
<td>16 (88.9%)</td>
<td>2 (11.1%)</td>
<td>-</td>
</tr>
</tbody>
</table>

*The Chi-Square statistic and Fisher’s Exact Test showed no significance and Cramer’s V showed a weak relationship between the categories.

The main areas of expertise are identified Table 4.2. Of the participants who signified expertise in sports biomechanics, kinematics, sports performance and kinetics showed the highest percentage of expertise.

Table 4.2 Researchers’ Expertise
The main areas of expertise of the researchers; sub disciplines of biomechanics

<table>
<thead>
<tr>
<th>Area of Expertise</th>
<th>Number of participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports Biomechanics</td>
<td>61</td>
</tr>
<tr>
<td>Kinematics</td>
<td>45</td>
</tr>
<tr>
<td>Sports Performance</td>
<td>43</td>
</tr>
<tr>
<td>Kinetics</td>
<td>34</td>
</tr>
<tr>
<td>Injury &amp; Rehabilitation</td>
<td>17</td>
</tr>
<tr>
<td>Gait Analysis</td>
<td>15</td>
</tr>
<tr>
<td>Functional Movement</td>
<td>14</td>
</tr>
<tr>
<td>Ergonomics</td>
<td>4</td>
</tr>
<tr>
<td>Tissue Biomechanics</td>
<td>4</td>
</tr>
<tr>
<td>Cardiovascular</td>
<td>2</td>
</tr>
</tbody>
</table>
What Aspect of Human Movement Do you want to measure?

![Graph showing the percentage of participants for different aspects of human movement measures.]

**Figure 4.3 Human Movement Measures**
The main aspects of human movement measures by researchers

Table 4.3 outlines the main aspects of human movement measures by researchers. A graphical representation of these findings can be seen in Figure 4.3. Sports performance, ground reaction forces, muscle activity and gait studies are the human movement measures performed by the majority of researchers.

**Table 4.3 Human Movement Measures**
The main aspects of human movement measures by researchers

<table>
<thead>
<tr>
<th>Human Movement Measures</th>
<th>Number of Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports Performance</td>
<td>43</td>
</tr>
<tr>
<td>Ground Reaction Forces</td>
<td>39</td>
</tr>
<tr>
<td>Muscle Activity (electrical and/or mechanical)</td>
<td>36</td>
</tr>
<tr>
<td>Gait (Walking, Running, Sprinting)</td>
<td>27</td>
</tr>
<tr>
<td>General Physical Activity</td>
<td>8</td>
</tr>
<tr>
<td>Nerve Conduction Studies</td>
<td>3</td>
</tr>
</tbody>
</table>
4.3.2 Nature and Use of Sensors

The Frequency of Use of Sensor Devices

![Graph showing the frequency of use of sensor devices]

**Figure 4.4: Frequency of use of sensor devices**
Various sensor devices and their frequency of use by researchers

Table 4.4 identifies the frequency of use by sports biomechanics experts of the various sensor devices and if these sensors should be included in a single multi-channel device, Figure 4.4 and Figure 4.5 gives a graphical representation of this data. The force platform, accelerometer and EMG devices are the most frequently used. The accelerometer EMG, GPS and gyroscope are the devices most desired in a multi-channel device.
<table>
<thead>
<tr>
<th>Sensor device</th>
<th>Use of sensor devices</th>
<th>Within a single multi-channel device</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Frequently</td>
<td>Less Frequently</td>
</tr>
<tr>
<td>Force Platform</td>
<td>55 (90.2%)</td>
<td>4 (6.6%)</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>23 (44.2%)(^1)</td>
<td>13 (25.0%)</td>
</tr>
<tr>
<td>Electromyography (EMG)</td>
<td>20 (36.4%)</td>
<td>19 (34.5%)</td>
</tr>
<tr>
<td>Global Positioning System (GPS)</td>
<td>15 (41.7%)</td>
<td>10 (27.8%)</td>
</tr>
<tr>
<td>Inertial Measurement Unit (IMU)</td>
<td>13 (34.2%)</td>
<td>8 (21.1%)</td>
</tr>
<tr>
<td>Gyroscope</td>
<td>10 (32.3%)</td>
<td>8 (25.8%)</td>
</tr>
<tr>
<td>Magnetometer</td>
<td>5 (20.0%)</td>
<td>4 (16.0%)</td>
</tr>
<tr>
<td>Mechanomyography (MMG)</td>
<td>-</td>
<td>2 (14.3%)</td>
</tr>
</tbody>
</table>

\(^1\)Sensor device dependency on Injury and Rehabilitation expertise: Fisher’s Exact Test returned p < 0.0005; Cramer’s V was 0.516 showing a very high significance and a strong relationship. The non-experts frequently used the Accelerometer.

\(^2\)Sensor device dependency on Sports Performance expertise: Fisher’s Exact Test returned p = 0.011 (p <0.05), Cramer’s V was 0.509 showing a strong relationship between the categories. The non-experts rarely used the Gyroscope.
Figure 4.5: Sensors included in a single device
The sensor devices researchers would like to see in a single multi-channel device
4.3.3 EMG Specific Findings

What do you like about the EMG devices on the market?

A Likert Scale of features in an EMG system

A Likert Scale is used in Table 4.5 to categorise the EMG sensor specifications. Wireless transmission and usability were the most important features. See Figure 4.6 for a graphical representation of this data.
Table 4.5 EMG device specifications
A Likert Scale of features in an EMG system

<table>
<thead>
<tr>
<th>Sensor Specification</th>
<th>Like (%), N</th>
<th>Neutral, N</th>
<th>Dislike, N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wireless Transmission (Wi-Fi, Bluetooth, etc.)</td>
<td>45 (98.1%), 36</td>
<td>2 (4.1%), 6</td>
<td>2 (4.1%), 7</td>
</tr>
<tr>
<td>Usability (ease of movement - participant)</td>
<td>36 (73.5%), 33</td>
<td>6 (12.2%), 10</td>
<td>2 (4.1%), 6</td>
</tr>
<tr>
<td>Usability (ease of use - researcher)</td>
<td>33 (67.3%), 30</td>
<td>10 (20.4%), 12</td>
<td>10 (21.7%), 6</td>
</tr>
<tr>
<td>Software Analysis Tools</td>
<td>30 (65.2%), 30</td>
<td>10 (21.7%), 18</td>
<td>6 (13.0%), 18</td>
</tr>
<tr>
<td>Size (10 mm)</td>
<td>30 (62.5%), 30</td>
<td>18 (36.7%), 18</td>
<td>1 (2.0%), 1</td>
</tr>
<tr>
<td>Sampling Rate (1 - 2 kHz)</td>
<td>30 (61.2%), 30</td>
<td>18 (36.7%), 18</td>
<td>1 (2.0%), 1</td>
</tr>
<tr>
<td>Analog-Digital Converter (ADC)</td>
<td>29 (63.0%), 26</td>
<td>17 (35.4%), 17</td>
<td>5 (10.4%), 5</td>
</tr>
<tr>
<td>Bipolar (20 mm inter electrode distance)</td>
<td>26 (54.2%), 20</td>
<td>17 (35.4%), 27</td>
<td>10 (21.7%), 6</td>
</tr>
<tr>
<td>Anti-aliasing Filter</td>
<td>20 (42.6%), 18</td>
<td>27 (57.4%), 28</td>
<td>6 (13.0%), 6</td>
</tr>
<tr>
<td>Amplifier Gain (1000)</td>
<td>18 (39.1%), 13</td>
<td>28 (60.9%), 29</td>
<td>6 (13.0%), 3</td>
</tr>
<tr>
<td>Material (Ag-AgCl)</td>
<td>13 (28.9%), 11</td>
<td>29 (64.4%), 33</td>
<td>3 (6.7%), 3</td>
</tr>
<tr>
<td>Shape (Circular Disk)</td>
<td>11 (23.4%), 10</td>
<td>33 (70.2%), 33</td>
<td>3 (6.4%), 3</td>
</tr>
</tbody>
</table>

1Dependency on frequency of use: 81.8% of participants whom rarely use EMG, 91.1% across all levels of use.
2Dependency on frequency of use: 75.6% of participants across all levels of use.
3Dependency on frequency of use: 68.9% of participants across all levels of use.
4Dependency on frequency of use: 64.3% of participants across all levels of use.

What signal processing would you like to see for a device?

![Signal Processing Options](image)

Figure 4.7: Software Tools
Signal Processing Techniques researchers would like to see in an EMG system

Table 4.6 outlines the data analysis techniques participants would like included in a software package, filtering, rectification and RMS were most important. A graphical representation can be seen in Figure 4.7.
Table 4.6 Software Tools
Signal Processing Techniques researchers would like to see in an EMG system

<table>
<thead>
<tr>
<th>Software Analysis Tools</th>
<th>Agree</th>
<th>Disagree</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filtering</td>
<td>42 (97.7%)</td>
<td>1 (2.3%)</td>
<td>4 (9.3%)</td>
</tr>
<tr>
<td>Rectification</td>
<td>37 (86.0%)</td>
<td>2 (4.7%)</td>
<td>6 (14.0%)</td>
</tr>
<tr>
<td>Root Mean Square (RMS)</td>
<td>36 (83.7%)</td>
<td>1 (2.3%)</td>
<td>6 (14.0%)</td>
</tr>
<tr>
<td>Integrated EMG (iEMG)</td>
<td>31 (77.5%)</td>
<td>1 (2.5%)</td>
<td>8 (20.0%)</td>
</tr>
<tr>
<td>Spectral Analysis</td>
<td>30 (69.8%)</td>
<td>1 (2.3%)</td>
<td>12 (27.9%)</td>
</tr>
<tr>
<td>Linear Envelope</td>
<td>29 (69.0%)</td>
<td>2 (4.8%)</td>
<td>11 (26.2%)</td>
</tr>
<tr>
<td>Principal Component Analysis</td>
<td>25 (58.1%)</td>
<td>2 (4.7%)</td>
<td>16 (37.2%)</td>
</tr>
<tr>
<td>Wavelet Analysis</td>
<td>22 (52.4%)</td>
<td>1 (2.4%)</td>
<td>19 (45.2%)</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>12 (29.3%)</td>
<td>2 (4.9%)</td>
<td>27 (65.9%)</td>
</tr>
<tr>
<td>Independent Component Analysis</td>
<td>11 (25.6%)</td>
<td>2 (4.7%)</td>
<td>30 (69.8%)</td>
</tr>
</tbody>
</table>

The Awareness & Use of EMG Devices

![Graph showing the awareness and use of EMG devices](image)

Figure 4.8: EMG Systems
The awareness and use of EMG devices

The awareness and use of the various EMG devices can be seen in Figure 4.8; further information on the actual results is outlined in Table 4.7. Researchers were most aware of sensors developed by Delsys and Noraxon; these were also the most frequently used brands.
Table 4.7 EMG Systems
The awareness and use of EMG devices

<table>
<thead>
<tr>
<th>EMG Sensors</th>
<th>Aware of</th>
<th>Unaware of</th>
<th>Used</th>
<th>Not Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trigno Wireless EMG System (Delsys)</td>
<td>43 (68.3%)¹</td>
<td>20 (31.7%)</td>
<td>23 (36.5%)²</td>
<td>40 (63.5%)</td>
</tr>
<tr>
<td>TeleMyo 2400T (Noraxon)</td>
<td>37 (58.7%)</td>
<td>26 (41.3%)</td>
<td>20 (32.8%)³</td>
<td>41 (67.2%)</td>
</tr>
<tr>
<td>MyoSystem 1400A (Noraxon)</td>
<td>36 (57.1%)</td>
<td>27 (42.9%)</td>
<td>19 (30.2%)⁴</td>
<td>44 (69.8%)</td>
</tr>
<tr>
<td>Bagnoli Desktop EMG (Delsys)</td>
<td>29 (46.0%)</td>
<td>34 (54.0%)</td>
<td>12 (19.4%)</td>
<td>50 (80.6%)</td>
</tr>
<tr>
<td>Biometrics EMG Kit (Biometrics)</td>
<td>21 (33.3%)</td>
<td>42 (66.7%)</td>
<td>8 (12.7%)</td>
<td>55 (87.3%)</td>
</tr>
<tr>
<td>MyoTestPro (Myotest)</td>
<td>20 (31.7%)</td>
<td>43 (68.3%)</td>
<td>8 (12.7%)</td>
<td>55 (87.3%)</td>
</tr>
<tr>
<td>Clinical DTS (Noraxon)</td>
<td>19 (30.2%)</td>
<td>44 (69.8%)</td>
<td>1 (1.6%)</td>
<td>62 (98.4%)</td>
</tr>
<tr>
<td>Shimmer3 Development Kit (SHIMMER)</td>
<td>19 (30.2%)</td>
<td>44 (69.8%)</td>
<td>8 (12.7%)</td>
<td>55 (87.3%)</td>
</tr>
<tr>
<td>MyoTrac (Bio-medical)</td>
<td>12 (19.0%)</td>
<td>51 (81.0%)</td>
<td>1 (1.6%)</td>
<td>62 (98.4%)</td>
</tr>
<tr>
<td>TeleEMG Focus Machine (TeleEMG)</td>
<td>10 (15.9%)</td>
<td>53 (84.1%)</td>
<td>2 (3.2%)</td>
<td>61 (96.8%)</td>
</tr>
<tr>
<td>BioVolt &amp; BioFlex (BioControl Systems)</td>
<td>3 (4.8%)</td>
<td>60 (95.2%)</td>
<td>1 (1.6%)</td>
<td>62 (98.4%)</td>
</tr>
<tr>
<td>Dantec KEYPOINT Focus (Alpine Biomed)</td>
<td>3 (4.8%)</td>
<td>60 (95.2%)</td>
<td>1 (1.6%)</td>
<td>61 (98.4%)</td>
</tr>
</tbody>
</table>

¹Dependency on geographical region: Chi-Square: p = 0.083, Cramer’s V = 0.287. No significance however, 79.3% in the EMEA region and 70.6% in the AMER region were aware of this device.
²Dependency on geographical region: $\chi^2$ (2, N = 63) = 6.172, p = 0.048. Cramer’s V = 0.313, a moderate relationship between the categories: 47.1% in AMER region, 44.8% in EMEA region.
³Dependency on geographical region: $\chi^2$ (2, N = 61) = 7.054, p = 0.030. Cramer’s V = 0.340, a moderate relationship between the categories: 60% in AMER region.
⁴Dependency on geographical region: $\chi^2$ (2, N = 63) = 7.011, p = 0.028. Cramer’s V = 0.334, a moderate relationship between the categories; 52.9% in AMER region.

4.4 Discussion & Implications

This is the first study to present findings on the awareness and uses of sensor devices and the expectations of the community about these sensor devices. The results show that the members of this community have common expectations about sensor devices (see Table 4.5).

4.4.1 Participant Specific Demographics

A limitation of this survey was the fact that it was not published in languages other than English and therefore this may have presented a bias in responses towards those members who speak English fluently. It can be seen that the most responses came from the United States, the United Kingdom, Australia and Ireland. Given that the language of the society is English it was expected that this would not deter responses from researchers whose first
language was not English. The expertise of the researcher (see Table 4.2), the types of human movement measures performed (see Table 4.3) and the sensor devices they use (see Table 4.4) are all closely related.

4.4.2 Nature and Use of Sensors

Results outlined in Table 4.4 indicate that there is a desire by researchers to have a single multi-channel device. When monitoring athletes, there are multiple things to look at, from both a researcher and a coach’s perspective. Information about what the muscles, joint segments and the whole body are doing during a particular movement is fundamentally important to the practitioner. A profile of which muscles are active during particular sequences of movement can prove very beneficial in sports performance and injury prevention (Yu et al., 2008). This desire by researchers to have a multi-channel device for the analysis of sporting movements indicates that they believe it will be of benefit during testing to have multiple sensors on one device but the results show that not all sensors were desired. EMG devices were shown to be the most popular sensor in a multi-channel device and frequently used, however given that the survey was sent with an emphasis on the participants having used EMG devices, this result is expected. The accelerometer was the next most popular sensor sought in a multichannel device and was also shown to be one of the most popular sensor devices from the frequency of use scale. GPS devices were evenly spread across use categories, but participants agreed with its use in a multi-channel device. Gyroscopes and magnetometers were rarely used by participants but were found to be useful in a multi-channel device; however, more researchers are opting for the gyroscope. The majority of researchers rarely used Mechanomyography (MMG) sensors. As such its addition to a multi-channel device was shown to have less than 30% agreement. The majority of respondents chose to remain neutral.
4.4.3 EMG Specific Findings

The results show clearly that for EMG, a full wireless sensor is the most important feature to participants (see Table 4.5). Even participants who had not used, or rarely used EMG devices highlighted the need for wireless capability, which shows that sports biomechanists know that they want a fully wireless system, even if they have not used them. The ease of movement of the participant wearing the device is very important, highlighting the usefulness of wireless functionality. To achieve more ecologically valid results the need for non-encumbrance during human movement for participants is necessary, 73.5% of respondents want the device to be useable in terms of ease of movement for the participant. Responses from the open ended question also showed similar views. Wireless capability was the most important feature. One particular researcher stated that ‘Transmitter devices worn are always in the way’. There are many ways in which wireless sensors are better than the wired equivalent: less cumbersome for the athlete, the ability to perform tasks in their ecologically valid environment and an easier and quicker set up time for the practitioner (Kamen, 2014b). However, it is unknown if the signal quality is comparable (Wang & Liu, 2011) to wired devices. A study on a comparison of electroencephalography signals which were acquired from both wireless and wired systems showed no significant difference between data (Ries, Touryan, Vettel, McDowell, & Hairston, 2014). There is an opportunity for additional research on sports sensors to compare data acquired in both wireless and wired conditions.

The respondents mentioned that sensors should be as small as possible but they did not express preference for shape or material used. Operation time with a long battery life was found to be imperative. Functionality in various environments was notably important, such as indoor and outdoor testing and teaching demonstrations. Portability, reliability and durability were another high priority from the survey results, making sure there is no impedance of the participant’s movement. The devices need to be lightweight and
unobtrusive for the participant. Each of these features also show that wireless functionality is key, for devices to be portable and unobtrusive they need to be wireless. The need for a small, lightweight, wireless device which is easy to use and gives accurate and reliable results is what the practitioners are looking for.

Results indicate the importance that the software utilities are provided on board a device or as an accompanying package, Table 4.6. As indicated by respondents in the open ended question, the device needs to synchronise easily with existing hardware such as motion analysis systems, it also needs to easily export to Excel, Matlab, and other commonly used analysis packages. A critical component of accompanying software is the usability of both the acquisition and analysis components for the practitioner. It was noted that the software on the devices needs to be easy to use for teaching demonstrations while also have all the capabilities and data analysis techniques necessary for the required analysis with the ‘core functions easily accessible’. If the software is difficult to use and navigate through, it will not be used in the field.

Signal processing is an area which is generally under-utilised in the area of sports biomechanics. There are many well-known post processing methods which are commonly used such as rectification, filtering, RMS and other frequency domain techniques. It is understandable that these methods would be commonly applied to data, as these are what researcher’s categorise as ‘core functions’. Spectral Analysis and Power Spectral Density functions are performed in the frequency domain. These are more advanced signal processing methods and are not as well known. Other more advanced algorithms such as Principal Component Analysis, Wavelet Analysis, Neural Networks and Independent Component Analysis are least commonly used in the area of sports biomechanics. These algorithms can be used in feature extraction (Naik & Kumar, 2011), signal separation (Kilner, Baker, & Lemon, 2002; Nakamura, Yoshida, Kotani, Akazawa, & Moritani, 2004) or pattern
recognition (Lariviere, Gagnon, & Loisel, 2000; Wakeling, 2009) for example. A deep understanding about the inner workings of these algorithms is necessary before they can be applied to data. These techniques can be very useful in the area of sports biomechanics for recognising patterns in sports performance and possibly predicting injuries (Yu et al., 2008). Results could then be used to help with rehabilitation after injury or for technique improvements and prevention steps prior to injury occurring. Results showed many participants indicating a neutral reference for these techniques which may be due to lack of knowledge in the area. By creating a knowledge base in this area and having those processing techniques more readily available, there may be huge progress made in the analysis of human movement from a sports biomechanics viewpoint. A study on gait characteristics in people with dementia showed improvements in gait after a randomised controlled trial, resistance and functional training was completed during the trial (Schwenk et al., 2014). Similar trials on sensors devices are needed to determine if improvements in performance are possible. Future work needs to be done to evaluate whether multi-sensor devices can provide outcomes such as improvements in performance and reduced injury rates.

From the results gathered on features of the EMG devices there is a clear understanding by researchers of what is needed. Developers of sensor devices for use in sporting applications need to collaborate with practitioners to understand what works and what needs to be produced. The features of the well-known brands closely match that of the features highlighted in the responses to the survey. A huge advantage for companies is having a device with software tools which are user friendly and are compatible with the motion analysis systems. There is a benefit in having a system which operates without too much set up and additional coding to retrieve the data.
4.5 Conclusion

The aspects of human movement being analysed require many different metrics to develop improvement in performance or injury prevention methods. Sport biomechanists want one device and one software package, with all the necessary processes and data analysis techniques. With all of these measurement capabilities available on one device, a near complete picture of human movement can be formed. This can help provide deeper understanding of human movement and facilitate research in sports performance, injury prevention and rehabilitation. In conclusion, practitioners and coaches should seek out wireless sensor devices to aid with data collection in ecologically valid environments. This will align closer with the movement patterns and muscle activations athletes experience during their sport and give a more realistic picture rather than simulated results in a laboratory setting. However, while devices can be designed to achieve non-encumbrance and to collect and store more data without affecting performance, evidence is required to determine if these devices are superior to existing systems or if they will improve performance or prevent injury.
Chapter 5: Muscle activation sequencing of leg muscles during linear glide shot putting

“Athletics at the highest level is a sport within a sport”

Lindsey Vonn
5.1 Introduction

There are two main techniques for the shot put namely; the linear (glide) and the rotation and frequent comparisons have been made between these two techniques (Bosen, 1985; Stepanek, 1987). Stepanek (1987) compared the mechanics of both techniques and concluded that they are similar in both ‘mechanical principles and characteristic features’ however, the movement patterns in the initial phases are different. While the rotational technique may have better performance potential, the glide was more typically used by the ‘winners’ in major championship events (Stepanek, 1987). Despite the growing popularity of the rotation technique amongst male competitors in recent years, the glide remains the preferred technique used by the majority of female competitors. A pilot study by Judge et al. (2013) indicated that the majority of throwers still preferred the glide technique (60.4%) over the rotation (39.6%). This study also observed that the power clean was closely related to the performance but no significant difference between the power clean of athletes using the glide technique and the rotation was revealed (Judge et al., 2013). Stepanek (1987) also indicated that the glide technique is less skill demanding on the thrower and more training time would be required for mastery of the rotational technique compared with the glide.

The shot put has been a modern Olympic event for men since the Olympic revival in 1896, and the women's competition was introduced in 1948. Since then, the large performance differences that existed between men and women were progressively reduced until the 1980’s when the performance difference between men’s and women’s world records using a glide technique was 1.4% (Dyer, 1982, p. 161). This suggests that at the elite level, the mass difference in men’s and women’s implements (7.26 kg and 4.00 kg respectively) compensates effectively for the underlying differences between men and women. Furthermore, the similarity of the men’s and women’s best throwing performances using the glide technique (23.06 m and 22.63 m respectively) suggests that elite men and women may be equally
effective when using the glide shot put technique (M. J. Alexander, 1997; M. J. Alexander, Linder, & Whalen, 1996).

Extensive research exists on the biomechanics of the shot put technique and in general, the findings on the biomechanics of the glide have been effectively summarised by Zatsiorsky, Lanka, and Shalmanov (1981). Despite this extensive research, there is only limited research available on activation of leg muscles during shot putting. Some previous studies have examined electromyography (EMG) of the arms including, the pectoralis, the deltoideus, the triceps brachii, and the teres major (Hermann, 1962; Terzis, Karampatsos, & Georgiadis, 2007). Only two published studies have been found to date, examining EMG of the legs and these were limited to the EMG of the vastus lateralis and the soleus (Kyriazis, Terzis, Boudolos, & Georgiadis, 2009; Terzis et al., 2007). The lack of EMG data during the shot put can be attributed to technology constraints of the EMG systems. Previously EMG systems were tethered and the use of tape was necessary to keep wires from disturbing the movement patterns (Kyriazis et al., 2009). However, with advances in technology, wireless EMG devices are now available and the more complex movements such as shot put can be analysed with greater ease and accuracy (Howard et al., 2016).

In the shot put, throwers use their leg muscles to generate force to move the body quickly across the circle and it is only when they reach the front of the circle that the arms are used to propel and direct the shot. Since these muscles generate the forces and consequently the impulses to move the athlete and project the shot into the air, it is useful from a coaching perspective, to understand the sequence of muscle actions used in the activity since this could help coaches to refine their knowledge of the technical model for the event. Therefore, a comprehensive understanding of movement and muscle activation patterns is essential to objectively confirm the activation sequences of the leg muscles and provide new insights on muscle activation timings and levels throughout each of the key phases of the event. Given
the lack of research on EMG of leg muscles in the shot put and the central importance of those muscles in performance of the event, an analysis of leg EMG patterns is merited to provide representative data for the event and confirm or refute existing assumptions amongst coaches on how leg muscles are used in shot putting. Since males and females compete separately, using different implement masses, they could have differences in technique. Therefore it is justified to examine potential differences in activation sequences between males and females. There are also differences in structural characteristics such as: muscular strength, flexibility, physiological variables and injury rates between male and female athletes (M. J. Alexander, 1997; M. J. Alexander et al., 1996).

The aim of this study was to provide scientists and coaches with representative data on leg muscle activation patterns in the glide shot put. Data on muscle activation level, relative timings of activation, and the volume of EMG activity across the glide cycle were used to provide a profile of phasic muscle activity and activation intensity from the initiation of the movement to the release of the shot throughout the key phases of the glide technique shot put event. EMG analysis can provide much insight into the function of the musculoskeletal system and the EMG signal can be effectively analysed using techniques such as linear envelopes, average EMGs, root mean square and integrated EMG on muscle activity. The EMG linear envelope can give an estimate of the ‘volume’ of EMG activity (Kamen, 2014b) and this be used to identify onset/termination temporal thresholds of muscle activation. The EMG profile data should allow coaches to inform athletes which muscles are active during the throw and provide a basis for ensuring specificity of training programmes by matching training exercises to muscle activations and volumes. This type of analysis on muscle activations should advance technical knowledge of the event by understanding the way in which the muscles drive the key movements. Technical aspects of the glide using kinematic analysis have been extensively researched while analysis of muscle activations in the shot put
remains inadequate (Ariel, 1979; Bosen, 1985; Coh & Stuhec, 2005; Hubbard, deMestre, & Scott, 2001; Linthorne, 2001; McCoy, Gregor, Whiting, Rich, & Ward, 1984; McWatt, 1982; Stepanek, 1987; Terzis, Kyriazis, Karampatsos, & Georgiadis, 2012; Tsirakos, Bartlett, & Kollias, 1995; Zatsiorsky et al., 1981). Given the relative lack of research on muscle activations in shot putting, this study should provide new knowledge of muscle activations of the lower limbs during shot put. Profiles of muscle activations may be useful from a coaching perspective to allow comparison between how the muscle activity aligns with the key movements and coaching points already used. It has been hypothesised that there is no difference between males and females of similar competitive standard, in performance, timing of key events and muscle activations. Observing if differences exist in muscle activations and timings of key events across genders and how they contribute to the overall technique could aid improvement in performance with targeted technique and strength related exercises based on objective evidence of muscle actions (Kyriazis et al., 2009; Stone et al., 2003; Zaras et al., 2013). This research could provide useful in investigating training programs and targeted exercises for the glide technique.

5.2 Methods

5.2.1 Participants

15 right handed, experienced glide technique shot put throwers, 8 males (age 20.9 ± 1.1 years, height 1.88 ± 0.03 m, mass 85.6 ± 13.6 kg, personal best 11.50 ± 1.43 m) and 7 females (age 20.0 ± 2.4 years, height 1.71 ± 0.10 m, mass 82.1 ± 15.1 kg, personal best 11.53 ± 1.05 m) who were injury free at the time of testing, participated in the study. All participants were Irish national level shot putters who were experienced in the linear glide technique. Ethical approval was obtained from the University of Limerick, Faculty of Science and Engineering Research Ethics Committee and all participants completed an informed consent form before testing (see Appendix A). Participants were given 10 minutes
to perform a standardised warm up which involved up to two minutes of jogging at a self-selected, comfortable pace including skipping with arm swings, followed by isotonic movements to target and activate all muscle groups.

5.2.2 Equipment

Athletes performed the shot put on an IAAF standard indoor circle. The shot put sector was marked out to ensure throws landed within the appropriate area for a legal throw (see Figure 5.1). Appropriate IAAF approved indoor shot implements were used by the participants. Video data were collected using two Casio high speed video cameras (Casio EX-F1, Japan), recording at a frame rate of 240 Hz. The cameras were mounted on level, stable tripods at each side of the circle to enable easy determination of the kinematics and key events during the glide. Floodlights were used to enhance the lighting already available in the arena and each light was positioned at the back of the circle at a ~30° angle to ensure the movement could be viewed correctly and each phase was appropriately illuminated (see Figure 5.1).
Wireless EMG and accelerometer signals were obtained using a Delsys Trigno™ Wireless EMG system (Delsys Inc. Natick, MA. USA). The integrated electrodes were bipolar parallel-bar Ag/Ag-Cl, with an inter-electrode distance of 10 mm and 10 x 1 mm in size. The electrodes had a common mode rejection ratio of >80 dB, a signal bandwidth of 20 – 450 Hz and a resolution of 16 bits. The sampling rate was 2,000 Hz. The sensors were attached after the warm-up, with skin prepared and electrode placement according to SENIAM recommendations (Hermens et al., 2000): i) the skin was cleaned, shaved and cleansed with an alcohol wipe, ii) electrodes were positioned at the muscle belly, to avoid cross-talk from adjacent muscles, and parallel to the muscle fibres. No gel was needed since the sensors were designed for direct attachment to the skin using double-sided tape. Due to limitations in sensor numbers, only eight muscles were chosen for analysis.
Figure 5.2. Wireless EMG electrode placement on the lower limbs
The electrodes are placed on the following muscles according to SENIAM recommendations: (1) Right Rectus Femoris, (2) Left Rectus Femoris, (3 & 4) Right & Left Anterior Tibia (Accelerometer only), (5) Left Bicep Femoris, (6) Right Bicep Femoris, (7 & 8) Left Lateral & Medial Gastrocnemius, (9 & 10) Right Lateral & Medial Gastrocnemius.

EMG sensors were attached to the rectus femoris (RF), biceps femoris (BF), and the medial and lateral gastrocnemius (MG, LG respectively) on both the right and left legs. These muscles were chosen to provide representative data from each segment of the legs. Accelerometer sensors were attached to the skin on the anterior aspect of the tibia (AT); they were placed at one third of the tibia length from the proximal endpoint on both the right and left legs. The sensor positions during testing are shown in Figure 5.2.

5.2.3 Test Procedure
Each participant performed three sub-maximal warm up throws which were not recorded. For data acquisition, the participants completed six maximal - effort, glide throws, during which video, EMG and accelerometer data were recorded. Once all EMG data was examined to confirm signals recorded were of good quality, the three best throws with the highest performance were identified for data analysis. The video records were used to identify key
events in the throws from the start of the movement through to release point. To facilitate synchronisation of EMG and video data and identify key kinematic events, each participant was asked to stamp their right foot before throwing (foot stamp). The impact event was clearly observable in the video recordings and as a spike in the accelerometer traces (Kelly, Coughlan, Green, & Caulfield, 2012). All throwers were right handed, consequently the terms ‘preferred’ and ‘non-preferred’ are used throughout to distinguish between the stance (right) leg of the throw and the drive (left) leg in the throw.

5.2.4 Data Analysis

5.2.4.1 Synchronisation & Identification of Key Stages

The high speed video recordings from one camera, as all throwers were right handed, were visually inspected using QuickTime™ Player to identify temporal events of the throw using the frame counter option. The following events for the throw were identified (see Figure 5.3):

- Foot Stamp: Event to synchronise EMG and accelerometer system with the high speed video
- Start: First movement of non-preferred leg (drive leg) to initiate the glide to the middle of the circle
- Heel-Off: The heel off of the preferred (stance) leg lifts from ground to begin the glide
- Touch Down 1: The toe of the preferred leg first touches down after the glide
- Touch Down 2: The toe of the non-preferred leg first touches down after the glide
- Release: The shot put leaves the athlete’s fingers
5.2.4.2 Phases of the Throw

The key phases of the shot, adapted from (Stepanek, 1987; Terzis et al., 2007; Tidow, 1990; Young & Li, 2005) are defined as follows for this study (see Figure 5.3):

- The Initial (Preparation) Phase: This phase is the pre-flight phase; it begins when the thrower is at the back of the circle at the ‘Start’ and finishes with the rear (preferred) foot ‘Heel-Off’.

- The Flight (Glide) Phase: This phase begins with the rear foot ‘Heel-Off’ and finishes with the rear foot ‘Touch Down’.

- The Delivery Phase: This is broken down into 2 separate phases:
  - The Transition Phase: This phase begins with the rear foot ‘Touch Down’ and finishes with the front (non-preferred) foot ‘Touch Down’. The end of this phase is known as the power position; here both feet are in contact with the throwing surface.
  - The Completion Phase: This phase begins with the front foot ‘Touch Down’ and finishes as the shot leaves the hand of the thrower; the ‘Release’.

Analysis of the EMG data was performed offline using a combination of Delsys proprietary software to extract the data, and custom Matlab code to analyse results. The EMG signal was cropped to the duration of the throw time identified using the high speed video. The beginning of the throw was identified as the movement of the non-preferred leg in the direction of the front of the circle in preparation for the glide. The end of the throw was defined as the instant of release; when the shot left the fingers of the participant.
5.2.4.3 Initial Processing of the Raw EMG Signal

All EMG data were initially processed using the following steps: 1. the DC offset was removed, 2. the raw signal was full-wave rectified and 3. a linear envelope was created for each trial using a low-pass 4\textsuperscript{th} order Butterworth Filter with a cut-off frequency of 10 Hz (Kamen & Gabriel, 2010c).

5.2.4.4 Calculating the onset and termination timings of EMG bursts

A double thresholding method (Hodges & Bui, 1996; Kamen & Gabriel, 2010c) was applied to the linear envelope of the EMG signal to identify the onset and termination timings of each of the muscles over the duration of the throw (see Appendix C). Baseline data was gathered from the time points before the foot stamp when the athlete was standing still. The mean and SD was calculated for each trial on these data. The minimum threshold for periods of muscle activity was defined as the baseline mean + 3SD to give a 99\% confidence interval (Di Fabio, 1987; Hodges & Bui, 1996; Kamen & Gabriel, 2010c). When the signal dropped below the minimum threshold for less than 40 ms, this was not considered as a period of inactivity; similarly if the signal was only above the minimum threshold for less than 40 ms it was not considered the onset of muscle activity (Hodges & Bui, 1996), see Figure 5.4. The timings
for each trial were recorded and normalised to 0 – 100% cycle times, with the first movement, start event = 0% and the release event = 100%. The ensemble mean and ensemble SD was calculated using the onset and termination times recorded in each trial to produce an EMG profile of the lower limbs during the shot put. The EMG of the RF of the preferred leg was also examined to identify the beginning of the glide phase; Kyriazis et al. (2009) mentioned that ‘silence’ in the EMG signal was observed during take-off of the preferred leg before landing back into the standing throw position.

5.2.4.5 Calculating the Ensemble Averages

To facilitate comparisons across participants and trials, various normalisation methods have been proposed (Albertus-Kajee et al., 2011; Ball & Scurr, 2013). In general the EMG obtained during a maximum voluntary isometric contraction (MVIC) has been preferentially used to normalise the EMG gathered during specific tasks but more recently it has been found that the EMG obtained during an MVIC is not an ideal representation of the maximum EMG recorded during a isotonic trial (Kyrolainen et al., 2005). Therefore in isotonic tasks the peak EMG recorded during the trial is proposed for normalisation of the EMG activity of multiple measures across participants and trials (Albertus-Kajee et al., 2011; Ball & Scurr, 2013; Kyrolainen et al., 2005). The linear envelope signals for each muscle and each trial were passed through a cubic spline function to give each signal the same number of samples. Each linear envelope signals was also normalised to the maximum amplitude recorded in that trial. The mean and SD of the curve was calculated for each muscle and each trial was combined as an ensemble-average.

5.2.4.6 Calculating the timing patterns of EMG bursts at greater signal magnitude

The EMG profile of the lower limbs was enhanced using a second thresholding method to determine periods of higher muscle activity during the throw. The maximum of each original linear envelope signal was recorded and each signal was normalised with respect to the
maximum peak. A higher muscle activity onset threshold was determined when the signal exceeded 50% of the maximum amplitude (see Figure 5.4). This high volume of muscle activity was gathered for each signal and the mean and SD was calculated.

5.2.5 Statistical Analysis

The timings of key events and muscle activation timings for both males and females were evaluated using Cohen’s d effect sizes accompanied by independent Student t tests (p values). The pre-set level for statistical significance was p ≤ 0.05 for all analyses. Given the sample size limitations, magnitude based inferences were used as the principal means to test hypotheses as recommended by Hopkins (2002). The null hypotheses were rejected when Cohen’s d > 0.2 (smallest worthwhile difference). Interpretation of the magnitude of difference was based on Cohen (1977) scale where: d > 0.2 small; d > 0.5 moderate; d > 0.8 large.
Figure 5.4. Sample EMG signal with threshold levels
The sample EMG signal shows a burst of activity around 20% of the cycle time, this burst is less than the minimum time (40 ms) and is not considered the onset. The solid light grey horizontal line represents the minimum threshold (mean +3SD) and the dashed light grey horizontal line represents the 50% maximum threshold (EMG signal ≥ 50% maximum amplitude).

5.3 Results

The mean results for male and female throwers of relative timings of key events during the throw and throwing performance are outlined in Table 5.1. The results show that the males threw marginally further than the females during testing. Cohen’s d indicated a small effect (0.47) between males and females (p = 0.110). The ‘Heel-Off’ event of the male throwers was later in the throw cycle than for the female throwers, a moderate to strong effect was found between males and females (d = 0.76; p = 0.011). The relative timing of ‘Touch-Down’ event of the preferred leg was earlier in the throw cycle for females than the males with a moderate effect size (d = 0.70; p = 0.020). By contrast, the ‘Touch-Down’ event of the non-preferred leg for the male throwers was earlier for the female throwers, with a small
effect size (d = -0.36; p = 0.264). Finally, the average glide time of the male throwers was longer than the female throwers with a large effect size (d = 1.06; p < 0.001).

<table>
<thead>
<tr>
<th>Preferred Leg Heel-Off (%)</th>
<th>Preferred Leg Touch-Down (s)</th>
<th>Non-Preferred Leg Touch-Down (s)</th>
<th>Throw Time (s)</th>
<th>Official Throw Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>42.4 ±9.2</td>
<td>55.3 ±8.3</td>
<td>63.8 ±7.6</td>
<td>0.98 ±0.14</td>
</tr>
<tr>
<td>Female</td>
<td>36.2 ±5.9</td>
<td>50.1 ±5.9</td>
<td>66.1 ±5.7</td>
<td>0.84 ±0.08</td>
</tr>
<tr>
<td>Cohen’s D</td>
<td>0.76</td>
<td>0.70</td>
<td>-0.36</td>
<td>1.06</td>
</tr>
<tr>
<td>T-test</td>
<td>p &lt; 0.05</td>
<td>p &lt; 0.05</td>
<td>p = 0.264</td>
<td>p &lt; 0.05</td>
</tr>
</tbody>
</table>

The EMG profile of the lower limbs is presented in Figure 5.5 for the male throwers. The muscle onset and termination times expressed as a percentage of the throw cycle time for the male throwers are provided in Table 5.2. The results show that the RF muscle of the preferred leg had the earliest mean onset time at 0.3% of the throw cycle, which is almost the initiation of the throw, followed by the preferred MG and the non-preferred BF. The preferred leg BF and the preferred leg LG then became active followed by the non-preferred leg RF and the non-preferred leg LG. The mean termination times of all the muscles were approximately at 100% of the throw cycle, although the non-preferred leg muscles terminated slightly after the preferred leg muscles. All the muscles analysed had periods of non-activity between the preferred leg ‘Heel-Off’ event and the preferred leg ‘Touch-Down’ event and again after the non-preferred leg ‘Touch-Down’ event (at the end of the ‘Transition Phase’). The high volume periods show that most muscles were highly active just before the ‘Heel-Off’ stage of the preferred leg, near the ‘Touch-Down’ events of both legs and in the ‘Completion Phase’.
Figure 5.5. An EMG profile of the eight lower limb muscles of the male throwers during the glide technique represented across the percentage cycle time. Muscle activation is represented as mean onset and mean termination times. The light grey areas represent periods where the volume of EMG activity was above the minimum threshold (mean + 3SD), and the diagonally striped light grey areas represent areas where the volume of EMG activity was below the minimum threshold for some participants. The dark grey indicates periods where the volume of EMG activity was above the 50% maximum threshold (≥ 50% maximum amplitude). The mean cycle times for the ‘Heel-Off’ and both of the ‘Touch Down’ stages are represented by a black vertical line with arrows each direction on a horizontal line above the horizontal bar chart representing the SD of the muscle activations.
Table 5.2 The onset and termination times of the lower limb muscles for the male throwers.
Onset and termination times of the EMG bursts of activity of the lower limbs above the minimum threshold are represented as mean ±SD as a percentage of the throw cycle time.

<table>
<thead>
<tr>
<th>Muscle</th>
<th>Minimum Mean ±SD (%)</th>
<th>Minimum Mean ±SD (%)</th>
<th>50% Maximum Mean ±SD (%)</th>
<th>50% Maximum Mean ±SD (%)</th>
<th>Preferred Threshold Mean ±SD (%)</th>
<th>Preferred Threshold Mean ±SD (%)</th>
<th>Non-preferred Threshold Mean ±SD (%)</th>
<th>Non-preferred Threshold Mean ±SD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preferred Rectus Femoris</td>
<td>0.3 ±0.6</td>
<td>3.6 ±6.1</td>
<td>9.0 ±7.6</td>
<td>24.0 ±6.1</td>
<td>84.3 ±8.3</td>
<td>93.9 ±6.5</td>
<td>100.0</td>
<td>93.9 ±6.5</td>
</tr>
<tr>
<td>Preferred Biceps Femoris</td>
<td>1.3 ±0.6</td>
<td>3.1 ±4.1</td>
<td>4.6 ±5.1</td>
<td>3.4 ±7.5</td>
<td>1.3 ±0.6</td>
<td>1.3 ±0.6</td>
<td>1.3 ±0.6</td>
<td>1.3 ±0.6</td>
</tr>
<tr>
<td>Preferred Lateral Gastrocnemius</td>
<td>2.8 ±1.4</td>
<td>50.3 ±9.3</td>
<td>23.7 ±2.6</td>
<td>44.4 ±9.8</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
</tr>
<tr>
<td>Preferred Medial Gastrocnemius</td>
<td>0.6 ±1.5</td>
<td>39.6 ±9.3</td>
<td>23.7 ±15.9</td>
<td>44.4 ±9.8</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
</tr>
<tr>
<td>Non-preferred Rectus Femoris</td>
<td>4.6 ±4.3</td>
<td>23.2 ±5.0</td>
<td>23.7 ±2.6</td>
<td>44.4 ±9.8</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
<td>2.0 ±0.7</td>
</tr>
<tr>
<td>Non-preferred Biceps Femoris</td>
<td>68.3 ±7.3</td>
<td>74.6 ±7.7</td>
<td>75.8 ±7.3</td>
<td>74.6 ±7.7</td>
<td>68.3 ±7.3</td>
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</tr>
<tr>
<td></td>
<td>±1.8</td>
<td>±5.1</td>
<td>±10.0</td>
<td>±10.8</td>
<td>±2.3</td>
<td>±1.6</td>
<td>±0.0</td>
<td></td>
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<td>--------------------------</td>
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<td>------</td>
<td>------</td>
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<td></td>
</tr>
<tr>
<td>50% Maximum</td>
<td>1.5</td>
<td>7.0</td>
<td>20.8</td>
<td>35.3</td>
<td>58.5</td>
<td>66.0</td>
<td>88.5</td>
<td>93.8</td>
</tr>
<tr>
<td>Threshold</td>
<td>±3.7</td>
<td>7.0</td>
<td>±10.5</td>
<td>±6.5</td>
<td>±9.3</td>
<td>±4.8</td>
<td>±4.9</td>
<td></td>
</tr>
<tr>
<td>Non-preferred Lateral Gastrocnemius</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>5.1</td>
<td>14.1</td>
<td>22.5</td>
<td>34.5</td>
<td>50.6</td>
<td>60.3</td>
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<td>±3.7</td>
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<td>22.2</td>
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<td>51.7</td>
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<td>±5.9</td>
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The EMG profile of the lower limbs for the female throwers is presented in Figure 5.6. The muscle onset and termination times as a percentage of the throw cycle time for the female throwers is displayed as mean ± SD (see Table 5.3). The preferred leg RF, preferred leg BF and non-preferred leg BF have the earliest mean onset times. The preferred leg MG and the preferred leg LG then become active followed by the non-preferred leg LG and the non-preferred leg MG. The mean termination times of all the muscles occur between 97% and 100% of the throw cycle and the majority of the non-preferred leg muscles terminate after the preferred leg muscles. Similarly to the male throwers, the female throwers had periods of non-activity between the preferred leg ‘Heel-Off’ and ‘Touch-Down’ events and again after the non-preferred leg ‘Touch-Down’ event (at the end of the ‘Transition Phase’). The periods of high volume were observed in most muscles just before the ‘Heel-Off’ event of the preferred leg, around the ‘Touch-Down’ events of both legs and in the ‘Completion Phase’
Figure 5.6 An EMG profile of the eight lower limb muscles of the female throwers during the glide technique represented across the percentage cycle time. Muscle activation is represented as mean onset and mean termination times. The light grey areas represent periods where the volume of EMG activity was above the minimum threshold (mean + 3SD), and the diagonally striped light grey areas represent areas where the volume of EMG activity was below the minimum threshold for some participants. The dark grey indicates periods where the volume of EMG activity was above the 50% maximum threshold (≥ 50% maximum amplitude). The mean cycle times for the ‘Heel-Off’ and both of the ‘Touch Down’ stages are represented by a black vertical line with arrows each direction on a horizontal line above the horizontal bar chart representing the SD of the muscle activations.
Table 5.3 The onset and termination times of the lower limb muscles for the female throwers
Onset and termination times of the EMG bursts of activity of the lower limbs above the minimum threshold are represented as mean ±SD as a percentage of the throw cycle time.

<table>
<thead>
<tr>
<th>Muscles</th>
<th>On Mean ±SD (%)</th>
<th>Off Mean ±SD (%)</th>
<th>On Mean ±SD (%)</th>
<th>Off Mean ±SD (%)</th>
<th>On Mean ±SD (%)</th>
<th>Off Mean ±SD (%)</th>
<th>On Mean ±SD (%)</th>
<th>Off Mean ±SD (%)</th>
<th>On Mean ±SD (%)</th>
<th>Off Mean ±SD (%)</th>
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<td>80.4 ±8.6</td>
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<tr>
<td>50% Maximum Threshold</td>
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<td>15.5 ±5.8</td>
<td>23.2 ±4.9</td>
<td>29.8 ±5.7</td>
<td>48.8 ±6.6</td>
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<td>86.1 ±4.7</td>
<td>98.2 ±3.1</td>
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<td>Preferred Biceps Femoris</td>
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<td>41.6 ±8.0</td>
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<tr>
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<td>26.6 ±7.2</td>
<td>37.1 ±10.1</td>
<td>48.3 ±8.1</td>
<td>57.4 ±5.1</td>
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<td>79.4 ±7.4</td>
<td>94.6 ±1.0</td>
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<td>Minimum Threshold</td>
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<td>44.3 ±3.9</td>
<td>58.1 ±6.7</td>
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<td>84.9 ±1.2</td>
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<td>50% Maximum Threshold</td>
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<td>61.18 ±8.0</td>
<td>80.9 ±10.1</td>
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<tr>
<td>Minimum Threshold</td>
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<td>44.2 ±5.6</td>
<td>71.5 ±12.9</td>
<td>76.8 ±12.6</td>
<td>81.9 ±8.2</td>
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<td>50% Maximum Threshold</td>
<td>3.3 ±3.6 20.4 ±11.4 29.5 ±17.7 41.4 ±19.7 48.8 ±15.0 56.1 ±14.8 57.6 ±11.0 67.1 ±7.7 81.4 ±15.0 88.7 ±11.1</td>
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<td>50% Maximum Threshold</td>
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<td>50% Maximum Threshold</td>
<td>12.0 ±9.3 22.5 ±7.5 34.7 ±3.8 42.2 ±3.7 56.8 ±8.3 64.8 ±9.4 75.9 ±4.9 86.9 ±6.1 88.6 ±4.8 97.4 ±3.4</td>
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The ensemble mean ±SD linear envelope EMG curve is provided for each muscle analysed, identifying the activity of the preferred and the non-preferred legs in Figure 5.7 for the male throwers. There were two mean peaks of the preferred leg RF occurring at approximately 25% and 75% of the throw cycle. The mean peak of the preferred leg BF occurred at approximately 90% of the throw cycle, and at 80% of the throw cycle for both the preferred leg LG and MG. The non-preferred leg, mean peaks occurred at approximately 85% of the throw cycle for the RF, 30% for the BF and 95% for the LG and MG. The highest normalised amplitude was 0.7 and this was observed in the preferred leg BF and the non-preferred leg LG and MG. Figure 5.8 provides similar analysis for the female throwers. There were two mean peaks of the preferred leg RF occurring at approximately 20% and 65% of the throw cycle. The mean peak of both the preferred leg BF and LG occurred at approximately 70% of the throw cycle and at 65% of the throw cycle for the preferred leg MG. The non-preferred leg’s mean peaks occur at approximately 80% of the throw cycle for the RF, 30% for the BF, 85% for the LG and 90% for the MG. The highest normalised amplitude was 0.6, with all muscles analysed approximately reaching this value.
Figure 5.7 Linear Envelope Mean Curves for the eight lower limb muscles of the preferred and non-preferred legs of the male throwers. The solid black line represents the mean curve and the light grey shaded region represents the SD above and below the mean.
Figure 5.8 Linear Envelope Mean Curves for the eight lower limb muscles of the preferred and non-preferred legs of the female throwers.

The solid black line represents the mean curve and the light grey shaded region represents the SD above and below the mean.
5.4 Discussion & Implications

This investigation provides representative data on the muscle activity of the lower limbs during the glide shot put technique in accomplished male and female shot putters. Inspection of the muscle activity of the throwers (see Figure 5.5 and Figure 5.6), during periods when the volume of EMG activity was greater than or equal to 50% of the maximum amplitude, show periods of high volume of EMG activity in the RF muscle of the preferred leg during the preparation phase. During this phase the thrower lowers the upper body and flexes the hip, knee and ankle joints of the preferred leg (Hay, 1993c, p. 473; Tidow, 1990) which is consistent with the quadriceps muscle group exerting high muscle activity in a near isometric contractile state. The periods of high volume activation appeared later in the throw cycle in the males and this could be attributed to differences observed in ‘Heel-Off’ times between the groups and the fact that the males begin the flight phase later than the females in the throw cycle. During the beginning of the preparation phase, the preferred leg BF shows a period of high volume muscle activity. Both the RF and BF were active together at this point which suggests that the muscles were co-activating to provide a stabilising effect in the stance leg. At the end of the preparation phase and the beginning of the flight phase the preferred leg BF shows a period of high volume and at this point the knee was extended and the hamstrings were most likely in eccentric contraction. This pattern of muscle activity occurred earlier for the females than the males (p < 0.05; d = 0.76), which may be due to the earlier relative timings of the ‘Heel-Off’ event (see Table 5.1). A period of no activity of the preferred leg RF was observed during the flight phase of the throw, which occurred later for the males than females (see Figure 5.5 and Figure 5.6), which was most likely due to the relative timing differences at beginning the flight phase, similar to that reported by Kyriazis et al. (2009). At this time, the knee and ankle joints of the preferred leg are in an extended position (Hay, 1993c, p. 474; Tidow, 1990) and the preferred leg RF is no longer contracting. Similarly, a
period of no activity of the preferred leg BF can be observed after ‘Heel-Off’ when the hamstrings are moving from an eccentric into a concentric contraction (see Figure 5.5 and Figure 5.6). A shorter period of high volume EMG activity was observed during the ‘Heel-Off’ event for the males compared with females (see Table 5.2 and Table 5.3) which may be due to technique differences in the extension of the preferred leg prior to the beginning of the glide. The preferred foot moves rapidly low across the circle (Tidow, 1990) and the preferred leg RF and BF muscle activity start again just before the ‘Touch Down’ of the preferred leg when the foot is vertically beneath the athlete’s centre of gravity (Hay, 1993c, p. 475). This type of pre-activation activity is commonly observed in isotonic running and jumping activities where a stretch-shortening cycle is involved (Komi, 2000). Table 3.1 showed that the relative timings of the ‘Touch-Down’ event of the preferred leg were earlier for the females than the males (p < 0.05; d = 0.70) and could explain the differences between the relative timings of the end of the non-activity period in the males and females observed in Table 5.2 and Table 5.3. During the transition phase, the higher volume of EMG activity of the preferred leg RF and the preferred leg BF is observed due to a stabilisation effect for the single leg stance point before the non-preferred leg ‘Touch-Down’ occurs. The relative timings of the ‘Touch-Down’ event of the preferred leg were earlier for the females than the males (p < 0.05; d = 0.70) which may explain why the timings of these bursts were earlier in the female throwers. The bursts of EMG activity were relatively shorter in the male throwers which could be attributed to the relative timings of the ‘Touch-Down’ event of the non-preferred leg occurring earlier for the male throwers than the female throwers (p = 0.264; d = -0.36), showing that there was a shorter time between the ‘Touch-Down’ events in the males. This is most likely due to the relatively shorter transition phase in male throwers and they tend to keep a shoulder hip separation which helps provide a torqued state (Tidow, 1990) when they land in the standing throw position. The female throwers allow their upper bodies
to rotate towards the line of the hips resulting in reduced torque, it therefore takes longer for the non-preferred leg to touch down thus the females have a relatively longer transition phase and the EMG bursts last longer than the males (see Table 5.2 and Table 5.3). This is commonly observed by coaches who will frequently advise athletes to minimise the time delay between non-preferred leg touch down and the preferred leg touch down events (Tidow, 1990). As the thrower moves from the end of the transition phase into the completion phase where rapid hip extension occurs and the trunk rotates towards the front of the circle (Tidow, 1990), the higher volume of EMG activity of the preferred leg RF and the preferred leg BF occurred later for the males than the females. This forceful hip extension action is often emphasised by coaches as a key factor in good shot put technique (Hay, 1993c, p. 477; Tidow, 1990) and is assumed to be driven by the gluteal muscles of the preferred leg. However this cannot be confirmed since gluteal muscle activations were not measured as part of this study. The final period of the higher volume of activity was observed just before the release when the athletes were moving into a full extended body position (Tidow, 1990) to release the shot. (i.e. a triple extension of the hip, knee and ankle joints). The muscle activity observed occurred later for the males but lasted longer for the females in the preferred leg RF while the opposite was observed in the preferred leg BF, with activity occurring earlier in the males and for a longer duration than the females. This could be attributed to the male throwers making better use of the full body extension of hip, knee and trunk where their hamstrings will activate. There may be differences in the technique of the female throwers whereby they are not fully extending and lowering their hips at release (Tidow, 1990). This position is similar to a slight squat, thus the quadriceps are activating. Similarly, the same high volume of activity can be observed in similar stages of the throw cycle for the preferred leg MG and LG: during the ‘Heel-Off’ stage, both ‘Touch Down’ stages, during the triple extension of the preferred leg as the trunk rotates towards the front of the circle and during
the final push as the body is rotated forward and the legs are fully extended just before release.

The non-preferred BF also plays an important role in the throw. High volumes of EMG activity were observed in the preparation phase, at the beginning and during the ‘Heel-Off’ stage showing that the backward swing of the non-preferred leg towards the front of the circle is central to allow the thrower to glide effectively across the circle during the flight phase (Tidow, 1990). This activity occurred earlier for the males but the duration of the bursts were longer for the females, which could imply the males have a shorter more forceful drive back and the females a slower more constant drive back. The relative timings of the ‘Touch-Down’ event of the non-preferred leg occur earlier in the males ($p = 0.264; d = -0.36$) which supports this. During the transition phase after both legs touch-down, the non-preferred leg BF showed a high volume of activity as the hamstrings braced for impact prior to and during the non-preferred leg touch down. This activity occurred earlier for the females and the duration was longer, although the activity terminated similar times. This could also be due to technique differences. The male athletes tend to keep a shoulder hip separation during the glide and transition phases which helps provide a torqued state (Tidow, 1990), whereas the female throwers allow a rotation of their upper bodies towards the line of the hips resulting in reduced torque (Tidow, 1990) and take longer to ground the non-preferred leg with the hamstrings bracing for impact for a longer duration. The non-preferred leg RF only takes effect during the transition stage and females showed periods of high volume earlier than the males. This could be due to the longer time between both ‘Touch-Down’ events in females throwers causing the quadriceps to contract for longer prior to and during impact. The final period of high volume of EMG activity was observed during the transfer of weight from the preferred to the non-preferred leg and drive through this leg to a fully extended position at release. The high volume activity observed in the non-preferred RF occurred earlier in the
females and for a slightly longer duration, but this activity terminated earlier for the female throwers. In the non-preferred BF the high volume activity occurred much earlier for the female throwers and ceased around the time the high volume activity begins for the male throwers. Similarly, the high volume of activity can be observed in the same stages of the throw cycle for the non-preferred MG and LG: during the drive of the free leg in the flight phase, during the ‘Touch-Down’ stage of the non-preferred leg, moving from the transition in to the completion phase and finally when the body is rotated towards the front of the circle and the legs are fully extended in preparation for release.

Visual inspection of the ensemble mean curves in Figure 5.7 and Figure 5.8 can provide insights into the variability between trials and participants. In the preferred leg, the peaks in the RF occurred at lower amplitudes and later than the females, the LG and MG were similar and the BF peaks occurred later but at higher amplitude. The non-preferred leg peak in the RF was later but higher in the males, the BF peaks were approximately the same across the genders and the LG and MG peaks occurred later in the males but at higher amplitude. These peaks which occur mainly later in the males than the females show similarities to the high volumes of activity from the EMG profiles (see Figure 5.5 and Figure 5.6). The male throwers began their glide slightly later than the females therefore the peaks would occur later. A greater variation from the mean can be seen in the preferred leg RF and MG for the male throwers, and in the non-preferred leg RF, LG and MG, and the preferred leg LG for the female throwers. These curves can also identify how the EMG activity of one participant compares to the average curve. An overlay of the curve from the thrower with the greatest performance and the thrower with the least performance could highlight where the main downfalls may be in terms of muscle activity for the thrower with the least performance.

Since few studies have examined the EMG of the lower limbs during shot put, the findings of this study provides novel information on muscle activity of the lower limbs for scientists,
coaches and practitioners. This data confirms the anecdotal evidence used by coaches, previously this muscle activity was not actually known and coaches were relying on kinesiology data. Given the lack of research of EMG on lower limb muscles in the shot put, this analysis of leg EMG patterns will provide initial representative data for the event. Coaches can use this data to advance their knowledge of the event and create more specific training for their athletes by comparing how they perform relative to the athletes in this study. This study was limited due to the availability of EMG sensors and therefore only examined eight muscles of the legs. It is recommended that future work should examine EMG activity on other leg muscles which play important roles in the force generation in the glide, which would augment the representative data gathered in this study. The various muscles which should be considered for future studies would include: the vastus medialis, vastus lateralis, gluteus maximum, gluteus minimus, soleus and tibialis anterior. Although the glide is linear in movement overall, there are some aspects of rotation in the transition phase and for this reason it may also be necessary to examine the inclusion of muscles which contribute to the rotation from the hip. In this study, the muscle activity was gathered on accomplished national level throwers but an analysis of variations on phasic muscle activity in relation to performance level would be of benefit in advancing knowledge of the event. It would also be useful to compare the performance of the throw to various metrics, such as performance or timings of phases, gathered in this study to determine if sustained high volume of muscle activity correlates with an increase in performance or if the length of time of particular stages in the throw transfers to an increase in performance in future. It would be then necessary to investigate whether these results could be modified by training. All throws for this study were performed indoors on a standard IAAF wooden circle; this was to allow for constant temperature and to prevent variations in performances due to external factors. It is not known
if there would be a difference in muscle activations and timings if the test was conducted on an outdoor concrete circle. This could be an avenue for further research.

5.5 Conclusion

Results of this investigation present new data on muscle activations across the throw cycle using the glide technique. Differences observed in EMG activation patterns between the men and women correspond to the variations of timings of key events. The muscles produce the impulses which drive the movements, having the profile of muscle activations and the ensemble average curves will benefit coaches and athletes. The data confirms the anecdotal evidence used by coaches which was previously based off analysis of kinesiology data; it is now known when muscles are active across the glide technique. Further work can be done to compare the muscle activations of rotation and glide techniques as well as comparing activation patterns across throwing disciplines. It would also be useful to compare muscle activations of common coaching drills and exercises to the glide or rotation technique muscle activations. Coaches could then use this data to tailor training of the athletes to work on specific aspects of their technique. For researchers, the information on the muscle activity augments existing data on the kinematics and kinetics of glide technique. Overall, the use of the 50% threshold has provided a clearer representation of the activity of the muscles throughout the glide. This threshold level may also provide useful in partitioning the volume of EMG activity in other sporting movements.
Chapter 6: Muscle activation sequencing of the lower limbs during maximal sprinting

“You must do the things you think you cannot do”

Eleanor Roosevelt
6.1 Introduction

The sprint discipline in track and field athletics encompasses the 60 m (indoor only), 100 m, 200 m and 400 m events. The ‘stade’ (192 m) and the 'diaulos' (equivalent to the 400 m) were part of the Ancient Olympics. The classic 100 m and 400 m have been part of the Olympics since 1896 and in 1900 the 200 m was added to the programme. The best male 100 m performance is 9.58 s, 19.19 s in the 200 m and 43.03 s in the 400 m (IAAF, 2016). To fully understand the kinematics and kinetics of running the muscle activity patterns must be known and understood (Kyrolainen et al., 2005). Extensive research on sprinting already exists on kinematics, kinetics and EMG (J. L. Bartlett et al., 2014; Chumanov et al., 2007; Cronin & Hansen, 2006; Higashihara et al., 2010; Krzysztof & Mero, 2013; Novacheck, 1998; Nummela et al., 1994; Perrey, Racinais, Saimouaa, & Girard, 2010; Pinniger et al., 2000; Schache et al., 2012; Schache, Dorn, Wrigley, Brown, & Pandy, 2013; Silder, Thelen, & Heiderscheit, 2010; Stafilidis & Arampatzis, 2007; Swanson & Caldwell, 2000; Thelen et al., 2005; Vaughan, 1984; Wiemann & Tidow, 1995; Yu et al., 2008). However, due to advances in technology wireless EMG data can be acquired on athletes in their ecologically valid environments. Having EMG data gathered in ecologically valid environments provides more representative data which will benefit coaches and practitioners. The use of tethered sEMG system for analysing gait and running performance dominated previous studies which involved the athlete running or walking on a treadmill (Chumanov et al., 2007; Higashihara et al., 2010; Thelen et al., 2005). Sprinting or jogging on a treadmill is not identical with overground sprinting or jogging and very few treadmills allow athletes to reach maximum sprint speed, this therefore limits the ecological validity of treadmill running (Baur et al., 2007; Van Caekenberghe, Segers, Willems, et al., 2013; Wank et al., 1998). Motorised treadmills also contribute to hip extension, as the belt moves the foot of the participant backwards causing potential changes in the muscle activation timings and magnitudes (Van
Caekenberghe, Segers, Aerts, et al., 2013). Tethered sEMG system are therefore likely to cause the athlete to moderate the way they run due to the fact sprints need to be performed on a treadmill. For coaches monitoring sports performance, it is important that the results accurately reflect the activity in an ecologically valid environment. This identifies a need for examining the muscle activations during sprinting using wireless sEMG.

The aim of this study was to provide scientists and coaches with representative data on leg muscle activation patterns in the maximum speed phase of the sprint using wireless sEMG. Data on muscle activation level, relative timings of activation, and the volume of EMG activity across the sprint cycle were used to provide a profile of phasic muscle activity and activation intensity throughout the sprint cycle. A secondary aim was to explore the variations in timings between the results from previous literature (see Chapter 3) and the results from this study. The EMG profile data should allow coaches to inform athletes which muscles are active during the sprint and provide a basis for ensuring specificity of training programmes by matching strength training exercises, drills and plyometric exercises to muscle activations. This type of analysis on muscle activations should advance technical knowledge of the event by providing further information on the way in which the muscles drive the key movements.

Data were acquired from a study undertaken by colleagues in the Biomechanics Research Unit at the University of Limerick (Bolger & Healy, 2015). The purpose for this study was to convey the use of the algorithm developed in Chapter 6 in another sporting activity, in this case the muscle activity of the legs during maximal sprinting. It also provided practitioners with more up to date information, due to advances in technology, on muscle activation data of the lower limbs across the running gait cycle. A secondary purpose of this study is to compare the results of the onset and termination times to the composite profile created in Chapter 3, see Figure 3.2 (page 62).
6.2 Methods

6.2.1 Participants

Eight experienced male sprinters (age: 21.4 ±2.6 years, height: 1.77 ±0.06 m, mass: 72.95 ±7.03 kg, 60 m PB: 7.21 ±0.56 s\textsuperscript{1}, 100 m PB: 10.94 ±0.28 s\textsuperscript{1}, 200 m PB: 22.13 ±0.81 s\textsuperscript{1}, 400 m PB: 49.51 ±1.09 s\textsuperscript{1}) who were injury free at the time of testing, participated in the study (Bolger & Healy, 2015). All participants were at least national level sprinters. Ethical approval was obtained from the University of Limerick, Faculty of Science and Engineering Research Ethics Committee and all participants completed an informed consent form before testing (see Appendix A). Participants were given 30 - 45 minutes to perform their own athlete specific competition warm up.

6.2.2 Equipment

Athletes performed sprints on a 60 m indoor track. Wireless EMG and accelerometer signals were obtained using a Delsys Trigno\textsuperscript{TM} Wireless EMG system (Delsys Inc. Natick, MA. USA). The integrated electrodes were bipolar parallel-bar Ag/Ag-Cl, with an inter-electrode distance of 10 mm and 10 x 1 mm in size. There was a common mode rejection ratio of >80 dB, a signal bandwidth of 20 – 450 Hz and a resolution of 16 bits. The sampling rate was 2,000 Hz. The sensors were attached after the warm-up, with skin prepared and electrode placement according to SENIAM recommendations (Hermens et al., 2000): i) the skin was cleaned, shaved and cleansed with an alcohol wipe, ii) electrodes were positioned at the muscle belly, to reduce cross-talk from adjacent muscles, and parallel to the muscle fibres. No gel was needed since the sensors were designed for direct attachment to the skin using

\textsuperscript{1} Not all participants have recorded 60 m, 100 m, 200 m & 400 m times.
double-sided tape. EMG sensors were attached to the gluteus maximus (GM) rectus femoris (RF), vastus lateralis (VL), biceps femoris (BF), semitendinosus (ST) and the medial and lateral gastrocnemius (MG, LG respectively) on both the right and left legs. Kinematic data were collected via the Cortex software (version 5.0; Motion Analysis Corp., Santa Rosa, CA) using six Eagle and five Hawk infrared Motion Analysis Corporation cameras (sampled at 200 Hz). Makers were attached using modified Helen Hayes model; 53 reflective markers were placed on anatomical landmarks with 16 of these accounting for segment marker clusters (C-motion, 2016). The 3D system was calibrated before each participant and a static test was undertaken to ensure all markers could be seen by the infrared cameras (see Figure 6.1).

![Figure 6.1 Static Test using 3D motion analysis](image)

EMG sensors were attached to the legs and skins were worn over the sensors to ensure there was no movement of the sensors due to motion artefact. The reflective markers were attached last for tracking purposes on the 3D video.

### 6.2.3 Test Procedure

Each participant performed three sub-maximal sprints as part of their warm up which were not recorded. For data acquisition, the participants completed a maximum of three maximal – effort sprints, during which 3D video, EMG and accelerometer data were recorded. Both systems were synchronised using an external source Delsys Trigger Module (SN: 1345).
Once all EMG data and 3D video data was examined to confirm the signals recorded were of good quality and the markers were all within the testing volume, the two best sprints were identified for data analysis. The 3D video was used to identify key events in the sprints from the initial foot ground contact of the subsequent foot ground contact of that leg. The test set up can be seen in Figure 6.2.

![Test set up](image)

**Figure 6.2 Test set up**
The test set up included the 3D motion analysis system, the EMG system, timing gates and the Optojump system.

### 6.2.4 Data Analysis

#### 6.2.4.1 Synchronisation & Identification of the Key Events

Both systems were synchronised using the external source Delsys trigger module. The recording volume for the motion analysis system allowed for three stride lengths (left-right-left or right-left-right). The time for initial contact (IC) and toe off (TO) of each leg was gathered (Bolger & Healy, 2015). A threshold value was set to identify the IC and TO of the
foot using visual3D, see Figure 6.3. The sample number for these key events was recorded and then converted into absolute time, to be used with the EMG data.

Analysis of the EMG data was performed offline using a combination of Delsys proprietary software to extract the data, and custom Matlab code to analyse results. The EMG signal was cropped to the duration of the running gait cycle using the absolute time values recorded from the 3D motion capture system (Bolger & Healy, 2015). The beginning of the gait cycle was the IC of either the left or right foot, and the end of the gait cycle was the IC of the same leg (see Figure 2.20, page 43).

6.2.4.2 Initial Processing of the Raw EMG Signal

All EMG data was initially processed using the following steps: 1. the DC offset was removed, 2. the raw signal was full-wave rectified and 3. a linear envelope was created for each trial using a low-pass 4th order Butterworth Filter with a cut-off frequency of 10 Hz (Kamen & Gabriel, 2010c).
6.2.4.3 Calculating the onset and termination timings of EMG bursts

The double thresholding method (Hodges & Bui, 1996; Kamen & Gabriel, 2010c) used in Chapter 6 was applied to the linear envelope of the EMG signal to identify the onset and termination timings of each of the muscles over the duration of the running gait cycle (see Appendix C). Baseline data was gathered from the time points before the athlete began the sprint. The mean and SD was calculated for each trial on these data. The minimum threshold for periods of muscle activity was defined as the baseline mean $+ 3\text{SD}$ (Di Fabio, 1987; Hodges & Bui, 1996). When the signal dropped below the minimum threshold for less than 40 ms, this was not considered as a period of inactivity; similarly if the signal was only above the minimum threshold for less than 40 ms it was not considered the onset of muscle activity (Hodges & Bui, 1996). The timings for each trial were recorded and normalised to 0 – 100% cycle times, with the IC at 0% and the IC of the same leg again at 100%. The ensemble mean and ensemble SD was calculated using the onset and termination times recorded in each trial to produce an EMG profile of the lower limbs during sprinting.

6.2.4.4 Comparisons of the onset and termination times across previous research

The onset and termination times in Chapter 3 were gathered from a selection of papers in sprinting, means and SDs were calculated and a profile of the composite times was created. The mean onset and mean termination times above the minimum threshold from this study were compared to the mean times in Chapter 3. The difference between these times was calculated, a positive value signifies the wireless EMG times from this study had an earlier onset or termination time, a negative value signifies the wireless EMG times from this study had a later onset or termination time than the times reported in Chapter 3.

6.2.4.5 Calculating the Ensemble Averages

The linear envelope signals for each muscle and each trial were passed through a cubic spline function to normalise the signals across the time base; giving each signal the same number of
samples. Each linear envelope signals was also normalised to the maximum amplitude recorded in that trial. The mean and SD of the curve was calculated for each muscle and combined as an ensemble-average.

6.2.4.6 Higher Threshold Determination

The EMG profile of the lower limbs was enhanced using a second thresholding method similar to Chapter 6 to determine periods of higher muscle activity during the running gait cycle. The maximum of each original linear envelope signal was recorded and each signal was normalised with respect to the maximum peak. A higher muscle activity onset threshold was determined when the signal exceeded 50% of the maximum amplitude; see Figure 5.4 (page 113). The higher volume of muscle activity was gathered for each signal and the mean and SD was calculated.

6.3 Results

The timings of the IC and TO were gathered from the 3D video capture. The IC was set as 0 s and the TO and subsequent IC were calculated with respect to the IC. Table 6.1 shows this timing data in absolute values and as a percentage of the gait cycle. The TO event occurred between 15.7% and 28.1%, and the stride was between 0.40 s and 0.49 s.

<table>
<thead>
<tr>
<th>Table 6.1 Stride Timing Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute and relative timings of the Toe-Off (TO) and the absolute stride time</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentage Gait Cycle (Range)</th>
<th>Toe-Off (21.7 ±3.1%)</th>
<th>Stride Time (0.44 ±0.03 s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Time (Range)</td>
<td>0.10 ±0.01 s (0.06 s – 0.13 s)</td>
<td>0.44 ±0.03 s (0.40 s – 0.49 s)</td>
</tr>
</tbody>
</table>

The EMG profile of the lower limbs is presented in Figure 6.4. The periods of muscle activity were identified using the ensemble mean and ensemble SD gathered from the double thresholding method using the minimum threshold and the 50% maximum threshold. The
muscle onset and termination times expressed as a percentage of the sprint cycle time are provided in Table 6.2 and Table 6.3. The GM, ST and MG are active through all phases of the running gait cycle. The RF and VL are active in the stance phase, early swing phase and late swing phases. The BF is active in the stance phase and mid-to late swing phase. The LG is active in the stance phase and early swing phase and again in the late swing phase.

Table 6.2. The minimum threshold onset and termination times
Onset and termination times of the EMG bursts of activity of the lower limbs above the minimum threshold are represented as mean ±SD as a percentage of the running gait cycle time.

<table>
<thead>
<tr>
<th>Muscle</th>
<th>Onset Time Mean ± SD (%)</th>
<th>Termination Time Mean ± SD (%)</th>
<th>Onset Time Mean ± SD (%)</th>
<th>Termination Time Mean ± SD (%)</th>
<th>Onset Time Mean ± SD (%)</th>
<th>Termination Time Mean ± SD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectus Femoris</td>
<td>0.8 ± 2.2</td>
<td>26.4 ± 5.1</td>
<td>36.3 ± 4.6</td>
<td>62.6 ± 5.7</td>
<td>81.4 ± 13.6</td>
<td>100.0 ± 0.0</td>
</tr>
<tr>
<td>Vastus Lateralis</td>
<td>0.9 ± 2.7</td>
<td>26.1 ± 0.0</td>
<td>36.6 ± 1.6</td>
<td>57.0 ± 23.7</td>
<td>99.6 ± 1.9</td>
<td></td>
</tr>
<tr>
<td>Biceps Femoris</td>
<td>0.4 ± 1.4</td>
<td>29.8 ± 8.1</td>
<td>57.0 ± 23.7</td>
<td>99.6 ± 1.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semitendinosus</td>
<td>0.23 ± 0.8</td>
<td>99.4 ± 2.9</td>
<td>83.3 ± 10.5</td>
<td>99.7 ± 1.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gluteus Maximus</td>
<td>2.5 ± 12.2</td>
<td>99.8 ± 0.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lateral Gastrocnemius</td>
<td>4.1 ± 12.5</td>
<td>68.2 ± 13.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medial Gastrocnemius</td>
<td>4.3 ± 11.2</td>
<td>99.2 ± 2.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The higher volume of activity can be seen across all muscles in the braking phase (early stance), in the propulsion phase (late stance) and in the pre-activation phase (late swing). The muscles vary in high volumes of muscle activity across the recovery phase (early and mid-swing). The ensemble average curves of all muscles can be seen in Figure 6.5. These curves show high activity at similar points in the gait cycle as seen in Figure 6.4. The ipsilateral leg GM, VL and ST have normalised peaks between 0.5 and 0.6 in the late swing phase. The ipsilateral leg MG has a peak of 0.5 in the mid-swing and the RF has a peak of 0.6 in the early swing. The BF and LG have peaks of 0.6 and 0.5 respectively in the stance phase. The contralateral leg has peaks of 0.6 in the late stance phase for the GM and MG. The
contralateral leg VL, BF, ST and LG have peaks between 0.5 and 0.6 in the early and mid-swing phase. The contralateral leg RF has a peak of 0.5 in the late swing phase.
Figure 6.4 The EMG profile across the sprinting gait cycle
Muscle activation is represented as mean onset and mean termination times. The light grey areas represent periods where the volume of EMG activity was above the minimum threshold (mean + 3SD), and the diagonally striped light grey areas represent areas where the volume of EMG activity was below the minimum threshold for some participants. The dark grey indicates periods where the volume of EMG activity was above the 50% maximum threshold (≥ 50% maximum amplitude). The toe-off (TO) is positioned approximately at 28% of the gait cycle (the latest TO event recorded across participants).
Table 6.3. The 50% maximum threshold onset and termination times
Onset and termination times of the EMG bursts of activity of the lower limbs above the 50% maximum threshold are represented as mean ±SD as a percentage of the running gait cycle time.

<table>
<thead>
<tr>
<th></th>
<th>Onset Time</th>
<th>Termination Time</th>
<th>Onset Time</th>
<th>Termination Time</th>
<th>Onset Time</th>
<th>Termination Time</th>
<th>Onset Time</th>
<th>Termination Time</th>
<th>Onset Time</th>
<th>Termination Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
<td>Mean ± SD (%)</td>
</tr>
<tr>
<td>Rectus Femoris</td>
<td>3.6 ± 6.4</td>
<td>12.2 ± 7.6</td>
<td>22.6 ± 6.8</td>
<td>36.6 ± 2.0</td>
<td>37.1 ± 5.7</td>
<td>47.8 ± 4.2</td>
<td>56.6 ± 3.2</td>
<td>64.7 ± 7.3</td>
<td>81.5 ± 5.2</td>
<td>94.7 ± 5.5</td>
</tr>
<tr>
<td>Vastus Lateralis</td>
<td>1.7 ± 3.3</td>
<td>9.4 ± 6.5</td>
<td>30.2 ± 6.4</td>
<td>40.1 ± 6.4</td>
<td>48.5 ± 4.1</td>
<td>51.6 ± 1.9</td>
<td>58.8 ± 0.5</td>
<td>67.0 ± 11.0</td>
<td>84.9 ± 7.0</td>
<td>97.0 ± 5.1</td>
</tr>
<tr>
<td>Biceps Femoris</td>
<td>2.1 ± 2.9</td>
<td>8.1 ± 6.8</td>
<td>17.3 ± 10.6</td>
<td>25.0 ± 6.3</td>
<td>38.9 ± 2.7</td>
<td>53.4 ± 6.3</td>
<td>56.0 ± 7.4</td>
<td>67.9 ± 10.0</td>
<td>85.6 ± 10.2</td>
<td>96.9 ± 6.3</td>
</tr>
<tr>
<td>Semitendinosus</td>
<td>0.6 ± 1.2</td>
<td>6.0 ± 2.8</td>
<td>17.1 ± 5.9</td>
<td>30.1 ± 8.7</td>
<td>46.5 ± 8.6</td>
<td>58.1 ± 16.8</td>
<td>67.9 ± 10.0</td>
<td>76.0 ± 5.5</td>
<td>95.6 ± 10.2</td>
<td>96.9 ± 6.3</td>
</tr>
<tr>
<td>Gluteus Maximus</td>
<td>0.1 ± 0.0</td>
<td>5.6 ± 4.7</td>
<td>15.9 ± 5.9</td>
<td>34.8 ± 6.6</td>
<td>41.6 ± 3.6</td>
<td>48.8 ± 5.2</td>
<td>61.8 ± 9.1</td>
<td>73.1 ± 10.6</td>
<td>85.5 ± 8.7</td>
<td>92.3 ± 13.7</td>
</tr>
<tr>
<td>Lateral Gastrocnemius</td>
<td>1.9</td>
<td>10.1 ± 8.3</td>
<td>18.1 ± 7.4</td>
<td>26.5 ± 3.9</td>
<td>39.3 ± 1.0</td>
<td>48.4 ± 6.0</td>
<td>69.2 ± 9.1</td>
<td>78.2 ± 9.4</td>
<td>89.6 ± 2.8</td>
<td>99.7 ± 1.3</td>
</tr>
<tr>
<td>Medial Gastrocnemius</td>
<td>5.6</td>
<td>13.1 ± 13.6</td>
<td>59.1 ± 8.7</td>
<td>85.4 ± 14.5</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 6.5 The ensemble averages of each muscle analysed across the sprinting gait cycle. The solid black line represents the mean curves and the light grey shaded region represents the SD. The ipsilateral leg activity is the left column and the contralateral leg activity is the right column.
The difference between onset and termination times gathered in this study using the minimum threshold and in Chapter 3 can be seen in Table 6.4.

Table 6.4 The difference between onset and termination times
A negative value indicates that the onset/termination times of the data in this study were later than the times reported in previous studies. A positive value indicates that the onset/termination times of the data in this study were earlier than the times reported in previous studies.

<table>
<thead>
<tr>
<th>Muscles</th>
<th>Onset Time (%)</th>
<th>Offset Time (%)</th>
<th>Onset Time (%)</th>
<th>Offset Time (%)</th>
<th>Onset Time (%)</th>
<th>Offset Time (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus Maximus</td>
<td>-2.52</td>
<td>15.00*</td>
<td>77.00*</td>
<td>0.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hamstrings (BF &amp; ST)</td>
<td>-0.35</td>
<td>-7.41</td>
<td>15.79</td>
<td>0.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calves (LG &amp; MG)</td>
<td>-4.19</td>
<td>-49.47</td>
<td>-6.32</td>
<td>0.59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quadriceps (RF &amp; VL)</td>
<td>-0.90</td>
<td>-6.75</td>
<td>-0.47</td>
<td>4.00</td>
<td>8.44</td>
<td>0.28</td>
</tr>
</tbody>
</table>

*The gluteus maximus showed no activity during the late stance and early to mid-swing phase in the results from Chapter 3. The results from this study indicate that it was active above the minimum threshold across all phases of the gait cycle.

6.4 Discussion & Implications

The purpose of this study was to highlight the use of the algorithm developed in Chapter 5. It can be seen from the methods and results that the double thresholding algorithm can be adapted and applied to other track and field events, in this case sprinting. Inspection of the high volume of muscle activity in Figure 6.4 provides insight into the technique of these sprinters. The GM is the first muscle to activate in the braking phase directly after IC (see Table 6.3), at this point there is a slight period of flexion of the hip joint to absorb the forces at impact (Hay, 1993b, p. 407; Williams, 2000). The next muscles to activate are the hamstrings, followed by the quadriceps. In the early stance phase, the agonist and antagonist muscles co-contract allowing stabilisation. The calves provide interesting insight as the LG is first to activate, then the MG activates. This could be due to the way in which the foot makes contact with the ground, prior to IC the foot supinates (Williams, 2000) and the IC is the lateral aspect of the 5th metatarsal (MH5), high on the ball of the foot (Nett, 1964). During the ground contact the foot pronates and the weight shifts onto the ball of the foot and
TO event occurs at the first metatarsal (MH1). The calves are also activating to provide a stabilisation effect for the ankle joint. The LG undergoes an eccentric contraction when the foot is dorsiflexed, during the early stance phase, and the plantar flexion to begin the TO event is initiated by a concentric contraction during the late stance phase, high volumes of activity can be seen in the LG (see Figure 6.4) in the early stance and late stance phase. In the propulsion phase the GM is the initial driver, followed by the hamstrings. The GM and the hamstrings are the main hip extensors, after the IC the hip movement quickly returns to extension (Hay, 1993b, p. 408; Williams, 2000). The maximum hip extension occurs directly after TO. The hamstrings are acting as both hip and knee extensors (Wiemann & Tidow, 1995) in the stance phase after IC in the propulsive part of the stance phase, the BF activity in the late stance phase helps the knee flexion to begin after TO (Williams, 2000). The quadriceps are also activating here as the knee extensors as the leg moves into triple extension at TO (Hay, 1993b, p. 408; Wiemann & Tidow, 1995).

As the sprinter moves into the recovery phase (early swing) knee flexion occurs again (Hay, 1993b, p. 409), the knee flexion makes it easier to swing the leg through to the next foot strike (Hay, 1993b, p. 409; Williams, 2000). At this point in the early swing the GM, hamstrings and quadriceps are all active, the hip joint is extended and knee flexion is beginning. This activity is seen again in the GM, hamstrings and quadriceps during the mid-swing, here the knee is fully flexed and contralateral contact is occurring (see Figure 6.4). When the contralateral leg is in the fully extended position after contralateral TO, hip flexion of the ipsilateral leg is occurring and the athletes thigh is in a horizontal position (Hay, 1993b, p. 409). At this point the GM, hamstrings and quadriceps are all active (see Figure 6.4). The RF plays a role in hip flexion and knee extension, high volumes of activity can be seen at these points in Figure 6.4. In the late swing phase (pre-activation) the quadriceps are first to activate as the knee extends and prepares drive through the ground and begin the cycle
again. The GM and the BF are active here in preparation for foot strike, both are activating in an eccentric contraction to slow flexion of the hip and extension of the knee (Williams, 2000). At this point in the gait cycle the hamstring strain injuries are likely to occur, as this is the point of peak stretch of the hamstrings and the contraction is moving from eccentric to concentric (Chumanov et al., 2007; Williams, 2000). The calves also have high volumes of activity in the recovery phase, this could be due to the fact that the foot is plantar flexed directly after TO and remains in this position until the late swing phase when the foot is preparing for IC of the next cycle.

Visual inspection of the ensemble mean curves in Figure 6.5 can provide insights into the variability between trials and participants. Similar to the results from Chapter 6, these curves can also identify how the EMG activity of one participant compares to the average curve. An overlay of the curve from the sprinter with the quickest performance and the sprinter with the least quick performance could highlight where the main downfalls may be in terms of muscle activity for the sprinter with the least quick performance. For example a lack of muscle activity in the calves may highlight that the sprinter is leaving their foot dorsiflexed during the recovery phase instead of keeping the ankle joint stiff and the foot in a plantar flexed position to prepare for the ground contact in the following cycle.

The results of this investigation provide representative data on the muscle activity of the lower limbs during the maximum speed phase in accomplished male sprinters. Results provide a similar insight to those in Chapter 3 when using the minimum threshold to gather onset and termination times of the muscle activity. Further insights into the muscle activity of the lower limbs during maximal sprinting were gathered using the 50% maximum threshold. They augment the kinematic data by drawing attention to the points in the gait cycle where higher volumes of EMG occur. This data confirms the anecdotal evidence used by coaches, and augments the kinematic data on sprinting. Given the advancements in
technology into wireless sEMG devices, this analysis of leg EMG patterns will provide representative data for the event. Coaches can use this data to advance their knowledge of the event and create more specific training for their athletes by comparing how they perform relative to the athletes in this study. It has been found that coaches select sprint drills based on what other successful coaches were doing rather than basing their selections of scientific research (Whelan, Kenny, & Harrison, 2016). The use of sprint technique drills can be adapted and modified to mimic sprint technique, and muscle activity of these drills can be examined and compared to the muscle activity of the sprint to help decide which drills are most suitable for sprint training. Similarly in the use of resistance-based training programs, Bolger, Kenny, Lyons, and Harrison (2015) concludes that there is a need for research to determine if there is a true transfer between resistance-based exercises and sprint training.

This study was limited due to the availability of EMG sensors and therefore only examined between 12 and 14 muscles of the legs. It is recommended that future work should examine EMG activity on other leg muscles which play important roles in the force generation in sprinting, which would augment the representative data gathered in this study. The various muscles which should be considered for future studies would include: the vastus medialis, gluteus minimus, semimembranosus, soleus and tibialis anterior. In this study, the muscle activity was gathered on accomplished national and international level sprinters but an analysis of variations on phasic muscle activity in relation to performance level would be of benefit in advancing knowledge of the event. It would also be useful to compare the performance of the sprint to various metrics gathered in this study to determine if sustained high volume of muscle activity correlates with an increase in speed or if the length of time the foot is in contact with the ground transfers to a decrease in speed. It would be then necessary to investigate whether these results could be modified by training. As the sensors were surface mount, kinesio tape was used as an added method to secure the sensors to the
legs. The sprinters also wore skins over the sensors to further minimise any movement artefact which may occur due to the rapid movement of sprinting. All sprints for this study were performed indoors; this was to allow for constant temperature and to prevent variations in performances due to external factors.

### 6.5 Conclusion

Results of this investigation present a new interpretation of the data on muscle activations across the running gait cycle during a maximal sprint. The use of the 50% threshold is useful from a coaching perspective as it augments existing kinematic data. Future studies can examine training drills and exercises anecdotally used for sprints training to discover if similar muscle activity and patterns exist for these exercises. For the researcher it is important to have such information on the muscle activity to allow more extensive research into the sprint technique. Comparisons were sought with previous studies on sprinting using tethered and data logging systems and across the wired and wireless systems in overground sprinting. The results of this study show that similar data can be gathered using the tethered and data logging systems if great care is taken to ensure the validity of the environment. Results of this study show also that the double thresholding algorithm can be expanded and used across a variety of applications in sport, particularly in track and field athletics where key kinematic events of the full cycle are easily defined.
Chapter 7: Thesis conclusions and future directions

“If I have seen further than others, it is by standing upon the shoulders of giants”

Isaac Newton
7.1 Introduction

This chapter contains the conclusions, limitations and recommendations of the research. This section outlines a brief summary of topics covered in each of the chapters. The second section (7.2) outlines the key findings and implications of the research based on the aims addressed in Chapter 1. The third section outlines the constraints of the research and the final section discusses future avenues of research and questions which can be taken from this research.

A detailed background on various areas of biomechanics with an emphasis on sports biomechanics (specifically Track and Field athletics), sensor devices and EMG was provided (see Chapter 2). Due to the wide range of sensors available to practitioners there was a need to examine the culture around various sensor devices, their use amongst the sports biomechanics community and their applications in sport biomechanics. Sensor devices are utilised to characterise movement, improve performance and identify injury prevention techniques in various aspects of sport. A comprehensive review of current literature (see Chapter 3) and expectations of future research was necessary to highlight the use of EMG in sprinting, and to conclude that a more up to date profile of EMG activity across the various leg muscles in sprinting was necessary with the advanced wireless sensing technology. A survey which was conducted (see Chapter 4) outlined that sensor devices need to be small and cause little encumbrances due to the versatility and nature of sport. In sport there is a need for utilising non-invasive wireless sensor devices so athletes’ movement can be performed with ease in an ecologically valid environment. There is also the added benefit to practitioners as it allows testing to take place in the participants’ ecologically valid environment and with a quicker set-up. With these recent advances in technology and an increase in future studies utilising these technologies there was a need to examine further areas in track and field athletics in which not much information on muscle activities were
available. Shot Putting is one such area, EMG analysis and a profile of muscle activity was developed where previously due to technology constraints this was not possible (see Chapter 5). The analysis of maximal sprinting using wireless EMG was also necessary to provide more up to date knowledge on the muscle activities using newer technologies (see Chapter 6). Finally the main limitation associated with sEMG due to their non-invasive nature was cross-talk; this is an area still where more analysis needs to be done to discover if it is possible to combat cross-talk using advanced signal separation methods. The sEMG signals were explored using FastICA for signal separation and recreation of signals due to misplacement of electrodes (see Appendix D).

### 7.2 Key findings and implications of the thesis

The purpose of this research was to allow for a greater understanding of EMG signals and muscle activity across human movement by utilising powerful algorithms and data processing techniques across a range of disciplines. Therefore the aim of this research was to provide a novel contribution to the area of sports biomechanics in terms of EMG analysis and signal processing. The key findings and implications were:

- An in depth review of the literature on sEMG and sprinting was accomplished. It was found that analysis to date was restricted due to technology constraints, it is expected that an increasing number of studies utilising wireless technologies for sEMG and sprinting will be undertaken to advance the knowledge of both coaches and practitioners on muscle activations and sequencing of the lower limbs during sprinting.

- A survey of biomechanists on their use of sensor devices was conducted and information on the best EMG systems and the specifications desired by researchers
was gathered, highlighting wireless sensors as the most sought after technology by practitioners.

- The timings and sequencing of muscle activations in the shot put were gathered from a target population of athletes, who were at least national level throwers. Representative data on the muscle activations during the glide technique in shot put are now available due to this research for both male and female athletes. The data confirms some of the anecdotal evidence used by coaches which was previously based on analysis of kinesiology data; it is now known when muscles are active across the glide technique. With further analysis of drills and exercises specific to the shot put, coaches could be informed on useful exercises to tailor training of the athletes to work on specific aspects of their technique. For researchers, the information on the muscle activity augments existing data on the kinematics and kinetics of glide technique.

- Using similar techniques the timings and sequencing of muscle activations in sprinting were gathered from a target population of athletes, who were at least national level sprinters. By collaborating with colleagues in the Department of Sports Science and Physical Education representative data on the muscle activations during maximum overground sprinting are now available utilising wireless technologies. With additional analysis of sprint drills and strength training exercises, comparisons of the muscle activations to overground sprinting could be gathered to highlight the important drills and exercises in sprinting for coaches to work on with their athletes.

- The use of the 50% threshold provided a greater insight into the muscle activity as the higher volumes of activity coincided with key events in both the shot put throw cycle and the sprint gait cycle. If there was only EMG analysis it would be possible to
estimate the timings of the key events based on data acquired using the 50% threshold level.

- The reduction of cross-talk during isometric and isotonic contractions was explored on a target population of athletes from various backgrounds (see Appendix D). The use of FastICA for signal separation was explored across a variety of isotonic movements in two muscle groups. Results showed that there were possible variations of the mixing matrix which could have been due to the isotonic nature of the movements; it was decided that isometric contraction should be explored to minimise any movement of the sensor over the area of muscle being analysed.

- The recreating of ideal signals during isometric contractions due to the misplacement of electrodes during EMG analysis was explored on a target population of athletes from various backgrounds (see Appendix D). The use of FastICA for signal recreation was explored on an isometric contraction for one muscle group. In few instances output signals were shown to be correlated more closely with the ideal signals.

### 7.3 Constraints of the thesis

- The numbers of participants in each study were approximately average for human movement studies; however a greater sample size would be necessary to achieve statistical significance. To give an indication of the statistical significance in these cases effect sizes were used.

- Participants were all healthy young adults with no injuries, who were at least recreationally active. The results of this research cannot be compared to or applied to different populations such as the elderly, sedentary or those with clinical problems. The sample studied was not a typical sample of the whole population.
• The amount of data gathered was limited due to participant numbers and available sensors:
  
  o Technically proficient national level athletes are limited in numbers in Ireland which limits the numbers of available participants. Due to college and work commitments athletes may not have been in the country or available for testing.

  o There were a limited number of wireless sEMG devices available for use at different stages of the research. There were 16 sensors in total, however at certain stages various sensors were faulty reducing the number of sensors available. The data acquisition in the studies reflected these reduced number of sensors.

  o In the shot put study muscle activations were only acquired on the rectus femoris, biceps femoris and medial and lateral gastrocnemius muscles.

• Only 2D high speed video data was collected on the shot putters. It may have been useful to collect 3D video analysis, however due to the 3D motion analysis system requiring transportation and set-up for each testing location this was not feasible. 2D analysis still provided adequate information for the analysis steps.

• There was no automatic synchronisation between the high speed video camera and the EMG system. Synchronisation had to be performed between the two systems in the processing stage. Stringent steps were followed to insure correct synchronisation of systems; however human error could cause data to be slightly out of sync. The trigger system which was available for the 3D motion analysis system and the EMG system
provided a much cleaner and more accurate synchronisation. This was unavailable at the time of the testing performed using the 2D high speed video camera.

- For the study on cross-talk, sEMG was only acquired using the wireless sensor devices from Delsys which were designed to reduce cross-talk during acquisition. The use of general bipolar sEMG electrodes may have been better suited to this study.

### 7.4 Directions of future research

While this research has addressed a series of related research questions, it has also raised important issues which require further investigation. Future work should address these important issues:

- The survey of biomechanists and the technologies they use should be revisited in 10 years to examine how the technologies have evolved and how the expectation and knowledge of the biomechanists progressed with the advancements made. It would also be useful to see how the demographics differ over a 10 year period.

- This research has implemented the use of both the double thresholding algorithm and a threshold of 50% of the maximum normalised amplitude. Breaking down the thresholding into two separate methods allows a greater insight into the muscle activations in terms of volume of EMG activity in particular sporting movements. This added thresholding step could provide useful for future researchers.

- Due to the limitation of sensor numbers in the shot put study muscle activations were only acquired on the rectus femoris, biceps femoris and medial and lateral gastrocnemius muscles. Future studies should look at the other muscles of the lower limbs which practitioners expect to have a substantive role, such as the vastus
medialis and vastus lateralis, the gluteal muscles and muscles which contribute to the rotation aspect of the glide in the delivery stage of the throw.

- Muscle activation patterns in the rotation shot put technique should be examined and compared to that of the glide. It may be useful to gather information from the muscle activations to pin point areas in which each of the techniques result in better overall performances. Also, it would be useful to analyse specific aspects of the technique to understand if it can be maximised or if more emphasis should be placed on that aspect due to a direct correlation with increasing performance.

- The muscle activation patterns across the other throwing disciplines should be examined and compared to the shot put to discover similarities and differences across the throwing disciplines.

- Variations across muscle activation patterns in the different sprint events should be examined. The activation patterns in bend running versus straight running, the acceleration phase vs. maximum speed phase vs. maintenance phase and the activation patterns in the short sprints vs. the long sprints.

- The muscle activation patterns during training drills and exercises should be examined to highlight the drills and exercises which provide similar muscle activation patterns to the specific movements in sprinting and shot putting. This can also be done across the range of track and field events.

- A study into the feasibility of an android/iOS application which streams the EMG data real time from the acquisition software program on the PC should be undertaken. This application should have the ability to perform simple data processing of the signals and display real time results to the coach and athlete. Results could be
displayed in the form of a linear envelope of the EMG signals across the sporting movement which would be overlaid on the mean ± SD curve of the ensemble averages of the representative datasets previously available. The athlete and coach could see how the performance compared to the average athlete or elite athlete, depending on previously available data.

- Future work in examining cross-talk in sEMG data should include the use of general bipolar sEMG electrodes which do not include extra processing in the acquisition stage. Acquiring the true sEMG signal gathered from the sensor at each location is important when examining what each sensor site picks up as regards muscle activity from the muscle in question and from adjacent muscles. The Delsys sEMG sensors were patented technologies which were double differential electrodes. Reviewing the literature and studies by Carlo J. De Luca and his collaborators, showed that they had designed the sensors to minimise cross-talk before the signals were ever processed after acquisition.

- The use of non-stationary ICA algorithms and ICA algorithms used in conjunction with other processing techniques should also be examined.

### 7.5 Conclusions

The primary focus of this research was on movements in track and field athletics with an emphasis on sprinting and throwing. The literature review on sEMG and sprinting provided information on timings and muscle activations across the running gait cycle. The profile of previously gathered muscle activity provided a summary of findings from previous research which could aid future research in this area. The review showed a bias to the muscles analysed due to technology constraints and highlights that the use of wireless technology may provide a more accurate representation of the data as it will be collected in an ecologically
valid environment. Novel contributions have been made by providing representative data of muscle activations of the lower limbs in shot putting and sprinting utilising wireless technologies. This data will provide useful for coaches and practitioners by augmenting existing data on kinematics and kinetics and with added information on muscle activations during drills and specific exercises it would be possible for coaches to tailor training to work on specific technique aspects for the athletes. Overall, this research has furthered information on the muscle activity of the lower limbs in ecologically valid environments for both the glide shot put technique and maximal overground sprinting. This research has also provided more questions and possible avenues for research around the use of ICA for the reduction of cross-talk and the recreation of signals.
References


Appendix A  Ethics Information

A.1 Questionnaire – Chapter 4

Ethics was approved for the questionnaire on the 9th of April 2014, application number 2014_03_02_S&E by the Faculty of Science and Engineering Ethics Committee.

A.1.1 Cover Letter

To whom it may concern,

Recently I have become a first time student member of the International Society of Biomechanics in Sport as I begin my career in research. I am excited by the prospects and look forward to making most of your acquaintances at the conference this coming July. As part of my research I would like to invite you to take part in a short questionnaire entitled “A survey of sensor devices and their uses in Sports Biomechanics”. Please click here to access the questionnaire.

Completion of this survey should take you a maximum of 15 minutes. This questionnaire has been ethically approved and is completely anonymous and confidentiality is guaranteed. Please note you are under no obligation to participate in this study and you are free to withdraw from the study at any time without giving a reason.
I would like to take a moment to thank you for taking the time to participate and look forward to reviewing your responses to this questionnaire. I am very excited by this project and look forward to presenting my findings. I am happy to discuss my findings with other researchers who are interested in this topic. If you have further questions regarding this research please feel free to get in touch with either myself or one of my supervisors using the email addresses listed below.

If you have concerns about this study and wish to contact someone independent, you may contact: The Chair, Faculty of Science & Engineering Research Ethics Committee, University of Limerick, Limerick. Tel: 061 202802

Yours sincerely,

Róisín Howard
Ph.D. Researcher
University of Limerick
roisin.howard@ul.ie

Dr. Richard Conway
Electronic & Computer Engineering Department
University of Limerick
richard.conway@ul.ie

Dr. Drew Harrison
Physical Education & Sports Science Department
University of Limerick
drew.harrison@ul.ie

A2
A.2  EMG studies – Chapters 5 - 7

Ethics for all studies including EMG and Accelerometer measures was approved on the 22\textsuperscript{nd} September 2014, application number 2014_09_01_S&E by the Faculty of Science and Engineering Ethics Committee.

A.2.1  Participant Consent Form

\hspace{1cm} \includegraphics[width=\textwidth]{Participant_Informed_Consent.png}

\hspace{1cm} \textbf{Participant Informed Consent}

I confirm that all aspects of my participation have been fully explained to my satisfaction. I am fully aware of the risks of the study and know that I can withdraw from the study at any time should I choose to.

I confirm that I meet the selection criteria of:

- Regular training and participation in sports involving a sprint component
- Not currently injured
- Above a minimum age of 18
- Below a maximum age of 65
- Have no existing medical ailment which may deter me from the study

\textbf{AGREEMENT TO CONSENT} – If you agree to participate in this research study please sign below. You will be issued with a photocopy of this form, for your own records.

I, .................................(PRINT NAME) consent to participate on an anonymous basis, in the research study outlined above.
A.2.2 Participant Information Sheet

The Evaluation of Electromyography and Accelerometry on Specific Track & Field Events with an emphasis on Sprint Performance

Participant Information Sheet

Thank you for your interest in this study. The research that you are being asked to contribute to relates to examining specific track and field events with an emphasis on sprint running performance. Should you partake in the study you will be provided with your test results.

The following pages describe the research study and detail the procedures involved.

Please read the attached subject information sheet thoroughly. To organise testing sessions, please complete the table below. Your contact details are required for the sole purpose of
contacting you in relation to organising testing sessions. *This information is kept secure and confidential.*

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You have been asked to participate in a research study. You are under no obligation to participate in this study. In order to decide whether you do or do not want to participate in this study, you need to fully understand the risks and benefits to allow you make an informed decision. You have to be between the ages of 18 and 65 to participate. This process is known as INFORMED CONSENT.

This research focuses on the evaluation of 3D analysis and electromyography and accelerometry in: …………………………. (INSERT EVENT); with an emphasis on sprint performance. As part of this research you will be tested in 20m sprint, and your specific event. The whole process takes approximately 2 hours to complete.
The Evaluation of Electromyography and Accelerometry on Specific Track & Field Events with an emphasis on Sprint Performance

Risks:
Participants may anticipate mild delayed onset of muscle soreness (DOMS), however there will be no additional risk of injury arising from this study as the participants commonly perform these tasks on a weekly basis. The warm up will be specifically designed to ensure that participants are fully warmed up and that their bodies are physically ready for the demands of the testing procedure. The investigator is a qualified first aider and will be on site to address any strains, sprains or muscle pulls. Participants will also be made fully aware that they do not have to progress with testing if they feel any such injury is possible.

On the day you should wear appropriate training/exercises gear i.e. running shorts, runners, and/or appropriate event shoes, t-shirt etc. The researcher will start by measuring your stature (height) and weight then proceed as follows:

**Warm up** – all participants will participate in a standardised warm up of approx. 15 minutes duration. This warm up will ensure that your body is physically prepared for the tasks ahead.

**Test day routine** – The study will incorporate 2 days of testing, with each test day incorporating 1 testing session.

- **Test day one** will involve one testing session to determine baseline values in 20m sprint and your specific event performance. This will involve a standardised warm up followed by 3
submaximal trails in your specific event. Then you will perform 3 x 20m sprints and finally 3 trials in your specific event.

-**Test day two** will involve an identical testing session as day 1.

On the first testing day subjects will perform a short (15minutes approx.) pre designed warm up, after all subjects are adequately warmed up they will be asked to maximally perform 3 x 20m sprints and then their specific event trials with a complete and full recovery between all trials.

Markers will be placed on each participant to identify segments. Integrated wireless EMG and accelerometers will also be place on each subject as they perform each trial. All data will be recorded with the 3D motion capture system and the DelSys Trigino System. In the case of hurdles, sprints or any of the jumps being the specific event the Optojump system will be places alongside the lane to measure stride pattern.

On the subsequent testing days all tests will be repeated as described above. You will receive a copy of your results that could be of benefit to you.
The Evaluation of Electromyography and Accelerometry on Specific Track & Field Events with an emphasis on Sprint Performance

If you have concerns about this study and wish to contact someone independent, you may contact: The Chair, Faculty of Science & Engineering Research Ethics Committee, University of Limerick, Limerick. Tel: 061 202802.

All results will be kept secure and confidential at all times.

If you have any questions about the research project please contact:

Principal Investigator
Dr Richard Conway

&

Dr Drew Harrison FISBS
University of Limerick
Castletroy,
Limerick,
IRELAND
Email: richard.conway@ul.ie
Email: drew.harrison@ul.ie

Róisín Howard
Email: roisin.howard@ul.ie
Appendix B  Supplimentary Data

B.1 The Questionnaire – Chapter 4

1. This research project has been approved by the University of Limerick’s Faculty of Electronic & Computer Engineering Research Ethics Committee.

By ticking the 'agree' box below you are adhering to the following points and may participate in this study.

✓ I have read and understood the participant information provided above.
✓ I understand what the project is about, and what the results will be used for.
✓ I am fully aware of all the procedures involving myself, and of any risks and benefits associated with the study.
✓ I know that my participation is voluntary and that I can withdraw from the study at any stage without giving reason.

○ Agree
○ Disagree
2. Gender
   - Male
   - Female

3. How long have you been involved with Biomechanics related research?
   - 0 - 4 years
   - 5 – 9 years
   - 10 – 19 years
   - 20 – 29 years
   - 30 years +

4. Age

5. What are your main fields of expertise?
   (Tick all appropriate)

   - Allometry
   - Cardiovascular
   - Ergonomics
   - Functional Movement
   - Gait Analysis
   - Injury & Rehabilitation
   - Kinematics
   - Kinetics
   - Sports Biomechanics
   - Sports Performance
   - Tissue Biomechanics
   - Other (please specify all that apply)

6. In what country do you reside?

B10
7. Please indicate your frequency of use of the following sensor devices.

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Ireland

Other (please specify)

[ ]
8. Please indicate your awareness and use of the following sensor devices.

(See images below)

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</table>
Please make note of any other EMG devices you may have used that are not mentioned above:

Shimmer3 Development Kit, SHIMMER

Trigno Wireless EMG System
MyoTrac
Bio-medical

TeleEMG Focus Machine

Dantec KEY Focus

BioFlex
BioControl

Biometrics Kit
Bagnoli Desktop EMG System
DelSys

Clinical Direct
Transmission System

TeleMyo 2400T
Noraxon

MyoSystem 1400A
Noraxon
9. What do you like about the EMG devices on the market?

<table>
<thead>
<tr>
<th>Feature</th>
<th>Like</th>
<th>Neutral</th>
<th>Dislike</th>
<th>N/A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (10mm)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Bipolar (20mm inter-electrode distance)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Shape (Circular Disk)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Material (Ag-AgCl)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Usability (Ease of movement for the subject)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Usability (Ease of use for the researcher)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Wireless Transmission (Telemetry, Wi-Fi, Bluetooth, etc.)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Amplifier Gain (1000)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Anti-aliasing filter</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Sampling Rate (up to 1kHz)</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Analog to Digital Converter</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Software analysis tools</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>
Please leave any additional comments on what you like/dislike about the devices here:

10. What aspect of human movement do you want to measure?

<table>
<thead>
<tr>
<th></th>
<th>Strongly Agree</th>
<th>Agree</th>
<th>Neutral</th>
<th>Disagree</th>
<th>Strongly Disagree</th>
<th>N/A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electromyography</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Mechanomyography</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>○</td>
<td>○</td>
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<td>○</td>
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<tr>
<td>Gyroscope</td>
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<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Magnetometer</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>GPS</td>
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<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
</tbody>
</table>

Please specify any other specific movements you would like to measure here:

11. What are you as a biomechanist looking for in a device?

(Please give as much detail as possible for each category)

Electrode Shape

Electrode Size

Electrode Material
12. What sensors would you like to see in a low power wireless device?

Please specify any additional devices you would like to see and why:

13. As regards signal processing, what analysis methods would you like to see?

<table>
<thead>
<tr>
<th>Analysis Method</th>
<th>Agree</th>
<th>Neutral</th>
<th>Disagree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectification</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Filtering</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Integrated EMG (iEMG)</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Root Mean Square (RMS)</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Linear Envelope</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Spectral Analysis</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
</tbody>
</table>
Wavelet Analysis  ○  ○  ○  ○
Neural Networks  ○  ○  ○  ○
Principal Component Analysis (PCA)  ○  ○  ○
Independent Component Analysis (ICA)  ○  ○  ○

Please specify other analysis methods you would like to see available for use:

14. I would like to take this opportunity to thank you for taking part in this survey. If you have any comments or points to add in relation to this study please enter them below.

B.2 Shot Put – Chapter 5

Table 1 Performance metrics of the Shot Putt athletes from Chapter 5

<table>
<thead>
<tr>
<th></th>
<th>Standing Throw (m)</th>
<th>Glide Throw (m)</th>
<th>Overhead Throw (m)</th>
<th>20m Sprint Time (s)</th>
<th>CMJ Before (cm)</th>
<th>CMJ After (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female Day 2</td>
<td>9.60</td>
<td>9.93</td>
<td>9.95</td>
<td>2.89</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Male Day 1</td>
<td>8.56</td>
<td>8.97</td>
<td>9.97</td>
<td>2.66</td>
<td>40.33</td>
<td>41.68</td>
</tr>
<tr>
<td>Male Day 2</td>
<td>8.70</td>
<td>9.28</td>
<td>10.82</td>
<td>2.57</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>All Day 1</td>
<td>9.03</td>
<td>9.64</td>
<td>9.91</td>
<td>2.87</td>
<td>31.40</td>
<td>30.90</td>
</tr>
<tr>
<td>All Day 2</td>
<td>9.38</td>
<td>9.76</td>
<td>10.17</td>
<td>2.81</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Appendix C  Thresholding Matlab Code

C.1 Chapter 5 & Chapter 6

C.1.1 Theory behind the calculation of the onset and termination timings

The raw EMG signal had to go through some post processing prior to determining the onset time: the DC offset was removed, the signal was full wave rectified and final a low pass filter of 10 Hz was applied to create a linear envelope. A double thresholding method (Kamen & Gabriel 2010, Hodges & Bui 1996) was used to identify the onset and termination timings of a burst of EMG activity. The initial threshold was defined as the baseline mean + 3SD (Di Fabio 1987, Hodges & Bui 1996), the signal must exceed this level to be considered on and drop below to be considered off. The second part of the thresholding to determine if the burst duration was longer than 40 ms. If the EMG signal exceeded the initial threshold but the duration was less than 40 ms it was not considered an onset of activity; similarly if the signal was only below the initial threshold for less than 40 ms it was not considered the termination of muscle activity (Hodges & Bui 1996). The mean value of the EMG signal was calculated at each timestamp and compared to the initial threshold, a “1” was used to signify the EMG being “on” and a “0” was used to signify the EMG being “off”. Once these values were calculated, this signal was passed through the second thresholding step to determine if a duration of “on” lasted for more than the minimum time, and similarly for a duration of “off”. If the signal was “on” for a duration which was greater than the minimum time and there was an “off” period of less than the minimum time, this was corrected to “on”, similarly if the signal was “off” for a duration which was greater than the minimum time and there was an “on” period of less than the minimum time, this was corrected to “off”.

C20
C.1.2 Matlab function: emgonoff_RH

```matlab
function [onoff_T2, time_on, time_off] = emgonoff_RH( leemg, meanemg, sdemg, fs, min_time, num_sd )
% onoff_T2 = emgonoff_RH( leemg, meanemg, sdemg, fs, min_time, num_sd )
% finds time and indices of onset and termination times for rectified
% EMG data
% leemg = input file linear envelope of emg data ( 1 column vector )
% fs = Sampling Frequency
% min_time = Minimum burst time
% meanemg = mean of the EMG signal
% sdemg = standard dev. of th EMG signal
% num_sd = number of standard deviations above resting rms emg to trigger
% an "ON"
%
% Default values:
% num_sd = 3SD

%% Check inputs for defaults
if nargin < 3, error('Not enough inputs'); end
if nargin < 4, fs = 1925.93; end; % Sampling Frequency
if nargin < 5, min_time = 0.10; end; % Minimum burst time
if nargin < 6, num_sd = 3; end; % Number of Standard Deviations

%% preallocate arrays
temp(length(leemg), 1) = 0;
onoff_T1(length(leemg),1) = 0;

%% Create threshold value
threshold = meanemg + num_sd*sdemg;

%% Create thresholding signal
% Double Thresholding part 1
% Compare each point to the mean + 3SD
for n = 1:length(leemg)
    temp(n,1) = leemg(n);
    if temp(n,1) > threshold         % if LE of EMG is >
        onoff_T1(n,1) = 1;              % threshold at that point
        time_on = time_on + min_time;     % set to 1 to show signal
    else
        onoff_T1(n,1) = 0;              % as on!
    end;
end;
% Find the on and off time points
```

[time_on, time_off] = OnOffTimePts(onoff_T1);

%% Update threshold signal to eliminate blips in EMG signal!
%% Double thresholding part 2
onoff_T2 = onoff_T1;
for i = 1:min(length(time_on),length(time_off))
    if time_on(1) == 1
        % signal is on first
        %-----------------|___|-----------------
        if (i ~= length(time_on) & onoff_T2(time_off(i)-1) ~= 0)
            if (time_on(i+1) - time_off(i) < floor(min_time*fs))
                onoff_T2(time_off(i):time_on(i+1), 1) = 1;
            end;
        end;
    end;

    %-----------------|___|-------
    if (i ~= 1 & onoff_T2(time_on(i)-1) ~= 1)
        if (time_off(i) - time_on(i) < floor(min_time*fs))
            onoff_T2(time_on(i):time_off(i), 1) = 0;
        end;
    end;

    elseif time_off(1) == 1
        % signal is off first
        %______|-----------|--|--------- signal is on with an off
        blip
        if (i ~= 1 & onoff_T2(time_off(i)-1) ~= 0)
            if (time_on(i) - time_off(i) < floor(min_time*fs))
                onoff_T2(time_off(i):time_on(i), 1) = 1;
            end;
        end;

        %_________|--|____________ signal is off with an on
        blip
        if (onoff_T2(time_on(i)-1) == 0)
            if (time_off(i+1) - time_on(i) < floor(min_time*fs))
                onoff_T2(time_on(i):time_off(i+1), 1) = 0;
            end;
        end;

    end;
end;

% Check for the updated on and off time points
[time_on, time_off] = OnOffTimePts(onoff_T2);
end
C.1.3 Matlab function: OnOffTimePts

```matlab
function [time_on, time_off] = OnOffTimePts(signal)
% [time_points] = findChangeOnOff(signal)
% finds the time points in the vector at which the signal changes
% from 1 to 0 or from 0 to 1

% 0 to 1
time_on = find(diff(signal) == 1) + 1;

% 1 to 0
time_off = find(diff(signal) == -1) + 1;

% Add start point to the vector if the signal is on or off first
if signal(1) == 1
    time_on = [1; time_on];
end;

% Add end point to the vector if the signal is on at the end
if signal(end) == 1
    time_off = [time_off; length(signal)];
end;

end
```
Appendix D  The exploration of cross-talk using Independent Component Analysis

D.1 Introduction

The purpose of this section was to explore the use of Independent Component Analysis (ICA) on surface Electromyography (EMG) data. The aim was to distinguish between individual muscle activations in adjacent muscles and to explore the recovery of EMG signals due to misplacement of electrodes.

D.2 Background

The main disadvantage of surface electromyography (sEMG) is its limitation to superficial muscles which makes it difficult to isolate the individual muscle activity due to cross-talk. Cross-talk is interference which is picked up on the EMG signal from adjacent muscles. Figure 2.18 (page 39) shows an example of how sEMG sensor may pick up cross-talk from adjacent muscles. SENIAM recommendations were created for many reasons, one being to help reduce the amount of cross-talk gathered as a result of surface mount electrodes. By placing the sensor in the belly of the muscle it is more likely to pick up a single muscle, but due to the non-invasive nature of these electrodes, signals from the adjacent muscles will also be picked up and added to the overall signal. For example, in the case of the quadriceps muscle group, if the sensor is placed correctly to gather information on the rectus femoris (RF), then the sensor will also pick up information from both the vastus lateralis (VL) and the vastus medialis (VM). It is also possible that the deeper muscle, the vastus intermedius (VI),
will be recorded. The practitioner acquiring these signals has no way of checking if there is cross-talk and to what extent.

Cross-talk is a common problem associated with sEMG in sporting applications. The use of sEMG sensors is limited to superficial muscles due to the non-invasive nature of surface mount sensors. Isolation of the electrical activity of just one muscle has proven difficult. Multiple muscles contribute to a movement; as a result, electrical activity from the muscle of interest and the adjacent muscles can be recorded and “mixed-in” by the sEMG sensor. The combined signal is gathered and analyzed, with the user being unaware (Kamen & Gabriel, 2010). Cross-talk is especially common in sprinting as more muscle fibres from other muscles are recruited to maintain the speed throughout. It is possible to explore algorithms to isolate the dataset from each muscle. Some relatively new analysis techniques are available which may enhance EMG analysis of sprinting. Among these are principal component analysis (PCA), independent component analysis (ICA), and wavelet analysis. These algorithms can be used in feature extraction (Naik & Kumar, 2011), signal separation (Kilner, Baker, & Lemon, 2002; Nakamura, Yoshida, Kotani, Akazawa, & Moritani, 2004a, 2004b) or pattern recognition (Lariviere, Gagnon, & Loisel, 2000; Wakeling, 2009). They could provide very useful in the area of sports biomechanics for recognising patterns in sports performance and possibly predicting injuries (Yu et al., 2008). Results could then be used to help with rehabilitation after injury or for technique improvements and prevention steps prior to injury occurring. By creating a knowledge base in this area and having those processing techniques more readily available there is potential for advancement of analysis of human movement from a sports biomechanics view point.
D.3 Theory of ICA

ICA is a method for finding underlying factors or components from multidimensional statistical data, more simply a dimension reduction technique which can return data that were originally hidden from the larger data set (Hyvärinen, Karhunen, & Oja, 2002b). It is a general-purpose statistical technique to linearly transform observed random data (Hyvärinen & Oja, 2000). The “cocktail party problem” is the common analogy used when describing the use of ICA (Haykin & Chen, 2005). Take for example two people speaking simultaneously at one side of the room and two microphones held in different locations in the room. The microphones record two signal, denoted as $x_1(t)$ and $x_2(t)$. Each of these recorded signals are a weighted sum of the speech signals from the two speakers, denoted as $s_1(t)$ and $s_2(t)$. This can be expressed as linear equations: (Hyvärinen & Oja, 2000):

$$x_1(t) = a_{11} s_1 + a_{12} s_2$$  \hspace{1cm} \text{(D.1)}
$$x_2(t) = a_{21} s_1 + a_{22} s_2$$  \hspace{1cm} \text{(D.2)}

Here, $a_{ij}$ are parameters that depend on the distance of the microphones from the speakers and using matrix notation, $x$ can be the random vector of the mixtures $x_1$ and $x_2$, and $s$ the random vector with the speech signals $s_1$ and $s_2$. The mixing model for ICA can thus be written as (Hyvärinen & Oja, 2000):

$$x = As$$  \hspace{1cm} \text{(D.3)}

Where $A$ is a square 2x2 matrix with entries $a_{ij}$. To solve this problem, the assumption that $s_1(t)$ and $s_2(t)$ are statistically independent must be made. The estimation of $a_{ij}$ based on the independence of $s_1(t)$ and $s_2(t)$ allows the separation of the two original source signals $s_1(t)$ and $s_2(t)$ from their mixture $x_1(t)$ and $x_2(t)$ using ICA.
Centring, whitening and dimensionality reduction are pre-processing steps for ICA algorithms. They are necessary in order to simplify and reduce the complexity of the problem for the actual iterative algorithm. Centring is used to create a zero mean signal by subtracting the mean from the signal.

\[ x = x - E[x] \quad \text{(D.4)} \]

Whitening removes any correlations in the data. It reduces the number of parameters to be estimated. A new vector (\( \tilde{x} \)) is obtained and its components are uncorrelated and their variances equal unity, basically the covariance of this matrix equals the identity matrix (Hyvärinen, Karhunen, & Oja, 2002a; Hyvärinen & Oja, 2000):

\[ \varepsilon(\tilde{x}\tilde{x}^T) = I \quad \text{(D.5)} \]

Eigenvalue decompositions of the covariance matrix can be used to perform whitening by:

\[ \tilde{x} = ED^{-1/2}E^Tx \quad \text{(D.6)} \]

Whitening transforms the mixing matrix into:

\[ \tilde{x} = \tilde{A}s \quad \text{(D.7)} \]

Dimension reduction is the process of reducing the number of random variables under consideration. After the pre-processing steps are performed ICA can be applied. ICA rotates the whitened matrix back to the original space by performing rotations to minimise the Gaussianity of the data projected. Kurtosis, the normalised version of the fourth moment \( E[y^4] \) is the classical measure of non-Gaussianity. The kurtosis of \( y \) is defined by (Hyvärinen & Oja, 2000):
\[ \text{kurt}(y) = \mathbb{E}\{y^4\} - 3(\mathbb{E}\{y^2\})^2 \quad \text{D.8} \]

For a non-Gaussian random variable kurtosis is non zero; random variables with negative kurtosis are called subgaussian and with positive kurtosis are called supergaussian (Hyvärinen & Oja, 2000). Negentropy is also a measure of non-Gaussianity and is classically measured using high-order moments. The negentrophy, \( J \), of \( y \) is always non-negative and it is zero if \( y \) has a Gaussian distribution. It is defined by (Hyvärinen & Oja, 2000):

\[ J(y) \approx \frac{1}{12} \mathbb{E}\{y^3\}^2 - \frac{1}{48} \text{kurt}(y)^2 \quad \text{D.9} \]

There are different approaches for ICA estimation (see Hyvärinen & Oja (2000) for a detailed explanation on other methods). For example minimising the mutual information is done by finding an invertible transform that minimises the mutual information; it is approximately equivalent to finding the 1-D subspaces in which the projections in those subspaces have maximum negentrophy. FastICA is a very efficient method. This description of fastICA is concentrated on the one-unit version (Hyvärinen & Oja, 2000). The fastICA algorithm finds a direction, a unit vector \( w \) such that non-Gaussianity of the projection \( w^T x \) is maximised. Non-Gaussianity is measured by the approximation of negentrophy \( J(w^T x) \) as in Equation D.9. A fixed point iteration scheme is used in fastICA to find the maximum of the non-Gaussianity of the projection. It can be derived as an approximate Newton operation, where \( g(u) = u \exp(-u^2/2) \) is the derivative of the non-quadratic function \( G(u) = -\exp(-u^2/2) \). The basic fastICA algorithm is as follows:

1. An initial weight vector \( w \) is chosen.

2. Let \( w^+ = \mathbb{E}\{x g(w^T x)\} - \mathbb{E}\{g'(w^T x)\}w \)
3. Let \( w = w^+ / \| w^+ \| \)

4. If not converged, go back to step 2.

Note that convergence means that the old and new values of \( w \) point in the same direction, i.e. their dot-product is (almost) equal to 1. Once ICA estimates the mixing matrix, \( A \), and the sources can be recovered by multiplying the observed signal, \( x \), with the inverse of the mixing matrix (where \( W = A^{-1} \)):

\[
\mathbf{s} = \mathbf{Wx}
\]

The criteria necessary to satisfy the conditions of ICA are as follows:

- Components must be statistically independent
- Independent components must be non-Gaussian

**D.4 Suitability of sEMG signals**

The electrical activity of a muscle contraction satisfies each of the criteria for ICA. Each muscle can be assumed to be an independent source, as the set of motor units in each muscle are well separated from the other muscles. Similarly, the muscle activity can be assumed to be made of independent motor unit action potentials (MUAP). These MUAPs are individual pulses and the finite sum of these is non-Gaussian (Naik, Kumar, & Arjunan, 2010). The aim of this chapter is to expand on previous research (Howard, Conway, & Harrison, 2015a, 2015b, 2016) and explore the use of ICA on EMG signals to reduce cross talk from the gathered data, isolating the individual muscle contributions and giving a cleaner original signal.
D.5 Limitations of ICA

The independent components are found in ICA by maximising the statistical independence of the estimated components. By identifying individual muscles as independent the ICA algorithm can be applied. It can then be used for the separation of muscle activity in situations where there is a lot of cross talk between muscles which are nearby, and in the removal of other artefacts from sEMG (Djuwari, Kumar, Naik, Arjunan, & Palaniswami, 2006). There are certain limitations to the use of ICA. The first is that the mixing matrix varies over time during isotonic contractions. The second limitation, again to do with the mixing matrix, is the fact that the scaling factor is unknown. The resultant outputs of the ICA algorithm return the original sources however scale, sign and order are not preserved. It is also important to note that the number of mixed signals must be greater than or equal to the number of source signals.

D.6 Applications of ICA

Isolating electrical activity shares many similarities with the analogy of the “cocktail party problem” for ICA (Brown, Yamada, & Sejnowski, 2001). ICA has been used across a broad range of applications in areas such as audio processing, image processing, biomedical signal processing and telecommunications. Effective results have been found in audio signal separation using ICA and blind source separation (BSS) (Folorunso, 2014). Results are shown to be effective for this application. A method using ICA mixture models was effective in classifying complex image textures and in the removal of noise and filling in missing pixels in images (Te-Won & Lewicki, 2002).
The area of biomedical signal processing has a variety of examples where ICA can be of use (James & Hesse, 2005). Table 2 outlines the variety of papers which made use of signal separation methods such as ICA and BSS. ICA has been used with EMG data on the removal of artefacts due to ECG (Butler, Newell, Hubley-Kozey, & Koze, 2009; Hu, Mak, & Luk, 2009; LeVan, Urrestarazu, & Gotman, 2006; Mak, Hu, & Luk, 2010; Willigenburg, Daffertshofer, Kingma, & van Dieen, 2012), signal classification (Naik, Al-Timemy, & Nguyen, 2015; Naik, Selvan, & Nguyen, 2015) and decomposition of Motor Unit Action Potential Trains (MUAPTs) (Garcia, Akazawa, & Okuno, 2003; Garcia, Okuno, & Azakawa, 2005; Ren, Yan, Wang, & Hu, 2006). Contamination of EMG signal with ECG is common when trunk muscles are under observation. This extra data can yield misinterpretations of the data (Willigenburg et al., 2012). ICA was shown to produce favourable results when EMG and ECG signals were statistically independent (Willigenburg et al., 2012). However, there may have been some bias in the assessment as the normalisation may have affected the ratio of ECG amplitude between channels. Mak et al. (2010) developed an automated artefact detection algorithm; it successfully identified ECG artefacts with 100% sensitivity and 99% specificity and removed the ECG signal from EMG recordings. Results were compared between the ICA approach and a filtering approach with a significantly higher correlation value (0.80 – 0.97) in the ICA based approach. Hu et al. (2009) also removed ECG contamination from EMG signals in the assessment of back muscles. In static postures the RMS and median frequency show significant decreases and increases respectively (p < 0.05). Significant improvements in identifying patients with lower back pain were found after ECG removal (Hu et al., 2009).

Signal classification on finger flexion actions were studied by (Naik et al., 2010). It was found that across different MVICs that the similar patterns of EMG were as a result of a high-
level of cross-talk. Using ICA, results show that across various MVIC levels there is a separation of patterns of EMG (Naik et al., 2010). Naik et al. (2015) compared three ICA methods, JADE, infomax and fastICA, the highest classification accuracy was found using fastICA. All the p-values obtained showed significance, ranging from $p = 4 \times 10^{-4}$ to $8 \times 10^{-4}$.

In a study to identify anterior or posterior sensor placement for EMG sensors, Naik et al. (2015) identified that simple finger flexion can be identified with sEMG sensors on posterior muscles.

Decomposition of EMG signals is the separation of MUAPTs from sEMG signals. It is a useful technique to measure the MU activity to acquire a better physiological and diagnostic understanding of neuromuscular activities (Nakamura et al., 2004). Nakamura et al. (2004) concludes that MUAPTs can be separated into independent components using fastICA and that fastICA can be regarded as a pre-processing technique before EMG signal decomposition. It was also noted that for contractions at higher MVIC level it would have been more difficult to separate the MUAPTs due to the additional MU recruitment. Similarly Garcia et al. (2005) and Ren et al. (2006) utilised ICA in decomposition of sEMG signals. Garcia et al. (2005) utilised a template matching technique and ICA to separate MUAPs up to a 30% MVIC level. Ren et al. (2006) analysed artificial and real EMG signals using a combination of wavelet filtering and ICA decomposition. The method proposed showed reduced processing time and de-noised signals. Staudenmann et al. (2007) observed improvements of muscle force estimation on PCA-reduced data using ICA. However, this data was gathered without any co-contraction from antagonist muscles, future work needs to address thesis limitations.
In Kilner et al. (2002), a novel BSS algorithm to remove electrical cross-talk in EMG activity from the hand was utilised to assess task dependent modulation. Kilner et al. (2002) concluded that sEMG recording may be useful once cross-talk is removed in the assessment of population synchrony changes. Kilner et al. (2002) concluded that if there is synchrony between MUAPs that the EMG signals should be first differentiated several times to allow for significant cancellation of positive and negative phases of the MUAPs. This should produce a negligible correlation between the EMG signals and remaining correlation can be considered cross-talk from adjacent muscles which can be removed using BSS. There are however limitations to this study, the fact that only 5 of the muscles used to control the hand were recorded, this means only 5 source signals can be returned which is likely to contain EMG from multiple muscles. This algorithm does guarantee that there is no common activity in any two recordings (Kilner et al., 2002).

Multiple ICA algorithms were used across the variety of studies, such as fastICA, JADE, sub-band decomposition ICA, along with other processing algorithms such as BSS, wavelet transforms and filtering. FastICA was used in 8 of the articles reviewed highlighting the possible usefulness of this algorithm in EMG analysis. All of the papers reviewed highlighted the possible use of ICA in signal separation but also limitations of their studies. It is important to understand that there is still a lot of research necessary in the area of cross-talk in sEMG signals. Multiple algorithms have yet to be analysed appropriately. There is an opportunity to explore the use of multiple BSS algorithms and observe usefulness of them for use with sEMG. None of these articles aimed to explore the use of ICA to recreate ideal signals using misplaced electrodes which may be a possible research avenue.
<table>
<thead>
<tr>
<th>Authors</th>
<th>Application Area</th>
<th>EMG system &amp; electrodes</th>
<th>Electrode Placement</th>
<th>EMG features</th>
<th>Data Analysis Methods</th>
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<tr>
<td>Naik et al. (2015)</td>
<td>Gesture Classification</td>
<td>Bipolar electrodes</td>
<td>Forearm</td>
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<td>Bipolar electrodes</td>
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<td>RMS</td>
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<td>Remove ECG from EMG recordings</td>
<td>Porti 17 (bipolar electrodes), TMS-Enschede</td>
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<td>RMSRE &amp; Correlation Coefficients of Linear Envelope, Mean Power Frequency</td>
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<td>ECG artefact removal from EMG signals</td>
<td>Bipolar electrodes, BTS EMG system</td>
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<td>Correlation coefficient</td>
<td>High-pass Butterworth Filter, FastICA High-pass Butterworth filter &amp; filtering by adaptive sampling (FAS)</td>
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<td>Butler et al. (2009)</td>
<td>Removal of ECG from EMG</td>
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<td>Upper and Lower Rectus Abdominis, External Oblique</td>
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Table 2 The use of ICA in Biomedical Signals
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<th>Electrodes Type</th>
<th>Muscle Targets</th>
<th>Methods</th>
</tr>
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<td>Removal of ECG from EMG</td>
<td>Bipolar electrodes</td>
<td>Latissimus Dorsi, Erector Spinae (L3 &amp; L5), Quadratus Lumborum, External Oblique</td>
<td>RMS, Median Frequency, FastICA</td>
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<td>Siew-Cheok et al. (2009)</td>
<td>µRhythm Extraction – EEG/EMG</td>
<td>HD_EMG grid (13 x 10 electrodes), BIOSEMI</td>
<td>Triceps Brachii</td>
<td>FastICA (2.4)</td>
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<td>Staudenmann et al. (2007)</td>
<td>Muscle Force Estimation</td>
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<tr>
<td>LeVan et al. (2006)</td>
<td>Removal of EMG and EKG from scalp EEG</td>
<td>Electrode array</td>
<td>Biceps Brachii</td>
<td>ICA</td>
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<td>Poree et al. (2006)</td>
<td>Separating EEG, EOG and EMG during sleep</td>
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<td>Ren et al. (2006)</td>
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<td>ICA</td>
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<td>Garcia et al. (2005)</td>
<td>Decomposition</td>
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<td>MUAPTs, FastICA</td>
<td>Novel Blind Signal Separation Algorithm</td>
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<td>Nakamura et al. (2004)</td>
<td>Separation of MUAPTs from sEMG</td>
<td>Arbo (bipolar electrodes)</td>
<td>Power &amp; Coherent Spectra, Cross Correlation between rectified EMGs</td>
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</table>
D.7 Testing the FastICA algorithm using predefined signals

Testing was performed by creating three known ‘ideal’ signals and eight signals which were known mixtures of these ideal signals. These eight mixtures were then grouped into 56 combinations as above and passed through the FastICA algorithm. Correlations before and after ICA was applied were calculated and a percentage increase of approximately 32% was observed after ICA was applied to the mixtures.

Three test signals \( (s_1, s_2, s_3) \) were created as follows (see Figure 1):

\[
s_1 = A \sin(2\pi f_1 t)
\]

where \( A = 1 \), \( f_1 = 100 \) Hz and \( t = [0: \frac{1}{100000}: 0.2] \)

![Figure 1 Original signals](image)
The original signals were added to a 3x10 cell, which contained the 3 original signals repeated 10 times to signify the number of repetitions:

```matlab
for i = 1:10
    origSigs(:,i) = {s1;s2;s3};
end
```

Eight mixed signals were created as the weighted sum of the original signals and stored in an 8x10 cell:

```matlab
mixedSigs{8,1} = []; 
for ii = 1:10
    for i = 1:8 
        mixedSigs{i,ii} = s1*r(i,1) + s2*r(i,2) + s3*r(i,3);
    end
end
```

The mixed signals were rearranged into a 56x10 cell with the one combination of the three of the eight mixed signals in each cell, repeated 10 times. Each cell element was passed through the FastICA algorithm. The output signal from ICA was a 56x10 cell with three output signals returned for each iteration. Figure 2 shows how the output signals compare to the original signals and the mixed input signals. An average increase in correlation of 39.6 ± 13.8 %, 18.3 ± 7.5 % and 28.2 ± 22.1 % was found across the 56 combinations of three output signals.
D.8 Methods

D.8.1 Pilot Test Protocol

Seventeen volunteers, 11 males (mean age ± standard deviation, 23.3 ± 3.1 years) and six females (mean age ± standard deviation, 23.7 ± 3.4 years), who were injury free at the time of testing, participated in this study. Ethical approval was obtained from the University of Limerick, Faculty of Science and Engineering Research Ethics Committee and all participants completed an informed consent form before testing (see Appendix A). All participants were familiar with variations of the calf raise exercise and the squat. Participants performed a standardised warm up consisting of two minutes of running at a self-selected, comfortable pace followed by two sets of ten isotonic stretches (forward and sideways hip swings, bodyweight squats, lunges). Electrodes were attached to the calves and the quadriceps muscle groups after the warm up. Data were acquired by the sensors on the D38.
calves while participants performed ten isometric calf contractions, ten repetitions of sitting calf raises, ten repetitions of standing calf raises and ten repetitions of ankle pops, all of which isolate the calves muscle group of the lower leg. Data were acquired by the sensors on the quadriceps during five repetitions of the back squat, five repetitions of the split squat, repeated on both sides, five repetitions with the back leg raised and repeated on both sides, five squat jumps and five countermovement jumps, all of which isolated the quadriceps muscle group and are commonly used by athletes to supplement event training.

D.8.2 Final Test Protocol

Twenty volunteers, 10 males (mean age ± standard deviation, 22.4 ± 2.9 years) and 10 females (mean age ± standard deviation, 24.8 ± 3.7 years), who were injury free at the time of testing, participated in this study. Ethical approval was granted by the University of Limerick Science and Engineering Research Ethics Committee and all participants provided informed consent in writing before testing. All participants were familiar with variations of the calf raise exercise. Participants performed a standardised warm up consisting of two minutes of running at a self-selected, comfortable pace followed by two sets of ten isotonic stretches (forward and sideways hip swings, bodyweight squats, lunges). Electrodes were attached to the calves muscle group after the warm up and data was gathered while participants performed three repetitions of ten isometric calf contractions to isolate the calves muscle group of the lower leg. Isometric contractions were chosen so as to keep the muscle length constant and the position of the sensor constant over the same volume of electrical activity for the full contraction. This was to allow for a constant mixing matrix, so there was no variation when ICA was applied to the signals. A dynamometer was used to measure the force during the isometric contraction.
D.8.3 Hardware

EMG signals were obtained using the Trigno™ Wireless EMG System (Delsys Inc. Natick, MA. USA). The sensors were attached after the warm-up, with skin prepared and electrode placement according to SENIAM recommendations: i) the skin was cleaned, shaved and cleansed with an alcohol wipe, ii) electrodes were positioned at the muscle belly, to avoid cross-talk from adjacent muscles, and parallel to the muscle fibres. No gel was needed since the sensors were designed for direct attachment to the skin using double-sided tape. During pilot testing electrodes were attached to the medial- and lateral gastrocnemius (MG, LG), the soleus (SOL), the rectus femoris (RF), vastus lateralis (VL) and vastus medialis (VM) of the dominant leg (indicated by the participant). Five extra electrodes were attached at incorrect positions to purposefully achieve cross-talk: two extra electrodes were added to the calf muscle group (see Figure 3(a)) and three extra electrodes were added to the quadriceps muscle group (see Figure 3 (b)).

For the final test set up electrodes were attached to the MG, LG and SOL of the right leg according to SENIAM recommendations, and eight extra electrodes were attached at incorrect positions to purposefully achieve cross-talk (see Figure 3 (c)): four extra electrodes were positioned around the ideal placement of LG, and four extra electrodes were positioned around the ideal placement of MG. The calf muscle group was chosen as there were fewer muscles on this segment and all muscles could be measured superficially using sEMG techniques. The quadriceps had deep muscles which were not accessible using sEMG. In the quadriceps, if the sEMG sensors were picking up cross-talk from the deeper muscles it was not possible to determine the proportion as there was no sEMG measurement for this muscle. The calves allowed sEMG measurements from all muscles which were contributing to the contraction. It was also decided to add more sensors around the calves to get a more in depth
examination of the signals from various positions on the muscle. The pilot study used sensors which were quite far from the ideal position; to recreate the signal due to incorrectly positioned electrodes, it would be more applicable that the sensors were close to the ideal placements.

Figure 3 Electrode Placement
The recommended placement of electrodes for each muscle group are outlined on the figure: (a) the quadriceps muscle group (VL, RF, VM & 3 extra electrodes); (b) the calves muscle group (SOL, MG, LG & 2 extra electrodes); (c) the calves muscle group (SOL, MG, LG & 8 extra electrodes).

D.8.4 Data Analysis

EMG data were gathered using proprietary Delsys software. All signal processing was performed offline. After acquisition, the data was exported and custom Matlab code was used to analyze the results (see Appendix C). EMG data was sampled at 1925.93 Hz, the fixed rate for this system. The force trace was sampled at 2 kHz for all the isometric
contractions. Once imported into Matlab the trace was resampled to 1925.93 Hz to match the EMG system. To synchronise the two traces the initial onset of the force and of the EMG was noted for each trial. The two values were compared and the force trace was truncated or padded at the start depending on whether the initial onset of the force was ahead of or lagging the EMG onset.

Figure 4 The linear envelope of the EMG signal overlaid on the force trace
The start and end of each contraction was determined using the force trace.

Once the traces were synchronised the on and off time points for the isometric contraction were gathered from the force trace. The EMG signals were truncated to these on off time points respectively, resulting in 10 separate signals for each sensor in the trial; see Figure 4 (above). The built in kurtosis function in Matlab was used to check the suitability of EMG signals for ICA. FastICA (Version 2.5) was the ICA algorithm applied (Gävert, Hurri, Särelä, & Hyvärinen, 1996-2005).
A schematic representation of the locations of the sensors is given in Figure 5. The signals from the ideal sensors were used for comparisons only and will not undergo processing. The signals from the non-ideal sensors were passed through the fastICA algorithm to determine which combination of three sensors returned the closest version of the three ideal signals. The signals were separated into 10 signals to represent the 10 contractions. To recreate the three ideal signals, multiple combinations of the non-ideal signals in groups of three were created (see Figure 6). As there were eight non-ideal signals gathered, a total of 56 combinations were possible without repetitions (see Table 3). This was broken down further, as each trial contained 10 separate contractions. A total of 560 matrices were passed through the FastICA algorithm for each trial.
Figure 6 The cell organisation of combinations of the non-ideal EMG signals for each contraction in each trial

There are 10 contractions per trial (labelled: A – L). There are 8 non-ideal signals recorded, a matrix of 3 signals is created for each combination (8 choose 3 = 56) of non-ideal signals (labelled: 1 – 56). The length of each contraction varies slightly, each contraction will have a different number of samples (labelled: 1 – n).

Three outputs were returned by the FastICA algorithm as a matrix in each case (see Figure 7). Prior to performing ICA a cross correlation was performed between each of the non-ideal signals and the ideal signals. This was to confirm that the signals from the misplaced electrodes were not highly correlated with the ideal signals. Eight cross correlations were performed on each of the ideal signals ten times. After ICA was applied the output signals from the fastICA algorithm were then correlated with each of the ideal signals, to determine which outputs corresponded to the signals from the three ideal placement electrodes (LG, MG, SOL). In this case 56 cross correlations were performed on each of the ideal signals ten times.
Table 3 The list of non-ideal sensors in their possible combinations as groups of three
There were eight non-ideal sensors; there are 56 combinations in which these eight sensors
can be arranged in groups of three as inputs to the fastICA algorithm

<table>
<thead>
<tr>
<th>Combination Number</th>
<th>Input 1</th>
<th>Input 2</th>
<th>Input 3</th>
<th>Combination Number</th>
<th>Input 1</th>
<th>Input 2</th>
<th>Input 3</th>
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</table>
**Figure 7 The input and output signals associated with the fastICA algorithm**

An example of one combination of a group of three sensors as inputs to the fastICA algorithm and the corresponding outputs which are versions of the signals gathered by the three ideal sensors (the bar above the sensor name is used to identify the outputs from the fastICA algorithm which are closely related to the original ideal signals).

Further analysis was done on these correlation values to determine which combinations of input signals returned the highest correlation of output signals with the ideal signals. Both of the initial test values of the three ideal signals vs the 8 non-ideal signals were rearranged into a cell of matrices with the correlations across the 56 combinations vs the three ideal signals. The maximum correlation value in each combination, for each ideal sensor was then stored in a temporary variable where a check was done to make sure the maximum value in each cell was not from the same ideal signal for each combination. These maximum correlation values were then stored for later comparison. The correlation values of the output signals after ICA was applied, underwent the same process. There were already 56 combinations vs the three ideal signals; the maximum correlation values were stored. Checks were also done on these...
to make sure that the maximum values chosen did not correspond to the same ideal signals. The percentage difference between the initial and final correlations was calculated, with a positive percentage indicating the correlation improved after ICA was applied to that combination of input signals.

D.8.5 Statistical Analysis

Variations in the correlation coefficient percentage differences between males and females were evaluated using Cohen’s d effect sizes accompanied by independent Student t tests (p values). Given the sample size limitations, magnitude based inferences were used as the principal means to test hypotheses (Hopkins, 2002). The null hypotheses were rejected when Cohen’s d > 0.2 (smallest worthwhile difference). Interpretation of the magnitude of difference was based on the Cohen (1977) scale where: d > 0.2 small; d > 0.5 moderate; d > 0.8 large.

D.9 Results

The change in correlation represented as a percentage is shown across the 56 combinations for the three ideal signals is presented in Figure 8 (below). The mean percentage changes observed ranged from -13 to +11% across all three signals. Certain combinations provided better results due to their proximity in placement to the ideal electrodes. On average, across the 56 combinations, there was a -2.3 ±4.5% difference between the correlations for the LG sensor after ICA was applied, -3.6 ±4.4% for the MG sensor, and -0.5 ±3.0% for the SOL sensor. Cohen’s d indicated no effect (-0.01) between males and females (p = 0.95) for the LG sensor, for the MG sensor a small effect was found between males and females (d = 0.21; p = 0.27), and similarly for the SOL sensor a small effect was found between males and
females ($d = 0.39; p < 0.05$), this could be due to muscle physiological differences which exist between males and females (M. J. Alexander, 1997; M. J. Alexander et al., 1996).

![Figure 8](image)

**Figure 8** The mean percentage correlation differences between the misplaced electrode before and after the ICA algorithm was applied

**D.10 Discussion**

This investigation identified that in this instance the ICA algorithm did not yield significant results in distinguishing between individual muscle activations. It cannot be used to recreate signals due to misplaced electrodes using this data and this application of fastICA. The correlation values showed that the output signals from the ICA algorithm were less correlated than the incorrectly positioned electrodes in most cases. It may be possible to expand this study further using the techniques mentioned in Kilner et al. (2002) to differentiate the...
signals multiple times to reduce the synchrony between the EMG signals. It is not known whether there is synchrony between the EMG signals, however there would be a benefit to performing the differentiation to identify for future studies if this was having an effect on the EMG signals. By failing to remove synchrony it could lead to a zero correlation between unrectified EMG signals even though the MUs in the neighbouring muscles show synchronisation.

A limitation associated with ICA was potential variation in the mixing matrix during muscle contraction. To reduce this possibility an isometric contraction was used to avoid variation in the area of muscle over which the sensor was recording. However, there may be still variation in the mixing matrix which may partially explain why the application of fastICA in this study cannot be used with sEMG signals. It may still be possible that even though the movement of the leg was restricted and an isometric contraction was performed that the area over which the sEMG sensor was recording did not remain constant. Further analysis of how to keep the recording area constant throughout the contraction is necessary.

Due to the non-invasive nature of surface mount electrodes, recordings are limited and may contain cross-talk. Extensive research on the true signal of the muscle using fine-wire or needle electrode may be necessary to get a better understanding of the true signal. ICA could then be applied to sEMG signals and compared to the true signal rather than to another sEMG signal which, although it is positioned where the most accurate recording site is, may still contain cross-talk, thus not being a valuable comparison for misplaced electrodes. Many of the studies analysed did not perform correlations between the EMG signals before and after so results cannot be compared. Mak et al. (2010) did perform correlations but these were based off the removal of ECG artefacts not the removal of cross-talk in EMG. Another
important thing to consider is the other studies which performed isometric contractions and measured the MVIC level noted that there were increases in RMS as the force of the contraction increased from 20% to 80% MVIC. The MVIC level was not measured in this study and variations across the level of force the athlete was producing could have an effect on the results. It would be important to measure the MVIC for each athlete first and then for the contractions which would be analysed a specific MVIC level should be adhered to.

**D.11 Conclusion**

This study shows that ICA in this form cannot be used in the removal of cross-talk from sEMG signals. ICA is an algorithm used for signal separation in many other areas and this study showed that it is not possible to use fastICA on sEMG measures of lower leg activity. The one major limitation of this study due to the fact that the recordings are from surface mount electrodes it is not known what the true EMG signal is for the specific muscle during these exercises and we cannot truly say that ICA cannot be used for sEMG signal separation. Unlike analysis in the separation of sound, we do not know what the true signals are. Further work needs to be done in this area to identify the true EMG signal. This may be done by making use of indwelling electrodes. This data could then be used as the control when comparing outputs from various ICA algorithms to identify which methods if any can be used to minimise cross-talk in surface measurements. It may also be possible to examine other forms of ICA or the use of ICA alongside other techniques to discover if they can be used to reduce or remove cross-talk from sEMG signals.
% load the data
load(origmatfile);

%% Initial Processing of Force Data
fin = 2000;
fout = 1925.93;
% downsample the force data
[ForceData_] = resampleR(fin, fout, ForceData(:,2));
% Get the start point
[init_force] = process_FD_init(ForceData_);

%% Initial Processing of EMG data
% Allign EMG sigs with Force Trace...
[~,~,leEMG,~,~,~,~] = process_sigs_ICA(LG);
% start point in EMG trace:  
[init_EMG] = process_FD_init(leEMG);
% Chop the beginning of trace with larger start point  
if (init_force > init_EMG)  
    newStart = init_force - init_EMG;
    ForceData_ = ForceData_(newStart:end);
elseif (init_EMG > init_force)  
    padding = ones((init_EMG-init_force),1)*min(ForceData_);
    ForceData_ = [padding; ForceData_]';
end
plot(ForceData_);

%% Final processing of Force Data
% Get the division points
[onoff_FD,~,~] = process_FD(ForceData_);
% divide up the contractions in the signal
[list of muscles returned_] = divEMGsig(divtype,filename, times, list of muscles);
% divtype = 1 to divide using force trace, divtype = 2 to divide every 100 samples...
% data stored to file
[LG_, MG_, SOL_, LG_N_, LG_E_, LG_S_, LG_W_, ...
MG_N_, MG_E_, MG_S_, MG_W_] = divEMGsig(1,filename, onoff_FD, LG, MG, ...  
SOL, LG_N, LG_E, LG_S, LG_W, MG_N, MG_E, MG_S, MG_W);
% number of contractions
rep = length(onoff_FD)/2;
% combinations of input signals
num_combos = nchoosek(8,3); % 56
combos = nchoosek(1:8, 3);

MixedEMG{num_combos,rep} = []; icasig{num_combos,rep} = []; W{num_combos,rep} = []; A{num_combos,rep} = []; temp_init{rep,3} = []; temp_after{rep,3} = []; temp_i_max{rep,1} = []; max_i_Index{rep,1} = []; temp_a_max{rep,1} = []; max_a_index{rep,1} = []; diff_corr_all{1,3} = []; diff_corr{rep,1} = []; procNonIdealSigs{num_combos,rep} = [];

idealSigs_ = [LG_; MG_; SOL_]; nonIdealSigs_ = [LG_N_; LG_E_; LG_S_; LG_W_; MG_N_; MG_E_; MG_S_; MG_W_];

% Create Matrix with ideal & non-ideal sigs
[R_init, Lag_init] = cross_corr_RH(idealSigs_,nonIdealSigs_, 0);

% Process the before correlations
for n = 1:rep
    for i = 1:3
        for j = 1:num_combos
            temp_init{n,i}(j,:) = [R_init(((i-1)*(9))+combos(j,1),n), R_init(((i-1)*(9))+combos(j,2),n), R_init(((i-1)*(9))+combos(j,3),n)];
        end
    end
end

% get the maximum correlation and its index for each input...
for i = 1:rep
    for j = 1:min(size(temp_init))
        [~, max_i_index{i,1}(j)] = max(temp_init{i,j},[],2);
    end
end

D52
% compare index of max value for each row to make sure the same
% signals do not compare to the same original...
for i = 1:length(max_i_index)
    for j = 1:length(max_i_index{i,1})
        % if 1st and 2nd max correlations are from same output
        if(max_i_index{i,1}(j,2) == max_i_index{i,1}(j,1))
            k = max_i_index{i,1}(j,2);
            % store 3 the correlations for that output
            vector = temp_init{i,2}(j,:);
            % get the new max correlation - it doesn't contain the
            % value in the location of previous max
            temp_i_max{i,1}(j,2) = max(vector(1:end ~=k));
            % store new max location for this output
            max_i_index{i,1}(j,2) = find(vector == temp_i_max{i,1}(j,2));
        end
        % if 1st and 3rd max correlations are from same output
        if(max_i_index{i,1}(j,3) == max_i_index{i,1}(j,1))
            k = max_i_index{i,1}(j,3);
            vector = temp_init{i,3}(j,:);
            temp_i_max{i,1}(j,3) = max(vector(1:end ~=k));
            max_i_index{i,1}(j,3) = find(vector == temp_i_max{i,1}(j,3));
        end
        % if 2nd and 3rd max correlations are from same output
        if(max_i_index{i,1}(j,3) == max_i_index{i,1}(j,2))
            k = max_i_index{i,1}(j,3);
            vector = temp_init{i,3}(j,:);
            temp_i_max{i,1}(j,3) = max(vector(1:end ~=k));
            max_i_index{i,1}(j,3) = find(vector == temp_i_max{i,1}(j,3));
        end
    end
end

%% Setting up inputs to ICA and performing fastICA
% Recreating the 3 ideal signals using a combination of only the
% non-ideal signals, multiple matrices set up as follows:

D53
for ii = 1:rep % number of contractions per trial...
% OR for i = 1:length(onoff_FD)/2
    for i = 1:num_combos
        MixedEMG{i,ii} = [nonIdealSigs_{combos(i,1),ii}'; ... 
                         nonIdealSigs_{combos(i,2), ii}';... 
                         nonIdealSigs_{combos(i,3), ii}'];
    end
end

% the matrix input to fastICA algorithm must contains 3 row vectors!
% Fast ICA - A = mixing matrix, W = separating matrix
    [icasig{i,ii},A{i,ii},W{i,ii}] = fastica(MixedEMG{i,ii},
    'numOfIC', 3, 'maxNumIterations', 10000, 'maxFinetune', 1000 );
end

% Setting up the output signals for further correlations
for i = 1: num_combos
    for ii = 1:rep
        procNonIdealSigs{i,ii} = icasig{i,ii}';
    end
end

for ii = 1:rep
    for i = 1:num_combos
        % pad the 3rd signal with zeros if it does not exist
        if (min(size(procNonIdealSigs{i,ii}))) == 2
            procNonIdealSigs{i,ii}(:,3) = zeros(max(size(procNonIdealSigs{i,ii})),1);
        end
        % pad the 2nd & 3rd signals with zeros if they do not exist
        if (min(size(icasig{i,ii}))) == 1
            procNonIdealSigs{i,ii}(:,2) = zeros(max(size(procNonIdealSigs{i,ii})),1);
            procNonIdealSigs{i,ii}(:,3) = zeros(max(size(procNonIdealSigs{i,ii})),1);
        end
        % pad the 1st, 2nd & 3rd signals with zeros if they do not exist
        if (min(size(icasig{i,ii}))) == 0
            procNonIdealSigs{i,ii}(:,1) = zeros(max(size(procNonIdealSigs{i-1,ii})),1);
            procNonIdealSigs{i,ii}(:,2) = zeros(max(size(procNonIdealSigs{i-1,ii})),1);
            procNonIdealSigs{i,ii}(:,3) = zeros(max(size(procNonIdealSigs{i-1,ii})),1);
        end
    end
end

D54
%% Cross-correlate (After ICA applied)
[R_after, Lag_after] = cross_corr_RH(idealSigs_, procNonIdealSigs, 1);

% some correleation values will return NaN as the input signal was 0
% replace the NaN values with 0
R_after(isnan(R_after)) = 0;

%% Prep xcorr variables for comparisons ...
% re-arrange the correlations into a new variable
for n = 1:3
    for i = 1:rep % 10 (num reps)
        for j = 1:min(size(idealSigs_)) % 3 (num sigs)
            temp_after{i,j}(:,n) = R_after((j+((num_combos)*(j-1))):((num_combos)*(j))+((1)*(j-1))),(i+((n-1)*11)));
        end
    end
end

% get the maximum correlation and its index for each ica output...
for i = 1:rep
    for j = 1:min(size(temp_after))
        % temp max contains the max correlation for each ideal
        % signal x the
        % number of contractions
        % max index contains the ica output position for the max
        % correlated
        % signal
        [temp_a_max{i,1}(:,j), max_a_index{i,1}(:,j)] = max(temp_after{i,j},[],2);
    end
end

% compare index of max value for each row to make sure the same
% signals do
% not compare to the same original...
for i = 1:length(max_a_index)
    for j = 1:length(max_a_index{i,1})
        % put in an extra check incase no ica signal was returned
        % and all
        % corr values are 0!
        if (temp_a_max{i,1}(j,1)== 0 && temp_a_max{i,1}(j,2)== 0 &&
            temp_a_max{i,1}(j,3)== 0)
            break;
        else
            % if 1st and 2nd max correlations are from same output
            if(max_a_index{i,1}(j,2) == max_a_index{i,1}(j,1))
                % Store the max correlation location for output 2
                k = max_a_index{i,1}(j,2);
                % store 3 the correlations for that output
                vector = temp_after{i,2}(j,:);
                % get the new max correlation - it doesn't contain
                % value in the location of previous max
                [temp_a_max{i,1}(j,2)] = max(vector(1:end ~=k));
            end
end

D55
% store new max location for this output

tmp = find(vector == temp_a_max{i,1}(j,2));
if (length(tmp) == 3)
    max_a_index{i,1}(j,2) = tmp(1);
elseif (length(tmp) == 2)
    max_a_index{i,1}(j,2) = tmp(1);
else
    max_a_index{i,1}(j,2) = tmp;
end

% if 1st and 3rd max correlations are from same output

if(max_a_index{i,1}(j,3) == max_a_index{i,1}(j,1))
    k = max_a_index{i,1}(j,3);
    vector = temp_after{i,3}(j,:);
    [temp_a_max{i,1}(j,3)] = max(vector(1:end ~=k)) ;
    tmp = find(vector == temp_a_max{i,1}(j,3));
    if (length(tmp) == 3)
        max_a_index{i,1}(j,3) = tmp(3);
    elseif (length(tmp) == 2)
        max_a_index{i,1}(j,3) = tmp(2);
    else
        max_a_index{i,1}(j,3) = tmp;
    end
    % if 3rd is now the same as 2nd ...
    if(max_a_index{i,1}(j,3) == max_a_index{i,1}(j,2))
        [temp_a_max{i,1}(j,3)] = min(vector) ;
        max_a_index{i,1}(j,3) = find(vector == temp_a_max{i,1}(j,3));
        max_a_index{i,1}(j,3) = 2;
    end

end

% if 2nd and 3rd max correlations are from same output

if(max_a_index{i,1}(j,3) == max_a_index{i,1}(j,2))
    k = max_a_index{i,1}(j,3);
    vector = temp_after{i,3}(j,:);
    [temp_a_max{i,1}(j,3)] = max(vector(1:end ~=k)) ;
    tmp = find(vector == temp_a_max{i,1}(j,3));
    if (length(tmp) == 3)
        max_a_index{i,1}(j,3) = tmp(3);
    elseif (length(tmp) == 2)
        max_a_index{i,1}(j,3) = tmp(2);
    else
        max_a_index{i,1}(j,3) = tmp;
    end
    % if 3rd is now same as 1st ...
    if(max_a_index{i,1}(j,3) == max_a_index{i,1}(j,1))
        [temp_a_max{i,1}(j,3)] = min(vector) ;
        tmp = find(vector == temp_a_max{i,1}(j,3));
        if (length(tmp) == 3)
            max_a_index{i,1}(j,3) = tmp(3);
elseif (length(tmp) == 2)
    max_a_index{i,1}(j,3) = tmp(2);
else
    max_a_index{i,1}(j,3) = tmp;
end
end
end
end
end

%% Comparing the before and after correlations
for ii = 1:rep
    for i = 1:num_combos
        % using the combos - 56, get the signal number that compares
to
        % each of the combos to compare the initial and final
        % correlations
        diff_corr{ii,1}(i,1) = (temp_a_max{ii,1}(i,1) - ...
            temp_i_max{ii,1}(i,1))*100;
        diff_corr{ii,1}(i,2) = (temp_a_max{ii,1}(i,2) - ...
            temp_i_max{ii,1}(i,2))*100;
        diff_corr{ii,1}(i,3) = (temp_a_max{ii,1}(i,3) - ...
            temp_i_max{ii,1}(i,3))*100;
    end
end

%% Rearrange the data for comparison across contractions
for n = 1:length(diff_corr) % 10 contractions
    for i = 1:min(size(diff_corr{n})) % 3 muscle correlations per combination
        diff_corr_all{1,i}(:,n) = diff_corr{n}(:,i);
    end
end
createTableCorrs(diff_corr_all);

%% Calculate the mean square error difference between before and after ICA
[m1,m2,mErr] = meanErr(idealSigs_,nonIdealSigs_,procNonIdealSigs,Lag_init,Lag_after ,combos);
createTableCorrs(mErr);

% Save processed data
save(newmatfile);
function [R, L] = cross_corr_RH(sig1, sig2, icaflag)
% function [R, L] = cross_corr_RH(sig1, sig2)
% R is the correlation value
% L is the lag value
% Using the corrcoef function to determine the output signal (sig2) which
% matches the input signal (sig1)
% Loop sizes
[r,c] = size(sig1);
% Ideal Sigs = 3, loop_out should be 3
loop_out = r;
% Num contractions = 10, loop_trials should be 10
loop_trials = c;
% Non Ideal Sigs = 8, loop_in should be 8
% ICA output sigs = 56, loop_in should be 56
[r,~] = size(sig2);
loop_in = r;
% pre allocate for speed
R(3,1) = 0;
L(3,1) = 0;
% If the signals have not been passed through ICA (loop_in = 8)
if ~icaflag
    % loop 3 times
    for i = 1:loop_out
        % loop 8 times (1 for test signals)
        for j = 1:loop_in
            % loop 10 times (1 for test signals)
            for k = 1:loop_trials
                % get the correlation value
                c = xcorr(sig1{i,k},sig2{j,k},'coeff');
                R(((i-1)*(loop_in+1)+j),k) = max(abs(c));
                % get the lag value
                [x,l] = xcorr(sig1{i,k},sig2{j,k});
                [~,z] = max(abs(x));
                lag = l(z);
                L(((i-1)*(loop_in+1)+j),k) = lag;
            end
        end
    end
% If the signals have been passed through ICA (loop_in = 56)
elseif icaflag
    % loop 3 times
    for i = 1:loop_out
        % loop 56 times
        for j = 1:loop_in
            % loop 10 times (1 for test signals)
            for k = 1:loop_trials
                % get the correlation value
                c = xcorr(sig1{i,k},sig2{j,k},'coeff');
                R(((i-1)*(loop_in+1)+j),k) = max(abs(c));
                % get the lag value
                [x,l] = xcorr(sig1{i,k},sig2{j,k});
                [~,z] = max(abs(x));
                lag = l(z);
                L(((i-1)*(loop_in+1)+j),k) = lag;
            end
        end
    end
end
D58
for k = 1:loop_trials
    % loop 3 times (ica returns 3 signals)
    for l = 1:min(size(sig2{j,k}))
        % compares 1 original signal to one of the column vectors of the ICA output
        c = xcorr(sig1{i,k},sig2{j,k}(:,l),'coeff');
        R(((l-1)*(loop_in+1)+j),(((i-1)*11)+k)) = max(abs(c));
        % get the lag value
        [x,lg] = xcorr(sig1{i,k},sig2{j,k}(:,l));
        [~,z] = max(abs(x));
        lag = lg(z);
        L(((l-1)*(loop_in+1)+j),(((i-1)*11)+k)) = lag;
    end
end
end
end

D.13 Additional References


D60


