Pattern analysis of surface electromyographic activity from hip joint muscles during the stance phase in osseo-integrated transfemoral amputees

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Presented as part of the requirements for the degree of Doctor of Philosophy

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Abstract

ABSTRACT

Although there have been considerable developments in surgical methods and prosthetic limbs, one quarter of transfemoral (TF) amputees remain dissatisfied with their prostheses. Function could be improved by establishing a communication link between the prosthetic limb and the residual limb. A potential non-invasive method of linking the limbs could be made by using surface electromyography (sEMG). The recent development of the osseo-integrated prosthesis (OP) allows electrodes to be freely attached without interference from the socket. This study’s objective was to investigate patterns of sEMG in TF amputees fitted with OPs during the stance phase of gait.

Two groups of subjects were investigated consisting of five TF amputees fitted with OPs and ten subjects with intact limbs. sEMG was recorded from five hip muscles of the amputee’s residual limb or the intact subject’s left limb as the subject walked along a level force platform. Kinematic data was also recorded from the amputee subjects. Prior to walking, the subjects were asked to perform isometric contraction of the recorded muscles. Four types of sEMG variables were determined for the amputees from the stance data. Principle component analysis (PCA) and cluster analysis were then applied to these variables.

All the amputee group’s muscles, both cleaved and intact, displayed increased activity during isometric muscle contraction. The sEMG recorded during the stance phase in the intact group corresponded to that reported in published literature. The sEMG measured from the amputees was similar to that of the intact group with the exception of adductor magnus. Inter-stance subject repeatability was low for both groups. The repeatability of stance sEMG for the intact group was lower than that published in previous studies based on the entire gait cycle. PCA of the sEMG for the amputee group revealed major co-contraction of muscles. Cluster analysis of multi-muscle matrices demonstrated significant cluster patterns for the stance phase. Cluster patterns showed little change when repeat measurements were taken eleven months later. The findings suggest that sEMG can potentially be harnessed to activate a micro-computer controlled prosthetic knee joint during locomotion for certain subjects.
Acknowledgements

My first thanks go to my original supervisor, the late Steve Hughes, for encouraging me to pursue a Ph.D.

Thank-you also to my current supervisor, Dr. David Ewins, for developing my research skills. Thanks also to Sally Durham for assistance with the data collection at The Gait Laboratory.

I would like to acknowledge my gratitude to the advice offered from the other PhD students, in particular Paola and David.

The most important contributors to this thesis are the volunteers fitted with osseointegrated prostheses and the students who volunteered to participate in this study. Without them this study would not have been possible. Many thanks for the time they have given.

I would like to acknowledge the financial assistance I received from the d'Oyly Carte Trust, the European School of Osteopathy and from my parents, Marlis and John Pantall.

Lastly, thank-you to my children, Felix and Alice for tolerating the long hours spent working on this PhD.
Nomenclature

ACWD – Adaptive Choi Williams distribution
A/D – Analogue to digital
AM – Adductor magnus
ANN – Artificial neural network
BMI – Body mass index
CCC – Cophenetic correlation coefficient
CMC – Coefficient of multiple correlation
CMRR – Common mode rejection rate
CPG - Central pattern generator
CS – Class separability
CT – Computerised tomography
CV – Coefficient of variation
CWD – Choi Williams distribution
DC – Direct current
DFT – Discrete Fourier transform
EMD – Electro-mechanical delay
FFT – Fast Fourier transform
GC – Gait cycle
GMED – Gluteus medius
GMAX – Gluteus maximus
GRF – Ground reaction force
HMM – Hidden Markov model
IMPF – Instantaneous mean power frequency
ISODATA – Iterative self analysis data analysis technique
LDA – Linear discriminative analysis
MDS – Multi dimensional scaling
MAV – Mean absolute value
MMG – Mechanomyogram
MPF – Mean power frequency
Nomenclature

MRI – Magnetic resonance imaging
MUAP – Motor unit action potential
MVC – Maximum voluntary contraction
NRMS – Normalised root mean square
OP – Osseo-integrated prosthesis
OPRA – Osseo-integrated prosthesis for the rehabilitation of amputees
PC – Principal component
PCA – Principal components analysis
PD – Potential difference
PSD – Power spectral density
QTFR – Quadratic time frequency representation
RC – Resistor / capacitor
RF – Rectus femoris
RMS – Root mean square
TO - Toe-off
SD – Standard deviation
sEMG – Surface electromyography
SENIAM – Surface Electromyography for the Non-Invasive Assessment of Muscles
SNR – Signal to noise ratio
STFT – Short-time Fourier transform
TF - Transfemoral
TFR – Time-frequency
TFL - Tensor fasciae latae
VL – Vastus lateralis
VR – Variance ratio
WPT – Wavelet packet transform
WT – Wavelet transform
WVT – Wigner Ville transform
ZC – Zero crossing
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Pantall, A.

2. Patterns of surface electromyographic activity recorded during the stance phase in transfemoral amputees with osseointegrated prostheses.
Pantall, A., Durham, S., Ewins, D.

3. Patterns of surface electromyographic activity during walking.
Pantall, A., Durham, S., Ewins, D.

4. Patterns of surface electromyographic activity during the stance phase in transfemoral amputees.
Pantall, A., Durham, S., Ewins, D.
XVII ISEK Conference , Niagara Falls, Canada, 18th – 21st June 2008

Poster Presentations

1. Analysis of surface electromyographic activity of selected hip muscles during normal walking in transfemoral amputees with osseointegrated prostheses
Pantall, A., Durham, S., Ewins, D.
European Workshop on Movement Science, Vienna, Austria, 2nd-4th June 2005

2. Variability of sEMG of five stump muscles during stance phase of gait in TF amputees with osseointegrated prostheses.
Pantall, A., Durham, S., Ewins, D.
Chapter 1

Introduction

1.1 Introduction

This chapter is an introduction to the author’s study, outlining topics relevant to the study and presenting the aims and hypotheses. A brief summary of chapter contents is provided in section 1.4.

The subject group involved in the study was composed of TF amputees. The annual incidence of TF lower limb amputations in the United Kingdom is low at about 1760 over the last ten years. The majority of these amputees are male and aged over 65 with the main reason for amputation being dysvascularity. In the United Kingdom most of the amputees are fitted with a prosthetic limb. However, despite vast improvements in prosthetics the current overall level of satisfaction with the performance of prostheses amongst users in the United States and Europe is about 75%. There is therefore a continuing need for further research into prosthetic design and biomechanics of the amputee.

One of the major disadvantages that the TF amputee has in movement is that he or she is unable to control voluntarily the movements of the prosthetic limb. A recent prosthetic development incorporates sensors into the prosthesis, data from which can determine the gait phase the subject is engaged in. The acquired information can then be used to modify the resistance to flexion and extension at the prosthetic knee. These ‘intelligent’ prostheses represent a partial reproduction of the neural control mechanism. However, the sensors used in these prostheses do not record neural information. Providing the prosthetic user with volitional control over the prosthesis can be achieved by coupling the neural system with the actuators of the prosthesis. sEMG represents a non-invasive indirect method of recording neural signals. This study recorded sEMG from amputee subjects. Reasons why this method was selected are presented in section 2.4. Although myoprocessors have been developed for the upper limb, there are no commercially available myoelectrically controlled lower limb prostheses available that the author is aware of.
Chapter 1. Introduction

A major problem associated with sEMG is that noise and interference will be present in the signal. Additionally, there is high variability in the sEMG of individual muscles between successive gait cycles. The development of the osseointegrated prosthesis should reduce the noise since there will not be movement noise from the socket. Noise and interference may be further reduced by applying different types of transforms to the raw signal. The issue of variability may be resolved by analysing several muscles simultaneously. This approach is supported by the central pattern generator (CPG) theory which states that impulses are emitted from groups of neurones in the spinal cord that then regulate the activity of several lower limb muscles simultaneously. Pattern recognition techniques such as cluster analysis have not, as far as the author is aware, been applied to sEMG data to identify different phases of the gait. Sepuldeva et al. (1993) have however used an artificial neural network (ANN) to classify joint angles and moments at the hip, knee and ankle based on sEMG information.

A second disadvantage the amputee has is that he will no longer have the available muscle power to move the lower limb as effectively as pre-surgery. The exception is for a small number of amputees fitted with the Ossur POWER KNEE™ (Ossur, Reykjavik, Iceland). Very little investigation has been conducted into the effect of amputation on the muscles in terms of histological changes, alteration in physiological functioning and muscle power. This lack of research into amputated muscle is in direct contrast to the financial resources directed towards developing the prosthesis. A lack of power of the residual limb muscles will result in the amputee compensating by excessively contracting the contralateral limb muscles and trunk muscles thereby resulting in an asymmetric gait and increased energy expenditure. No matter how technologically advanced the lower limb prosthesis is, if adequate muscle power is lacking the subject will not exhibit a satisfactory gait. Studies investigating the functioning of muscles in amputees are therefore required to provide more information.

1.2 Aims of the study

The clinical aims of the study are to provide answers to the following questions:

i. Do the cleaved muscles of a TF amputee display sEMG activity during resisted movement?
The surgery involved in osseo-integrated TF amputation involves cleaving the muscles of the thigh and suturing them to the surrounding fascia. This provides a weak fixation point. Contraction of the cleaved muscles will therefore cause less force to be exerted on the femur than an intact muscle. The functional effect of this radical surgery on the muscles is not known. Clinically, an understanding of the activity of cleaved muscles is important for surgeons since their fixation techniques should focus on maximising the muscle’s power. Additionally, this information will be of interest to rehabilitation personnel since if significant activity is present, it will justify promoting exercises targeted at the cleaved muscles.

ii. **What is the locomotor neural control mechanism following an amputation?**

There is currently a body of evidence, which points to locomotion being controlled by a small group of neurones within the spinal cord referred to as the central pattern generator (CPG). There have not been any studies investigating whether a similar locomotor control system is present in TF amputees in the short term or long term given the significant loss of proprioceptors, muscles and joints. Information about locomotor neural control systems would provide an insight into understanding how amputees learn to walk and also assist with developing rehabilitation methods.

iii. **Can sEMG be used as a natural sensor during locomotion?**

Current ‘intelligent’ lower-limb prostheses such as Otto Bock’s C-Leg™ (Otto Bock HealthCare, 15 Duderstadt, Germany) or Ossur’s Rheo Knee™ (Ossur, Reykjavik, Iceland) modify prosthetic knee joint movement depending on the information recorded from sensors monitoring joint position, force or pressure. The limitation of these sensors is that they do not detect the subjects’ movement intention. The utilisation of natural sensors such as from sEMG would permit a direct communication link between the subject and the prosthetic limb.

1.3 **Hypotheses**

This study tested a number of hypotheses as follows:

i) **The three cleaved muscles, rectus femoris, adductor magnus and biceps femoris have increased sEMG activity during resisted movement.**

This hypothesis relates to the first clinical aim of improved understanding of the function of cleaved muscle. The hypothesis was tested for each muscle by asking the
subject to resist a specific movement applied to his prosthetic limb. The sEMG was recorded from each muscle before and during the period the force was applied. The moving average value and frequencies were calculated and the changes in parameter value between the resting state and contracting state was determined.

ii) *Gluteus maximus, gluteus medius, rectus femoris, adductor magnus and biceps femoris will each display patterns of sEMG activity during stance.*

This hypothesis is relevant to the second aim namely understanding neural control of locomotion in TF amputees. To test this hypothesis subjects were asked to walk at their normal speed whilst sEMG from the five muscles was recorded. Four different parameters were determined for the stance phase from the sEMG data. Patterns for the individual muscles for each subject were calculated and the inter-stance and inter-day repeatability assessed using the coefficient of multiple correlation (CMC).

iii) *Co-contraction of the five residual limb muscles, gluteus maximus, gluteus medius, rectus femoris, adductor magnus and biceps femoris occurs during the stance phase of locomotion.*

This again relates to the second aim. The presence of co-contraction suggests an underlying CPG responsible for contracting muscles simultaneously as described in the introductory section. This hypothesis was tested by PCA to the sEMG of the five-recorded muscles.

iv) *The sEMG can be used to divide the stance phase into clusters*

This hypothesis links to both the second and third clinical aims. Evidence of clusters suggests an underlying CPG controlling the stance phase. Additionally, the presence of sEMG derived clusters during stance provides support for using sEMG as a natural sensor. The hypothesis was tested by applying cluster analysis to the main principal components (PCs) derived from the sEMG.

v) *sEMG patterns will not change over time.*

This hypothesis relates to the third clinical aim, the viability of using sEMG as a natural sensor. In order for sEMG to be used as a natural sensor, it is essential to know about the patterns of sEMG over time. Two TF amputees were retested 11 months later and their cluster patterns were compared.
1.4 Overview of content of chapters

The next chapter offers an introduction to electromyography. Chapter 3 provides a literary background to walking. Previous studies on sEMG patterns in intact subjects are described and issues of repeatability are discussed. Chapter 4 provides a literary background to amputation and prostheses including gait and sEMG patterns recorded in intact amputees. The topics of natural sensors and myoprocessors are covered in this chapter. This is followed by chapter 5, which discusses signal analysis of sEMG including a description of different variables, methods of feature reduction and pattern classifiers. Chapter 6 presents the materials used in the study and the methods selected. The results and discussion of the experimental work for this study are combined into three separate chapters. Chapter 7 contains the results and discussion for subject data, gait parameters and repeatability of these parameters. The sEMG recorded during locomotion, the four different types of parameters extracted from the sEMG for the stance phase and the repeatability of these parameters are presented and discussed in chapter 8. Chapter 9 describes and discusses the results obtained from PCA and cluster analysis of the sEMG for the TF amputee group. The conclusions relating to the aims and hypotheses presented in chapter 1 are provided in chapter 10. The final chapter describes the limitations of the study and offers recommendations for future development. The references, bibliography and appendices conclude the thesis.

1.5 Conclusion

This introductory chapter has introduced two procedures that could improve user satisfaction with their prostheses. These are the addition of natural sensors into the limb for control of the prosthesis and a better synthesis of the biomechanics of the hip joint of the residual limb to the mechanics of the prosthesis. Both these procedures require knowledge of the functioning of muscles in the residual limb. This study has collected and analysed data from the muscles of osseointegrated TF amputees, which furthers the knowledge of muscle functioning in this small but important group of amputees.
Chapter 1. Introduction

The original features of this study are that:

- The sEMG was recorded in osseointegrated TF amputees. The electrical activity of muscles from this group of amputees has not previously been reported.
- Detailed analysis of the sEMG was undertaken for the stance phase. Stance phase is the part of the gait cycle for which control of the prosthetic knee is most critical.
- This study analysed data from all the individual stances. Most previous research has used ensemble averages, which loses the inter-stance variability.
- This study investigated time frequency and time scalar parameters in addition to moving average values. Previous studies on sEMG activity during locomotion in both amputees and intact subjects have focussed on time dependent features of the muscles.
- Principal component analysis was applied to matrices containing all the stance data and muscle data.
- Cluster analysis was applied to the sEMG principal components. This method has not previously been applied to the sEMG recorded from TF amputees.
Chapter 2
Background material to surface electromyography

2.1 Introduction
This chapter presents an outline of electromyography focussing on surface electromyography. The following subsections provide firstly an overview of muscle physiology followed by a description of methods of muscle activity assessment. The remaining subsections are concerned with sEMG, including the hardware involved in collecting and processing the signal, problems associated with noise and interference and finally the functional significance of sEMG. A description of sEMG patterns recorded during walking in intact and TF amputees are contained in chapters 3 and 4 respectively. A discussion of signal analysis techniques is given in chapter 5.

2.2 Basic Muscle Physiology
A motor unit consists of an alpha motor neurone and all the muscle fibres it innervates. The number of motor fibres in a unit varies from 10 to over 1000. The muscle fibres of a motor unit are generally not clumped together but rather are interspersed through a large section of the muscle belly. Three main types of motor units have been identified in human skeletal muscle according to histochemical, metabolic and mechanical properties of the muscle fibres and electrical and physical characteristics of the motoneurones. These categories are type I (slow twitch, red, slow oxidative, fatigue resistant), type IIa (fast twitch, red, fast oxidative, fatigue resistant) and type IIb (fast twitch, white, fast glycolytic, fatiguable). The corresponding muscle fibres are type I, IIa and type IIb and are characterised by the structure of their myosin heavy chains. The fibre type is determined by the motoneurone innervating it. Altering the innervation of the muscle fibre will result in a transformation of the muscle fibres [Bárány & Close 1971]. Type II fibres are regarded as the ‘default’ type with fibres reverting to this type if innervation is disturbed or muscle activity halted.

Type I motor units are typically recruited at low forces and their motor neurones have small axons with low conduction velocities compared to the motor neurones in type IIa and IIb motor units. Within a muscle there will be a mixture of type I, IIa
and IIb muscle fibres although the distribution will vary depending on the particular muscle. For example, the lower limb extensor muscles have a greater proportion of type I fibres whereas the flexors have more type II fibres. The proportion of muscle fibres present in a particular muscle will be influenced by factors including gender, age and the side of the body [Bagnall et al. 1984; Hadar et al. 1983; Širca & Kostevc 1985; Thorstensson & Carlson 1987].

Contraction of a muscle fibre occurs at the end of a sequence of events taking place within the motor unit. The initial event is the transmission of an electrical impulse along the alpha motor neurone. When the impulse reaches the motor end plate, acetylcholine is released. The acetylcholine crosses the synaptic cleft, which then triggers depolarisation of the sarcolemma. The permeability properties of the sarcolemma can be represented by the Hodgkin-Huxley model in which three main ionic channels are present. These channels are the sodium, potassium and chlorine. The resting potential of a muscle fibre is from -70mV to -90mV with respect to the outside [Guyton 1982; Lamb & Hobart 1992; Moritani et al. 2004]. These channels in the resting state allow K⁺ ions to enter the cell but block the entrance of Na⁺ ions. The depolarisation occurs because of changes in the conductivity of primarily the sodium and potassium channels resulting in a flow of Na⁺ ions into the cell. Following depolarisation the resting potential rises to about +20mV.

The depolarisation lasts approximately 1ms to 5ms after which the membrane repolarises. The depolarisation edge moves along the sarcolemma and transverse tubules at a velocity of 3 m/s to 5 m/s [Guyton 1982; Moritani et al. 2004]. The change in potential of the membrane results in calcium ions being released from the sarcoplasmic reticulum, which then diffuse through the transverse tubules to the myofibrils. There the ions bind with troponin and result in movement of the myofibrils producing sarcomere shortening. The final event is muscle fibre contraction. The contraction lasts only as long as the duration of the circulating calcium which is from 10ms to 100ms long, being on average 33ms [Guyton 1982]. All the muscle fibres of the motor unit will contract following activation of the motorneurone. Motor units are activated approximately five to thirty times a second [Basmajian & De Luca 1985].
Chapter 2. Background material to surface electromyography

The motor unit action potential (MUAP) is the sum of all the action potentials generated by muscle fibres belonging to the same muscle fibre. The recording of the MUAP is not limited to the surface of the muscle fibres since the extracellular fluid, fascia and skin acts as a volume conductor through the movement of ions (see figure 2.1). Therefore, the MUAPs generated by depolarisation of the sarcolemma can be detected on the skin surface. The tissues between the skin and the muscle fibres have both capacitive and resistive properties [Lowery et al. 2004]. The permittivity and conductivity are dependent on the frequency of the electric field [Gabriel et al. 1996]. This results in the tissues acting as a low pass filter resulting in a surface signal that is attenuated, phase shifted and has a reduced mean frequency compared to the MUAPs.

![Figure 2.1](image)

**Figure 2.1.** Schematic view of generation of signal at surface electrode. The action potentials from a number of muscle fibres (2a) will cause an electric field to develop in the muscle, fascia and skin (2b). A potential difference can be recorded on the surface of the skin (2c).

### 2.3 Types of muscle contraction, force and fatigue

Muscle fibres can contract in several different ways. Three commonly described types of muscle contraction are isometric, concentric and eccentric. In an isometric contraction the length of the muscle remains constant as the muscle contracts whereas in a concentric contraction the muscle shortens as the muscle fibres contract. In an eccentric contraction the muscle lengthens as the muscle fibres contract.
Chapter 2. Background material to surface electromyography

The significance of the type of muscle contraction is that during a dynamic contraction (eccentric or concentric), the sEMG recorded from that muscle will be changing both in amplitude and frequency spectrum. Locomotion consists of groups of muscles contracting in a dynamic fashion. The resulting signals are nonstationary stochastic in nature and certain methods of signal analysis are not appropriate for this signal. This will be discussed further in chapter 5.

A further feature of muscle contraction is the force of contraction. Generally, the motor units are recruited according to the Henneman size principle as the muscle force increases. Small slow motor units are recruited first, followed by the larger units. As the strength of contraction increases the firing rate increases followed by recruitment of additional motor units. At approximately 80% of maximum voluntary contraction (MVC) all the motor units have been recruited so further contraction is achieved solely by increasing the firing rate.

Muscle fatigue will develop if a muscle remains contracted for long periods at a high force of contraction. Muscle fatigue is the result of a change in pH of interstitial fluid which affects muscle fibre velocity and the recruitment strategy of motor units. Discussion of how muscle fatigue relates to sEMG is contained in section 2.10.3.

### 2.4 Measurement of muscle activity

Indirect methods of recording muscle activity include sEMG and the mechanomyogram (MMG). MMG is a technique that records the physical change in size of a muscle as it contracts since the transverse diameter of the muscle will increase as the muscle fibrils slide between each other. Methods of measuring mechanical changes in muscle include the use of laser distance sensors, piezoelectric contact sensors, accelerometers and microphones [Orizio 2004]. The MMG is therefore a general term for recording physical changes in muscle independent of the type of sensor used. The MMG data recorded from contracting muscle is not analogous with sEMG data recorded from the same muscle [Cramer et al. 2000; Orizio 2004; Perry et al. 2001]. In a study conducted by Perry et al. (2001), the MMG amplitude was reported to increase in a linear fashion with power output whereas the sEMG increased exponentially. The study involved seventeen adults cycling and piezoelectric sensors were employed to record the MMG. The
Conclusion was that MMG amplitude is not sensitive to recruitment of fast-twitch muscle fibres as the muscle contraction increases. MMG recordings also are dependent on the mechanical properties of the muscle that will vary according to the velocity of contraction [Cramer et al. 2000]. Recording of muscle sound using an electric condenser microphone has been reported to increase in amplitude with increasing nerve stimulation of the muscle [Bolton et al. 1989]. However, there was not a clear linear relationship between the audiological signal emitted by the muscle and the force generated. In comparison to electromyography, limited research has been carried out on MMG particularly with regard to dynamic contractions during which the length of the muscle and the force generated is changing. Additionally, the effect of motion artefacts on MMG has not been analysed [Watakabe et al. 2001]. Therefore, although MMG is a valid method of analysing muscle activity, there is to date insufficient experimental data to interpret fully MMG findings. The remaining part of the chapter will therefore focus on electromyography.

2.5 Electromyography

Electromyography is the study of the MUAPs generated by muscle fibres. Electromyography has a long history dating back to 1791 when Galvani first recorded electrical signals generated by muscles. The signals were systematically investigated by H.Piper in 1912. The introduction of the microprocessor in the 1970s allowed highly complex analysis of EMG to be performed [Merletti & Parker 2004b; Basmajian & De Luca 1985].

Different types of electrodes are used to detect the potential difference (PD) produced by the depolarisation – repolarisation wave travelling along the muscle fibres. These include needle electrodes, wire electrodes or surface electrodes with reference to a ground electrode. A variety of needle electrodes are available such as single-fibre, monopolar, concentric and macro needles. Needle and wire electrodes allow individual motor unit action potentials to be assessed. They are useful for detecting changes in MUAP due to myopathy, neurogenic conditions or denervation of muscle fibres. The volume of muscle that a needle electrode can record MUAPs from is small, typically no more than 0.5mm from the tip of the needle. In contrast, surface electrodes will detect action potentials from small motor units within a distance of 0.5cm and from larger motor units within a distance of 1.5cm from the
recording surface [Winter 1990]. They are more appropriate in instances where information is sought on activity of whole muscles, patterns of activity and fatigue [Trontelj et al. 2004].

Surface electrodes are non-invasive and therefore are preferable for ethical reasons. However, a negative aspect of the surface electrode is that there is generally a substantial amount of unwanted signal or ‘noise’ and interference added to the ‘true’ sEMG signal arising from the MUAPs. This is because a number of different factors affect the signal recorded from the muscle fibres. These factors can be separated into intrinsic which relate to the subject’s morphology, and extrinsic which are the consequence of the experimental apparatus and methodology. The subject of noise will be discussed later in this chapter. The remaining sections of this chapter relate to surface electromyography.

2.6 Recording and processing of sEMG

Hardware processing occurs within the circuitry of the electrodes and amplifier. The four processes that the raw signal is subjected to by the hardware are signal detection, amplification, filtering and digitization.

2.6.1 Signal detection

Initial detection of the surface PD is performed by the electrodes. Surface electrodes may be unipolar or bipolar and vary in shape, size and interelectrode distance. Bipolar electrodes are preferential to unipolar since a differential amplifier can be used which decreases the common-mode noise and acts as a band-pass filter. A ground electrode acts as a reference point. Electrodes may be applied singly or in multi-array formation to a muscle. Surface electrodes are commonly constructed of silver–silver chloride mechanically pressed together. This combination produces an almost perfect non-polarizable electrode in which very little current flows between the skin and the electrode. Basmajian and De Luca (1985) recommend inter-electrode spacing of 1cm. Increasing the distance between electrodes increases the amplitude but decreases the bandwidth.

Optimal positioning of electrodes is essential to ensure that a high signal to noise ratio (SNR) is achieved, that there is good repeatability and also minimal cross-talk. Several reports have been published providing recommendations for electrode
Chapter 2. Background material to surface electromyography

placements. Zipp (1982) has provided diagrams for 18 muscles based on leadlines connecting anatomical landmarks. Basmajian and De Luca (1985) have recommended sensor placements for twenty-seven individual muscles. The recommendations were based on determining a position located midway between the distal motor endplate and tendon and in the central portion of the muscle. The latter recommendation was to minimize crosstalk from adjacent muscles. The most comprehensive guidelines for electrode placements are to be found in the ‘Surface Electromyography for the Non-Invasive Assessment of Muscles’ (SENIAM) report [Freriks & Hermens 2000]. This report was European Union initiative set up in 1995 and comprised sixteen groups from nine European countries. The aim of the initiative included developing recommendations regarding selection of hardware, placement of electrodes and subsequent analysis of the sEMG. The methodology involved a literature scan of one hundred and forty publications, questionnaires, developments of theoretical frameworks and practical workshops. The recommendations for electrodes and their placements included the following:

- Maximum diameter of electrode is 10mm
- The shape of the electrode is not significant
- Interelectrode distance < 20mm or ¼ of muscle length
- Longitudinally positioned between the motor end plate and tendon
- Transversely positioned away from the boundaries of other muscles
- A clinical test must be performed for each muscle.

2.6.2 Raw signal amplification

The sEMG before amplification is no greater than 5mV therefore amplification of this signal is often required for further processing. Amplification generally occurs in two stages, firstly within a pre-amplifier located within the electrode and then more distally within the main amplifier. The advantage of the pre-amplifier is that the noise arising from cable movement and the thermal noise generated within the main amplifier will not be amplified. The amplifier should have very high input impedance in order to maintain signal power [Gerleman & Cook 1992]. The input impedance of the amplifier has been recommended to be 100 times greater than the source input which is reported to be $10^4$ to $10^6$ ohms at the sEMG sampling frequency of 1000 Hz [Clancy et al. 2002; Gerleman & Cook 1992]. Another
requirement of the amplifier is that ideally all the frequencies within the bandwidth being investigated should be amplified equally and have the same phase change. The sEMG is usually recorded in differential mode with the difference in voltage, between two or three electrodes being measured (see figure 2.2).

\[ V_{SD} = V_1 - V_2 \]

(a)

\[ V_{DD} = V_1 - 2V_2 + V_3 \]

(b)

Single differential electrode

Double differential electrode

**Figure 2.2** Single differential system (a) and double differential system (b). Adapted from Merletti & Hermens (2004)

The differential voltage may be recorded from a single or double configuration. The Biometrics SX230 electrode (Biometrics Ltd, Gwent, UK) and the Delsys DE-2.1 (Delsys Inc; Boston, Ma) electrode are examples of single differential systems. The Delsys DE-3.1 (Delsys Inc; Boston, Ma) has a double differential configuration. The single differential system is the most commonly used configuration in sEMG applications [Merletti & Hermens 2004]. However, the double differential configuration reduces cross-talk, decreases the volume of muscle fibres being recorded and allows the conduction velocity to be estimated.

In theory, a differential amplifier should eliminate all the common noise or hum such as that arising from power sources. Therefore, only the true signal deriving directly from the MUAPs is amplified. In practice a proportion of the unwanted noise passes through and is amplified, the amount being dependent on the differential gain, \( A_d \), and common gain, \( A_s \), of the amplifier. The common mode rejection ratio (CMRR)
is a measure of how well the noise is blocked and is the ratio of the differential gain to the common gain. It can be expressed in decibels as follows:

\[ CMRR(dB) = 20\log_{10} \frac{A_d}{A_s} \]  

(2.1)

Ideally, the amplifier would have a CMRR of 100-120 dB to reject common mode voltages [Merletti & Hermens 2004]. However, since it is difficult to attain such high values common mode feedback may be incorporated where the common mode voltage is applied but in the opposite phase. Detailed coverage of the electronics of sEMG is provided in ‘Electromyography for Experimentalists’ [Loeb & Gans 1986].

### 2.6.3 Analogue filtering

The frequencies present in surface electromyography range from 10 Hz to 500 Hz (see figure 2.3).

As was mentioned in the previous section, the sEMG signal contains noise in addition to the signal from the contracting muscle fibres. Application of a high pass filter to eliminate the low frequency noise and a low pass filter to remove the high

![Figure 2.3](image-url)  

**Figure 2.3** Power spectral density graph for 5 hip joint muscles, gluteus maximus (glut max), gluteus medius (glut med), rectus femoris (rect fem), adductor magnus (add mag) and biceps femoris (bic fem) during a 10 second maximum voluntary contraction.
Chapter 2. Background material to surface electromyography

frequency noise will diminish the noise present. The selected filters should be chosen so that they result in minimal distortion of the true signal.

There is a considerable variation in values selected for low and high pass filters in sEMG studies that have been undertaken [Rose 2004]. High-pass filters generally have a cut-off of 10 Hz to 20 Hz and low-pass filters a cut-off of 500 Hz [Freriks & Hermens 2000]. These filters however will not remove the 50 Hz power line noise if present. An analogue notch filter can remove this noise although this type of filter will cause some of the signal arising from the MUAPs to be eliminated and a phase difference to be introduced. This will be discussed further in chapter 5.

Researchers have used different types of high pass and low pass filters. These include the Butterworth, Bessel and Chebyshev filters of varying orders and with a range of cut-off frequencies. Figure 2.4 illustrates the passband response of these three types of filters in addition to a simple resistor-capacitor (RC) filter.

![Figure 2.4. Comparison of four common 6-pole low-pass filters showing the amplitude response. [Horowitz & Hill 1998].](image)

Although the Chebyshev filter displays maximal sharpness of the 'knee' this is at the expense of ripples introduced within the passband. In contrast, the Butterworth filter has a maximally flat passband but a more rounded 'knee'. The latter feature is not a significant factor with regard to application to the sEMG signal since the sEMG power spectral density distribution does not display sharp cut-offs at the lower and higher ends of the spectrum. The disadvantage of the Butterworth filter is however, that the signal in the passband may undergo large phase shifts resulting in time
delays [Horowitz & Hill 1998]. That is, there will be a delay between when the motor unit action potential is generated and when it is recorded. The time delays introduced by application of the Chebyshev filter are even greater. The Bessel filter has an improved time-domain performance compared to the Butterworth and Chebychev filters although poorer amplitude–frequency characteristics. The phase shift may not be the same across the frequencies within the passband as shown in figure 2.5.

![Comparison of time delays for a 6-pole Butterworth filter and a 6-pole Bessel filter.](image)

**Figure 2.5.** Comparison of time delays for a 6-pole Butterworth filter and a 6-pole Bessel filter. [Horowitz & Hill 1998].

### 2.6.4 Analogue to Digital (A/D) conversion and sampling

The analogue signal representing the continuous changes in potential difference is normally converted to a digital signal. There are several different types of A/D conversion techniques each of which yields different values [Horowitz & Hill 1998]. The degree of resolution will be dependent on the amplifier gain and the A/D input range.

The sampling of the signal should be recorded at a minimum of twice the highest frequency within the signal, which according to the Nyquist theory preserves the frequency content of the signal [Merletti 1999]. Sampling at too low a frequency results in aliasing, where certain frequencies are incorrectly represented. A frequency of 1 kHz (2 x 500Hz) has been reported as the minimal necessary for accurate signal analysis [Freriks & Hermens 2000; Merletti 1999; Merletti & Hermens 2004]. More recent sEMG recommendations advise a minimum sampling of 2 kHz for surface recording [Hermens 2006]. Durkin and Callaghan (2005) however, conducted a study in which they investigated the effect of the sampling
frequency on sEMG signals. The results showed that although there were statistically significant differences for the time domain variables and mean power frequency when sampling at 1 kHz compared to 2 kHz and 20 kHz, the magnitude of the differences was very small. The conclusion drawn by Durkin and Callaghan was that in the case of sEMG little additional information was gained by over-sampling as opposed to sampling at the Nyquist critical frequency of 1 kHz. Sampling at greater than the Nyquist frequency does however provide information about the waveform. Although sampling at the Nyquist frequency should minimise the aliasing effect, some aliasing may still be present due to the occurrence of frequencies in the signal above 500 Hz.

2.7 Noise and interference

A sEMG signal contains a large amount of noise and interference. Noise is highly complex in structure, composed of many different signals, which may be independent or interact with one another. A detailed description of noise can be found in ‘Electromyography for Experimentalists’ [Loeb & Gans 1986]. The main causes and types of noise and interference are:

i. Motion artefact at the skin-electrode interface

During a dynamic movement, the surface electrodes will move relative to the underlying muscle fibres. The amount of gliding will vary according to the visco-elastic properties of the intervening tissue and how far the electrode position is from points where the skin is tethered to deeper tissues. The signal that is being measured during a dynamic contraction is therefore not arising from the same group of muscle fibres throughout the measuring period. A dramatic change in the sEMG will occur if the electrode moves over an innervation zone of the motor units. The sEMG signal may reduce in amplitude by 60-80% [Clancy et al. 2002]. An additional source of noise from the skin-electrode interface is due to stretching and compression of the skin. These physical distortions change the PD detectable on the skin. Good skin preparation reduces the artefacts created by physical skin distortion. Gel or paste minimises physical disturbance of the electrolyte layer [Clancy et al. 2002]. Another consideration is the presence of hairs on the skin. Hairs will alter the shape of the skin-electrode junction and the impedance of the space. Overall, the movement artefacts give rise to low frequency noise in the range of 0 - 10 Hz.
ii. Motion artefact arising from movement of cables
A current is produced in the cables by either the cables being subjected to a time-varying electric or magnetic field or if they are moved through a magnetic or electrical field [Clancy et al. 2002]. This type of noise can be minimised by preventing the leads forming loops. The frequency range of this artefact is 1-50 Hz and the magnitude can be equal to the detected sEMG.

iii. Thermal or Johnson-Nyquist noise
This arises because of the naturally occurring movement of electrons within the instruments. The amount of thermal noise is related to the temperature level and impedance. The mean squared of the voltage variance (v) per hertz of bandwidth is:

\[ \bar{v}_n^2 = 4k_BT\cdot R \]  

(2.2)

\( k_B \) - Boltzmann's constant in joules per kelvin,
\( T \) - the absolute temperature in kelvins
\( R \) - the impedance in ohms.

Thermal noise has a flat power spectral density (PSD) distribution and has a low amplitude compared to that of the sEMG.

iv. Noise generated by the amplifier.
Broadband noise can arise in the circuitry of the amplifier. For example, thermal noise may arise in the resistors of the amplifier. Shot noise will also be present due to the finite nature of the charge quantum. A third type of noise generated in the amplifier is flicker noise, which is caused by fluctuations in resistance. Flicker noise is dependent on the construction of the resistor [Horowitz & Hill 1998]. Amplifier noise is not however considered a major source of noise amounting to about 1.5 \( \mu \)V [Clancy et al. 2002].

v. Electromagnetic noise
Electromagnetic (EM) fields are present in the laboratory arising from lighting, batteries, power cords and electrical equipment. The occurrence of this EM field will cause hum interference due to magnetic or electrical reasons. Electrical causes of hum arise from the fact that the electrical leads and subject's body are capacitively coupled to the electric field inducing displacement currents. It is not possible to remove the interference completely. In the United Kingdom, the power line interference will cause increases in signal power at 50 Hz and multiples thereof.
Chapter 2. Background material to surface electromyography

vi. Direct current (DC) noise
This may be due to electrostatic noise and is increased when the subject wears polyester clothes and there is low atmospheric humidity [Basmajian and De Luca 1985]. Another cause may result from the PD on the surface of the skin, which will be discussed in the next section.

vii. Biological noise
This may result from electro-cardiographic signals, respiratory rhythm causing movement of tissues or cross-talk from adjacent muscles. Cross-talk arises from MUAP signals being detected from muscles in close proximity to the muscle one intends to measure. It is more a significant factor for smaller muscles since the range of surface electrodes is generally less than 1.5 cm distant from the electrode. Cross-talk can be minimised by using a double differential amplifier.

The amount of noise present in the sEMG can be decreased by skin preparation, cleaning of electrodes, correct placement of electrodes, minimising EM interference and appropriate choice of equipment and selection of signal analysis techniques. However invariably there will be a certain proportion of the signal that is made up of noise. The signal to noise ratio (SNR) is a measurement of the noise present and is the ratio of the amplitude of the desired signal to that of the noise. The SNR for a constant force, constant angle, non fatiguing muscle contraction is defined as the sample mean $\hat{s}$ divided by the standard deviation $\sigma$ [St-Amant et al. 1998]:

$$SNR = \frac{\hat{s}(t)}{\sigma}$$  \hspace{1cm} (2.3)

2.8 Intrinsic factors modifying sEMG
Every individual will display a unique sEMG profile for a given activity and muscle. This is the result of subjects having variable morphologies and physiological patterns of muscle activation. The consequence of this variability is that the absolute values of sEMG cannot be compared between individuals. Two important factors affecting the MUAP are the filtering effect of the tissue layers between the skin surface and the recorded muscle and the skin surface PD. These will now be discussed further.

The tissue between the active muscle fibres and the surface electrodes will act as a filter. Since higher frequencies are attenuated more than lower frequencies the tissue
can be regarded as a low pass filter. The decrement function for the sEMG amplitude is not linear with regard to skin depth but rather decreases rapidly near the surface of the muscle then less rapidly as the distance from the active fibres increases [Basmajian & De Luca 1985]. This is due to the variations in the impedance of the layers of the skin and underlying fascia with the superficial stratum corneum possessing a large impedance compared to the subcutaneous tissues [Lowery et al. 2004]. The conductivity values calculated for muscle and fat tissue vary considerably between individuals. In the case of muscle it has been estimated at between 0.093 S/m and 0.8 S/m at 100 Hz and from 0.02 S/m to 0.1 S/m [Lowery et al. 2004] for fat tissue. The filtering effect of the skin will also cause the bandwidth to decrease as its thickness increases [Basmajian & De Luca 1985].

There will be a small PD of about -5mV - 20mV on the skin surface [Rada et al. 1995]. This PD is a result of the ion composition within the epidermis produced by lipid metabolism, which in turn is regulated by enzymes [Denda 2002]. This PD will vary across the surface of the skin. The impedance of the skin influences the PD recorded by the electrodes. The impedance is affected by the presence of oils, sweat and cosmetics on the skin, the temperature of the skin and by dead skin cells.

2.9 Extrinsic factors modifying sEMG

The sEMG recorded from identical skin surface PDs will vary depending on the type of apparatus used and the signal processing techniques applied. Therefore, as described in section 2.5, some of the factors that will affect the recorded sEMG include the type of electrode selected, the placements of the electrodes, whether a single or double differential amplifier is used and the type of filter chosen. The choice of signal processing techniques discussed later in chapter 5 will also influence the recorded sEMG. The fact that sEMG is not an absolute measurement but dependent on the individual's morphology, apparatus and processing techniques means that comparisons between individuals and between studies are difficult.

2.10 Functional significance of sEMG

Having recorded a sEMG, applied filters to eliminate noise the next issue is what does this signal actually represent? The sEMG is composed of the signals from thousands of motor units albeit in a distorted form and combined with substantial amounts of noise. The amplitude of each motor unit action potential (MUAP) will
be dependent on the type of unit, the larger units having greater amplitude than the smaller. The frequency of the individual MUAPs varies reflecting the frequency of the motor neurone innervating the muscle fibres of that particular motor unit. The frequency may be as high as 120 Hz [Winters & Crago 2000]. Analysis of the sEMG signal can provide information on the force being generated by a muscle and neurophysiological information such as the type of motor units being activated.

2.10.1 sEMG and muscle force

Studies investigating the link between the EMG and the force generated by that muscle have examined both frequency and time-dependent EMG features. Over fifty years ago, Lippold (1952) demonstrated a linear relationship between the force of an isometrically contracting muscle (gastrocnemius) and the amplitude of the EMG. Other investigators however have reported an exponential relationship between force and EMG amplitude [Schultz et al. 1982]. Solomonow (1990) demonstrated how the EMG versus force relationship is dependent on the motor unit recruitment pattern. The SENIAM report summarises the current situation thus: 'no model has yet been described in which the state of the art from both worlds (EMG, muscle mechanics) is integrated' [Freriks & Hermens 2000]. One can therefore conclude that although during an isometric contraction the EMG amplitude will increase as the muscle force increases, there is no definitive mathematical relationship between the two parameters.

The relationship between the muscle force and PSD of the sEMG is not clear. Although one would anticipate a gradual increase in the mean frequency (MF) or median frequency (MDF) as the larger motor units are recruited with higher conduction velocities, this has not been conclusively demonstrated. A number of researchers have reported an increase in MF or MDF [Karlsson & Gerdle 2001; Doheny et al. 2007] whereas others have found no change [Petrofsky & Lind 1980; Bazzy et al. 1986]. This lack of consistency in findings between researchers may be due to the variations between subjects in the modulation effect of the skin and subcutaneous layers as described in section 2.8.
2.10.2 Electro-mechanical delay

The contraction of the muscle does not occur simultaneously with the sEMG. Instead, there is a short delay known as the electro-mechanical delay (EMD) between the sEMG and subsequent muscle contraction. Physiological reasons for the EMD include calcium ion channel kinetics and time for cross-bridges to form. Mechanical factors are compliance of joint capsules, ligaments, fascia and tendons. Additionally, the initial tension present in the muscle when the muscle contracts [Vint 2001] and the amount of tendon slack [Muraoka et al. 2004] will both influence the EMD. Signal processing techniques and threshold values selected, which are partially dependent on the apparatus, will further influence the EMD. The smoothing filter may result in temporal differences if allowances are not made. Loram et al. (2005), in a study measuring the length of gastrocnemius whilst standing, reported a time delay between the moving average sEMG and the length of gastrocnemius of 160 ms with a standard deviation of 50ms. The smoothing window selected was 100ms in duration. A similar EMD of 143ms was calculated by Lloyd and Besier (2003) using a 6 Hz filter to average the rectified data. In contrast, Hof (2003) reported a delay between cessation of force at the ankle joint and sEMG in the triceps surae of only 70ms. The linear envelope was formed using a time constant of 22ms.

An additional factor to consider with regard to EMD is the method involved in eliciting the muscle contraction. Voluntary contractions result in longer EMD than those obtained by electrical stimulation [Muraoka et al. 2004]. This difference is attributed to the synchronisation of motor units that occurs in electrically stimulated muscles and the difference in motor unit recruitment. The shape of the rectified raw sEMG will also influence the magnitude of the sEMG. Borg (2005) provides an example of two ramp signals with the same on/off time but different gradient signs. The application of cross correlation to these two signals indicates a phase shift of up to 40% of the ramp length despite them being equal in duration, and starting and ending at the same time. In conclusion, there is not a universally accepted value for the EMD during walking. A reasonable assumption based on previous studies is that the value is in the region of 100ms. However, since walking consists of cyclic shortening and lengthening of the musculo-tendinous complex with differing amounts of tendon slack the EMD during a walking cycle is likely to vary. The
concept of EMD is highly significant with regard to myoprocessor controlled prostheses since the longer the EMD the more time is available for processing the sEMG. This will be discussed further in chapter 5.

2.10.3 sEMG and muscle fatigue
Time frequency parameters have been extensively applied in determining onset of muscle fatigue [Bonato et al. 2001; Georgakis et al. 2003; Hostens et al. 2004; Karlsson et al. 2003; Knaflitz & Molinari 2003; Masuda et al.1999; Merletti et al. 1990; Pease 2003; Petrofsky & Lind 1980]. The studies reported that the frequency parameters decreased and mean amplitude increased as the duration of the contraction increased for both dynamic and isometric contractions. These two parameters are however related. During a sustained contraction, the proportion of the sEMG made up of low frequency components increases. Since the soft tissue acts as a low-pass filter a greater portion of the MUAPs will be recorded hence the signal amplitude will increase [De Luca 1984].

2.10.4 sEMG and muscle fibre composition
Additional microscopic information regarding the muscle fibre type composition has been extrapolated from the time frequency parameters [Kupa et al. 1995; Drost et al. 2006]. Kupa et al. (1995) electrically stimulated three different types of muscles in fourteen rats and recorded the sEMG of the muscles. The muscle fibres were then analysed using histochemical processes to determine muscle fibre types. Results from this study indicated that the median frequency correlated with the muscle fibre composition. A recent study by Farina et al. (2006) however, reported no correlation between the instantaneous mean power spectral density and myosin heavy chain structure of the vastus lateralis during a low powered cycling exercise.

2.10.5 sEMG and muscle activation
Clinically, analysis of sEMG frequently involves assessing whether the muscle is 'on' or 'off'. A threshold value is selected and the muscle is deemed to be in 'off' mode if the value of the parameter falls below this level and 'on' mode if it rises above the threshold. Johanson and Radtka (2006) have recommended a minimum threshold value of 15% of the maximum-recorded sEMG since it reduces crosstalk from surrounding muscles. Figure 2.6 illustrates ‘on-off’ mode of five muscles
during the gait cycle. Further discussion of patterns of sEMG activity during gait will be made in the next section.

<table>
<thead>
<tr>
<th>Muscle</th>
<th>Activity pattern</th>
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<td>Gluteus maximus</td>
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<td>Gluteus medius</td>
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<tr>
<td>Rectus femoris</td>
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<tr>
<td>Adductor magnus</td>
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<tr>
<td>Biceps femoris</td>
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</table>

![Graph showing activity pattern of five hip muscles](image)

**Figure 2.6.** 'On-Off' activity of five hip muscles. Modified from Sutherland (1984).

### 2.11 Conclusion

The aim of this chapter has been to provide background information on sEMG and basic muscle physiology. In conclusion, sEMG does provide a method of assessing muscle activity and indirectly the neuronal input. However, the sEMG is a signal that has been attenuated by the cutaneous and subcutaneous tissues sandwiched between the muscle and electrode. Additionally, the true signal originating from the muscle fibres will be contaminated by noise and interference. Thus, the sEMG signal should be regarded as a blurred distorted representation of the motor events occurring. The next chapter will introduce the topic of locomotion and present some of the sEMG studies that have been undertaken during locomotion.
Chapter 3
Background material to gait

3.1 Introduction
This chapter continues from chapter 2 in providing a literary background to the project. Section 3.2 introduces the theme of walking and the parameters that are used to characterise gait. Neuromuscular control theories with particular reference to the central pattern generator theory are described in section 3.3. This is followed by a review of sEMGs that have been recorded from intact subjects during locomotion. A discussion of the reproducibility of gait cycle sEMG patterns is contained within this section. Coverage of sEMG in TF amputees is made in the next chapter which introduces the subject of amputation.

3.2 Walking
Walking is a repetitive movement consisting of a variety of body segments moving in a cyclical fashion and with particular phase differences between individual segments. The lower extremity segmental movements are produced by a large number of muscles acting on the hip, knee, ankle and foot joints contracting at differing times during the gait cycle. The resultant moments produce movement of the joints about certain axes. There will however be differences in the timings, amplitudes, velocities and other features of the movements during the gait cycle between individuals with subjects having their own unique gait profile. Indeed the kinematic data characteristic of an individual has been used to identify subjects in a similar way to face recognition [Boulgouris et al. 2005]. The main aim of walking is to propel the centre of mass anteriorly with minimal consumption of energy and maximum stability. In the ‘normal’ subject, minimum consumption of energy is associated with minor oscillations of the centre of mass and with symmetry of gait. The latter feature is also important in an aesthetic context. The following subsections introduce different aspects related to walking.

3.2.1 Divisions of walking
Temporal events can be identified from force plate data, contact switch data, data from retro-reflective markers or video data. These events include foot strike, flat foot,
Chapter 3. Background material to gait

heel off, toe-off and vertical tibia [Winter 1987; Sutherland 1994]. The gait cycle is a repetitive ipsilateral event and is defined as the time the heel makes contact with the ground to the time when the heel again makes contact with the ground (see figure 3.1).

<table>
<thead>
<tr>
<th>PHASES</th>
<th>STANCE PHASE</th>
<th>SWING PHASE</th>
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<tbody>
<tr>
<td>PERIODS</td>
<td>INITIAL DOUBLE SUPPORT</td>
<td>SINGLE LIMB STANCE</td>
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<tr>
<td></td>
<td>INITIAL SWING</td>
<td>MID-SWING</td>
</tr>
</tbody>
</table>

Figure 3.1. Events of gait [Sutherland et al. 1994].

The functional demands of stance are greater than that of the swing phase since not only does the body have to be propelled smoothly forwards but also the individual muscles of the lower limb have to be contracted in such a way that stability is maintained particularly during the single limb support phase. Since the study, as outlined in chapter 1, will focus on the stance phase of the gait cycle (GC), more detail will be provided on this phase of the cycle. The average cycle is 1.06 seconds in duration [Popovic & Kalanovic 1993]. The cycle can further be divided into a period of stance and swing. The average gait cycle is composed of 62% stance phase and 38% swing phase [Sutherland 1994]. Each stance can be split into two periods of double support and one of single support. Another division, related to the task performed, is into a period of weight acceptance, single limb support and limb advancement (see figure 3.2). This scheme divides the tasks into eight phases.
Stance can be divided into four main divisions, namely weight acceptance (0-10% of GC), mid-stance (10-30% of GC), terminal stance (30-50% of GC) and pre-swing (50-60% of GC) [Perry 1992]. Winter (1987) partitioned the stance period into weight acceptance (from initial contact until maximum knee flexion), mid-stance and push off (from commencement of plantar-flexion to toe-off). These two periods run from the beginning to approximately 15% of the gait cycle and from approximately 40% of the gait cycle to the end of the stance phase. Another method of partition of the gait cycle is to split the stance and swing phases into early, mid and late states [Zlatnik et al. 2002]. All these systems of gait cycle divisions are based on events determined from kinematic or kinetic recordings. However, these events can be regarded as the end product of neural events occurring within the central nervous system. A different system of gait cycle division can be conceived based on neural locomotor control mechanisms. Ideally, the events determining transitions between phases in this classification method would be derived from direct neuronal recordings. However, acquisition of these recordings is invasive. The closest non-invasive method of obtaining an insight into underlying neural activity patterns during gait is through measurement of sEMG. Discussion of using sEMG to determine gait events is made in chapter 4.

Analysis of the gait cycle may involve the entire cycle or only parts of it, the type of division selected being dependent on what is being investigated. Many studies do not use specific measured events within the gait cycle to subdivide it into functional units. Instead, the units are frequently determined by the percentage of the gait cycle.
However, the percentage at which events occur will vary between individuals and indeed temporal characteristics for an individual will vary between strides. The standard deviation for stance duration is approximately 1.55% of mean stance duration in healthy young adults [Winter 1990]. A greater variation in intra-subject temporal gait characteristics is displayed in subjects such as TF amputees whose stance variability has been reported to be 4.61% compared to 2.73% for intact subjects [Bae et al. 2007]. The variations in stance for a subject over time have traditionally been considered to possess a random Gaussian pattern. However, recent studies have shown that they have a temporal structure to them [Dingwell et al. 1999; Hausdorff et al. 2000]. The implications of this are that if a subject is assessed over a short period, this may not be representative of the subject’s overall gait pattern.

Determination of a subject’s gait cycle will vary depending on the events identified, measurement system selected to record the events, definition of these events and the threshold values chosen. Events selected to identify commencement and the conclusion of the gait cycle typically involve heel strike and toe off. In subjects displaying abnormal gait, for example in children with cerebral palsy, the normal heel to toe-off gait may be absent thus rendering it inappropriate to use heel strike as an event [De Stefano et al. 2004]. Measurement techniques used to record events include force platforms, foot switches, video data and kinematic data from markers. The definition of the events will depend on the type of measurement system selected. The events recorded by the force platform mark the beginning of the heel contact and the end of the toe-off. In contrast, techniques based on marker data measure the end of heel contact and the beginning of toe-off [Ghoussayni et al. 2004]. These differences in event definitions result in shorter stance times calculated from foot compared to times calculated from force-plate data. The threshold selected to identify events from a force platform may vary from 2.5N [Wall & Crosbie 1996] to 10N [Ghoussayni et al. 2004]. The effect of using different thresholds is more significant in estimating time of toe-off since this event occurs over a longer time period than heel contact [Ghoussayni et al. 2004]. In summary, detection of events using force platforms, video data, marker data and footswitches are all valid methods. However caution must be exercised in comparing gait event timings derived using different recording techniques since the values will differ.
3.2.2 Kinematics of gait

The joints of the lower limb in addition to the pelvis and trunk exhibit a characteristic movement pattern during the gait cycle. Figures 3.3 and 3.4 illustrate the angular kinematics in the sagittal plane for the hip joint and knee joint respectively. The reader is referred to Inman et al. (1994) for further information regarding the kinematics of human locomotion.

![Graph of Hip Flexion/Extension](image1)

**Figure 3.3.** Hip flexion/extension during a gait cycle in a 7 year old child. [Sutherland et al. 1994] ——— opposite toe-off ——— opposite foot strike ——— toe-off

![Graph of Knee Flexion/Extension](image2)

**Figure 3.4.** Knee flexion/extension during a gait cycle in a 7 year old child. [Sutherland et al. 1994] ——— opposite toe-off ——— opposite foot strike ——— toe-off

3.2.3 Symmetry of gait

Studies have shown that in able-bodied subjects there is an asymmetry in gait with one limb being more active during propulsion and the other during the support phase [Sadeghi et al. 2000]. In subjects with intact limbs, an investigation by Ounpuu and
Winter (1989) reported no significant difference in stride time, stance percentage and double support percentage for the dominant compared to the non-dominant limb. However, the same study observed significant bilateral differences in sEMG for the medial hamstrings at toe-off and soleus for the entire stance. The conclusion drawn by Ounpuu and Winter (1989) was that the dominant side generates more energy than the non-dominant side. Other researchers have similarly found differences in sEMG in the muscles of the dominant compared to the non-dominant side [Adam et al. 1998; Merletti et al. 1994]. A study investigating knee kinematics in 40 individuals reported statistically significant differences in 25% of subjects in knee flexion and extension between the right and left sides during locomotion [Maupas et al. 2002]. The differences were not however linked to handedness. The same study reported that an investigation of kinetic parameters of the knees including peak torque, total work and average power revealed no statistical differences between sides. In their comprehensive review of gait symmetry, Sadeghi et al. (2000) reported that there was no conclusive evidence of the effect of lateral dominance on the lower limbs during locomotion in healthy individuals with intact limbs. In summary, gait asymmetry is a common finding but is not, according to current evidence, related to handedness.

3.3 Neural control of locomotion

The traditional view of regulation of locomotion was hierarchical in structure. The supraspinal centres represented the highest level of command sending signals to the spinal neurones, which then relayed signals on to the motorneurones causing contraction of the muscle. The musculoskeletal system was considered to respond passively to the nervous system. Research conducted over the last 20 years however suggests this hierarchical control system may not be entirely accurate. Current theories of locomotor control consider control to be a combination of descending signals from supraspinal centres, networks of spinal neurones spontaneously generating patterns of impulses, signals from the exteroceptors and proprioceptors and local spinal reflexes. The neural control of locomotion ensures smooth movement and the ability to alter speed, change direction, modify gait according to the incline, climb stairs, avoid obstacles and adapt gait to the terrain. Local reflexes include the monosynaptic stretch reflex.
The hypothesised groups of neurons in the spinal cord responsible for simple movement patterns are known as CPGs. There are two theories as to how spontaneous impulses in the CPGs are generated [Abbas and Full 2000]. The first theory proposes that certain neurones because of their cell membrane permeability have the ability to self generate neural impulses. These neurones are known as pacemakers. Spontaneous signal generation has been observed from neurones in the embryonic central nervous system and in the dorsal root ganglion [Blanton & Kriegstein 1991; Gang et al. 2002; Wall & Devor 1983]. The second theory is that the cyclic impulses originate from a small network of neurones (see figure 3.5).

Abbas and Full (2000) suggest that CPGs most probably consist of a combination of pacemakers and neural networks.

**Figure 3.5.** Schematic diagram of a network oscillator CPG. Neurones A, B and C form the CPG. Neurones A and B are in mutual inhibition with each other and therefore oscillate out of phase. Neurones B and C demonstrate recurrent inhibition which will affect the cycle and frequency of the CPG. Excitatory drive from higher centres triggers the oscillations and may affect frequency. Additional modulatory input from the supraspinal centres will alter the output from the CPG. The CPG will excite the motoneurone M resulting in contraction of the muscle fibres. The excitation is modulated by signals from interneurones I and by afferent input from the periphery. Afferent Ib fibres from Golgi tendon organs are illustrated here which excite the inhibitory interneurones. Sensory fibres (Ia) may directly stimulate the motoneurones or alter the activity of the interneurones. A further input to the inhibitory interneurones is from supraspinal centres. Adapted from Abbas and Full (2000).
There is a limited amount of clinical and experimental evidence to support the theory of the CPG. Experiments conducted on animals have reported patterns of neuronal activity within small groups of spinal cord segments associated with the control of locomotion. Perret (1983) found that the EMG activity of the muscles in the hind limb of the decorticate cat was similar to the activity recorded in the intact cat, the spinal cat and in the mesencephalic cat. Additionally the EMG signal in muscles of the limb in which the afferents had been cut was comparable to that observed in cats with normal afferent input. Little difference in activity was recorded in a curarized cat in which signals could not reach the spinal cord segments innervating the hindlimb from other parts of the body. The conclusion made was that the cat possesses spontaneously generating networks of neurones within the spinal cord with connections to the motorneurones. These networks are able to produce signals independently of activity from higher centres or from the periphery. Grillner et al. (1991) reported that studies on the lamprey revealed that locomotor units of only three segments long exist in the spinal cord that, with afferent input, can produce patterns of locomotor activity.

Recent research has found examples of locomotor CPG control in humans [Vaughan 2003; Pinter & Dimitrijevic 1999; Minassian et al. 2005]. Pinter and Dimitrijevic (1999) observed that following peripheral afferent stimulation in a complete spinal cord injury subject stepping movements could be initiated. No stepping movements were present in the absence of stimulation in contrast to the spinal cat in which locomotor movements were observable with no external stimulus [Full & Farley 2000]. Rhythmic activity of the lower limb could also be induced by electrical stimulation of the second lumbar spinal cord segment in this human subject. This activity was diminished in amplitude but increased in frequency following suppression of afferent impulses. A larger study involving 17 complete spinal cord injury subjects was conducted by Minassian et al. (2005). Epidural lumbar cord stimulation at 5 – 15 Hz produced lower limb extensions whereas at highly frequencies of 25 – 50 Hz stepping –like movements were induced.

The CPG, according to theory, will emit a specific signal for a discrete type of movement. This will produce a regular pattern of movement of the joints of the lower limb leading to a forward movement of the centre of mass of the individual.
Even in the TF amputee, in whom much of the appendage is lacking, it is reasonable to anticipate that cyclic activity will still be detected in the vestigial limb muscles based on the CPG theory. The CPG concept links in well with the Bernsteinian theory of movement. The Russian neuroscientist, Nikolai Bernstein developed the idea of movement as a structure. He is quoted in a paper by Stuart stating in 1940 that:

"movements are not chains of details but structures which are differentiated into details; they are structurally whole, simultaneously exhibiting a high degree of differentiation of elements and differing in the particular forms of the relations between elements". [Bernstein, cited in Stuart 2005]

The notion of movement composed of discrete elements underlies the method of pattern classification techniques applied to the sEMG which is described in chapter 6. This neural control of locomotion ensures smooth movement and the ability to alter speed, change direction, modify gait according to the incline, climb stairs, avoid obstacles and adapt gait to the terrain.

3.4 Walking and sEMG activity

3.4.1 Muscles of locomotion

Walking involves the co-ordinated contraction of a large number of muscles, with 20 muscles acting on the hip joint, 11 muscles on the knee joint, 12 muscles on the ankle joint and approximately 19 small muscles exerting forces on the foot [Warwick & Williams 1973]. In addition to movement of the lower limbs, there will also be motion of the trunk and upper limbs. This upper body involvement is important for the maintenance of balance.

3.4.2 sEMG of lower limb during locomotion

The sEMG of the hip joint muscles in normal adults has been measured during walking in a number of different studies [Kadaba et al. 1989; Kleissen et al. 1997; Nymark et al. 2005; Olree & Vaughan 1995; Ounpuu & Winter 1989; Patla 1985; Shiavi et al. 1987; Winter & Yack 1987; Yang & Winter 1982]. The ensemble sEMGs for five muscles each of which have a different action are shown in figures 3.6 and 3.7.
Table 3.1 illustrates the percentage of the gait cycle at which the major peaks are present for the five muscles illustrated recorded from nine studies. It can be observed that certain muscles are selected for recording with greater frequency than other muscles, with more data available for the muscles responsible for movements primarily in the sagittal plane than those effecting movement in the coronal plane.
Table 3.1. Comparison of timings of peak amplitude for five different hip muscles from eight different studies. GMAX-gluteus maximus. GMED-gluteus medius. RF-rectus femoris. AM-adductor magnus. BF-biceps femoris. NR – not recorded.

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<td>NR</td>
<td>30%</td>
<td>NR</td>
<td></td>
<td></td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0%</td>
<td>NR</td>
<td>70%</td>
<td>20%</td>
<td></td>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>BF</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>NR</td>
<td></td>
<td></td>
<td>5%</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
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</table>

Several observations can be made from the above table. Firstly, the studies are not consistent in their findings. In the case of GMAX and GMED some studies show these muscles have a single peak of activity during the loading phase of stance (5% - 10%). Other studies however suggest that these two muscles are biphasic with peaks at 10% of stance and another during early swing (70% - 75%). The majority of sEMG studies shown in table 3.1 for rectus femoris indicate that this muscle is biphasic with peaks during the early part of stance (10%) and a second peak during late stance / early swing (60%-70%). Adductor magnus is triphasic according to two of the studies with peaks at 10%, 30% and 75%-85%. A third study however reported that AM was biphasic with peaks at 25% and 70%. Three of the four studies recording the sEMG of biceps femoris were consistent in their findings, all reporting a single peak during the beginning of stance (0%-5%). A fourth study found a double peak, with the peaks occurring at 20% and 80%.

The differences in sEMG patterns between individuals can be accounted for by differences in noise levels and the intrinsic and extrinsic factors described in sections 2.8 and 2.9. Particular factors to consider are the speed of walking of the subject, the number of subjects, the location of the electrodes, the number of strides analysed and the method of amplitude normalisation. Table 3.2 provides details of these various factors for the eight different studies. Additionally, individuals display characteristic kinematic patterns of locomotion. Since there are an indeterminate
number of ways the muscles can contract to achieve a particular kinematic pattern, an individual will display variable sEMG patterns of activity.

Table 3.2. Details of five different factors from eight studies recording sEMG during locomotion. Each factor can influence the sEMG results.

|---------------|--------------------|------------------------|-------------------|-------------------------|---------------------|---------------------|-------------------|---------------------|-------------|-------------------|------------------|------------------|

The pattern of sEMG was observed by Grieve (1974) to be dependent on the speed of walking. Hidler and Wall (2005) however, did not observe any changes in muscle pattern activation at different velocities in seven subjects walking on a treadmill. The walking velocities tested were low (0.42 – 0.75 m/s). Nymark et al. (2005) compared kinematic and sEMG in eighteen subjects walking at normal, slow and very slow speed on a treadmill and overground. They observed that at slower walking speeds the sEMG amplitude decreased and there was a change in phasic timing.

Further factors affecting the sEMG are the length of the muscle, the velocity at which the length of muscle is changing, fatigue and temperature [Winter 1990]. The amplitude of the sEMG signal of lower limb muscles during locomotion is small compared to more energetic activities resulting in a lower signal to noise ratio (SNR) [Basmajian & De Luca 1985]. This will have repercussions on the reproducibility that is discussed in the following section.

3.4.3 Reproducibility

One of the aims of the study, as stated in chapter 1, is to investigate the application of sEMG as a natural sensor during locomotion to identify phases of stance. A fundamental requirement is that the sEMG displays high repeatability between gait cycles and over time for a subject.
A number of investigations have been undertaken on the variability of sEMG during locomotion [Erni & Colombo 1998; Gabel & Brand 1994; Granata et al. 2005; Guidetti et al. 1996; Kadaba et al. 1985; Kadaba et al. 1989; Kleissen et al. 1997; Shiavi 1987; Viitasalo & Komi 1975; Winter & Yack 1987]. Comparison of repeatability between studies is difficult as emphasised in the previous section. Different statistical techniques have been used to assess variability, which further confounds comparison. Pearson’s correlation coefficient (r), coefficient of variation (CV), variance ratio (VR), the CMC and intra-class correlation coefficient are methods that have been commonly employed. Another factor affecting variability is the number of gait cycles studied. Gabel and Brand (1994) investigated six different methods of measuring repeatability of surface EMG in the vastus lateralis and medial gastrocnemius in two subjects. The number of gait cycles and length of filtering window were varied in the analysis. The methods assessed were CV, VR, CMC, r, the Kolgomogorov–Smirnov T test and the Anova F-ratio. The conclusions were that CV, r and the ANOVA test stabilised after 20 cycles whereas VR, CMC and the Smirnov test were similar for all numbers of cycles. With increased smoothing, there was decreased variability. Gabel and Brand (1994) recommended that at least 20 cycles should be analysed to minimise variability. Erni and Colombo (1998), in a study recording the sEMG from 6 paraplegics during walking, reported significant correlations between CV and VR and between VR and r. Table 3.3 lists the results for within day repeatability of gait cycles. The between day, between trial and between clinic repeatability values are shown in table 3.4.

Table 3.3. Within day repeatability results for five hip muscles’ sEMG from six different studies.

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</thead>
<tbody>
<tr>
<td></td>
<td>VR</td>
<td>10 adults free speed</td>
<td>NR</td>
<td>11 children free speed</td>
<td>CV(%)</td>
<td>5 adults free speed</td>
<td>10 adults free speed</td>
<td>40 adults free speed</td>
<td>CV(%)</td>
</tr>
<tr>
<td>GMX</td>
<td>NR</td>
<td>10 adults free speed</td>
<td>NR</td>
<td>11 children free speed</td>
<td>VR</td>
<td>10 adults free speed</td>
<td>0.85(0.06)</td>
<td>56(9)</td>
<td></td>
</tr>
<tr>
<td>GMD</td>
<td>NR</td>
<td>10 adults free speed</td>
<td>NR</td>
<td>11 children free speed</td>
<td>VR</td>
<td>10 adults free speed</td>
<td>0.85(0.06)</td>
<td>54(9)</td>
<td>30 adults freespeed</td>
</tr>
<tr>
<td>RF</td>
<td>0.27(0.13)</td>
<td>0.55 (0.12)</td>
<td>53-63</td>
<td>0.12-0.25</td>
<td>0.86(0.05)</td>
<td>55(7)</td>
<td>56(9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adductor (type)</td>
<td>0.20(0.14)</td>
<td>0.38 (0.17)</td>
<td>0.11-0.25</td>
<td>0.12-0.25</td>
<td>0.75 (0.10)</td>
<td>80(10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hamstring (type)</td>
<td>0.20(0.14)</td>
<td>0.38 (0.17)</td>
<td>55-66 BF</td>
<td>0.11-0.25 BF</td>
<td>0.84 (0.07) lateral</td>
<td>62 (20.6)</td>
<td>62 (20.6)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.4. Between trials, between days and between laboratories repeatability results for 5 hip muscles from 3 different studies. Standard deviation in brackets. NR – not recorded.

<table>
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<tbody>
<tr>
<td>Method</td>
<td>VR</td>
<td>VR</td>
<td>CMC</td>
<td>CV (%)</td>
<td>CV (%)</td>
</tr>
<tr>
<td>Repeatability assessed</td>
<td>Between trials, same day</td>
<td>Between days</td>
<td>Between days</td>
<td>Between days</td>
<td>Across labs</td>
</tr>
<tr>
<td>GMX</td>
<td>NR</td>
<td>NR</td>
<td>0.82 (0.08)</td>
<td>61 (9)</td>
<td>NR</td>
</tr>
<tr>
<td>GMD</td>
<td>NR</td>
<td>NR</td>
<td>0.84 (0.06)</td>
<td>57 (8)</td>
<td>NR</td>
</tr>
<tr>
<td>RF</td>
<td>0.19-0.40</td>
<td>0.38-0.77</td>
<td>0.82 (0.07)</td>
<td>62 (10)</td>
<td>41 (14)</td>
</tr>
<tr>
<td>Adductor (type)</td>
<td>NR</td>
<td>NR</td>
<td>0.66 (0.12)</td>
<td>73 (12)</td>
<td>NR</td>
</tr>
<tr>
<td>Hamstrings (type)</td>
<td>0.12-0.46</td>
<td>0.34-0.75</td>
<td>0.80 (0.09)</td>
<td>66 (11)</td>
<td>44 (9)</td>
</tr>
</tbody>
</table>

The repeatability for cycles of the same trial is generally better than between trials on the same day, which in turn is better than between days. This pattern has also been reported for kinetic data. Winter (1987) measured a greater coefficient of variability for the moments estimated for the hip, knee and ankle for a subject measured between days than for another subject measured with only minutes between trials. This may indicate that walking patterns change over time although it may also be the result of altered placement of markers.

Varying neural output to the muscles during locomotion has been considered by some authors to be the main factor responsible for poor repeatability of sEMG [Rainoldi et al. 1999]. That is, not only is poor repeatability an indicator of potential error in electrode placement or excess noise but also an indicator of differences in neurological activity. The reproducibility of sEMGs can therefore potentially offer information about the neural control of locomotion. Reproducibility has been found to be statistically different for different subject groups. Kadaba et al. (1985) calculated high VRs of 0.4 – 0.8 for children with cerebral palsy compared to 0.1 – 0.4 for intact subjects. Granata et al. (2005) found children had higher VRs ranging from 0.328 to 0.657 whereas the VRs of healthy adults were significantly lower, ranging from 0.173 to 0.270. Although some investigations have been conducted on sEMG patterns during locomotion in TF amputees, which will be covered in the next
chapter, the variability of sEMG in this group has not, as far as the author is aware, been investigated.

The repeatability for sEMG is low compared to the high repeatability for sagittal joint movements and force-plate forces [Kadaba et al. 1989]. One explanation for this, other than fluctuating noise, can be found in the neural control of locomotion. The aim of locomotion is to propel the body forward, which is achieved by limb segments moving at specific velocities. The movement of the limbs is caused by contracting muscles. However, there are an indeterminate number of ways in which the different muscles can achieve the desired movement. Winter and Yack (1987) commented on the interplay of activity patterns between the hip extensors and the hip flexors for individual subjects during walking which varied between cycles.

Most gait repeatability studies have analysed the entire gait cycle. The gait cycle however consists of two functionally discreet parts, namely stance and swing. Shiavi et al. (1987) recommend that the gait cycle should be subdivided into stance and swing phases and variability calculated for each separately. Best repeatability has been obtained for subjects walking at their preferred walking speed, which is probably in part due to less variation in stance and swing timings [Shiavi et al. 1987].

During locomotion, the number of motor units being recruited will vary as will their frequency. In a transient sEMG, analysis of the amplitude alone is not sufficient to represent accurately the underlying neurophysiological events occurring. Rather, additional features should be used, in particular those derived from time-frequency analysis. Although some of the isometric repeatability studies have assessed the power spectrum [Nargol et al. 1999; Oliver et al. 1996] the majority of gait repeatability studies have only investigated sEMG amplitude characteristics. The subject of time–frequency parameters will be introduced in chapter 5.

Repeatability studies on isometric contractions yield high correlations compared to dynamic contractions. Muscles containing long parallel fibres give better repeatability results than those that are divergent or pennate [Rainoldi et al. 1999] and proximal muscles display greater variability then distal muscles [Olree & Vaughan 1995; Winter & Yack 1987]. The proposed theory for this latter observation is that proximal muscles play a more varied role than distal muscles in locomotion control resulting in more possible combinations of activity. Extensor muscles and
Chapter 3. Background material to gait

Muscles crossing two joints show greater variability [Patla 1985]. Granata et al. (2005) reported asymmetrical differences in repeatability for the same muscles. Repeatability for the gait cycle has mainly been assessed for the entire cycle. However, the amount of variability may be dependent, on which part of the movement cycle is analysed. Knaflitz and Bonato (1999) measured the EMG from the dorsal interosseous muscle when the index finger was adducted. The variability of the instantaneous median frequency (from Choi-Williams) for a number of cycles was reported to be dependent on which part of cycle was analysed.

The following quotes sum up the current situation regarding repeatability:

'Literature data on repeatability are neither complete nor satisfactory' [Rainoldi et al. 1999, p105].

'There is a lack of studies concerning the reproducibility of surface EMG during dynamic contractions' [Larsson et al. 1999, p352].

Further research is therefore necessary to determine the repeatability of sEMG for successive gait cycles.

3.5 Conclusion

This chapter has provided an overview of walking. The parameters used for determining the gait cycles and divisions thereof are derived from kinematic or kinetic data. An alternative method proposed in this chapter is to record sEMG to partition the gait cycle. The sEMG can be regarded as the end product of signals emanating from the central nervous system. One current difficulty associated with using sEMG is that there is poor repeatability compared to kinetic and kinematic parameters. However, according to the CPG theory of locomotion, discrete bursts of activity are released to a number of functionally related muscles. Analysis of groups of muscles should therefore reveal these CPG patterns during the gait cycle. The following chapter introduces the subject of using sEMG as a natural sensor. Details regarding the methods of pattern analysis are provided in chapter 6.
Chapter 4

Background material to transfemoral amputation and prostheses

4.1 Introduction

This chapter introduces amputation and prostheses. There is an initial overview of the history of prosthetics followed by sections on current prosthetic user satisfaction and an outline of the incidence of lower limb amputation. Muscle surgery in TF amputation is then described and the effect of surgery on the muscle and nerve fibres is discussed. This is followed by a description of different type of prostheses and by a summary of gait in TF amputees. The final section concludes with a discussion of micro-processor controlled prostheses and the attributes of natural sensors versus artificial sensors.

4.2 Historical perspective on amputation and prosthetics

Prosthetic limbs for TF amputees have been in existence since early Roman times. Hancock described the oldest Roman prosthesis dating back to 300 BC as being constructed of a core of wood with pieces of bronze and iron attached [Hancock 1929]. An early ‘peg-leg’ prosthesis is shown in the Danse Macabre fresco painted in 1490 in the Church of the Holy Trinity, Hrastovlje, Slovenia (see figure 4.1).

Figure 4.1. Man with ‘peg leg’ on fresco painted in about 1490 in the Church of the Holy Trinity, Hrastovlje, Slovenia
(accessed from http://www.burger.si/Hrastovlje/Hrastovlje_4.html)
The early appliances were very heavy and unwieldy composed principally of iron, steel and copper. Leather and cat-gut were frequently utilised for their elastic properties. A light weight model was developed in the late 16th century made of leather, paper and glue although its stability is not known [Hancock 1929]. The use of light weight metals such as aluminium was not possible until 1865 when the commercial production of aluminium started. Similarly, rubber was not available as a material until the late 19th century when rubber plantations began being developed.

The early prostheses were rigid, knee joints only being introduced during the 16th century. Initially the knee joints were fixed although over the next century moveable joints were developed with the movement triggered by pulling a device attached to the hip [Hancock 1929]. During the 18th century a non-locking knee joint was developed. Ankle joints were incorporated into the prosthetic limb from the 1750’s onwards. The initial ankle joint contained a spring although later versions were designed with a ball joint.

Different methods of attachment of the prosthetic limb to the residual limb have been attempted throughout the ages. The techniques varied from simple devices to attach the prosthetic limb to the residual limb to elaborate corset designs and shoulder straps firmly fixing the prosthesis to the contra-lateral upper limb. Osseo-integrated prostheses represent the most advanced procedure for attaching the prosthesis to the residual limb whereby the prosthesis is attached via a titanium rod to the femur (see subsection 4.5.2). Historically there has been an appreciation of different design requirements necessary for the prosthesis depending function. Some of the lower limb prostheses were developed purely for cosmetic purposes whereas others were produced for specific activities such as horse riding. Design has additionally been affected by financial considerations. Basic prosthetic arms were developed by the Count de Beaufort in the 19th century constructed of wood and leather specifically so that the poor people could afford them [Hancock 1929]. The First World War stimulated further development of prostheses. A simple prosthesis developed by Hans Spitzy in 1919 with a posteriorly supported knee joint and rigid foot is illustrated in figure 4.2.
Figure 4.2. Lower limb prosthesis developed by Hans Spitzy in 1919 [Fineman 1999].

Prosthetic limbs have developed alongside advancements in amputation surgery. Cauterisation of blood vessels was introduced in the 15th century prior to which crushing was the routine procedure for controlling haemorrhage. A further improvement was the ligation of individual blood vessels, begun in the 16th century. The use of the tourniquet, to cease blood flow was first mentioned in the 17th century. Maggots have been routinely used since the Middle Ages to remove necrotic tissue although with the widespread availability of antibiotics last century they fell out of favour. Sterile maggot therapy is now once again being introduced in some hospitals for wound healing [Mumcuoglu et al. 1999]. The discovery of anaesthesia, antiseptics, antibiotics and other drugs over the last 200 years have also improved survival rates from amputation surgery.

Over the last eighty years, there have been considerable developments in prosthetic design. Models are constructed of light weight materials including metal alloys, high density polyethylene, carbon fibres, aluminium, titanium and foam. The combination of these materials offers flexibility, low weight, durability and strength. In addition, knowledge of lower limb biomechanics gained from gait laboratories and computer modelling has allowed the movement of the prosthetic limb to be more
akin to human movement. Prosthetics have developed to the extent that a sprinter fitted with a lower limb prosthesis is seeing to compete in the Beijing Olympics [Tucker & Dugas 2007]. Three recently developed prostheses are illustrated in figures 4.3a, 4.3b and 4.3c. However, despite the improvements in prosthetic design, dissatisfaction is still expressed by TF amputees regarding their lower limb prosthesis. The next section will explore levels of dissatisfaction and possible causes for this.

Figure 4.3a. Cheetah™ (Ossur, Reykjavik, Iceland)

Figure 4.3b. Power Knee™ (Ossur, Reykjavik, Iceland)

Figure 4.3c. Otto-Bock C-Leg™ (Ossur, Reykjavik, Iceland) Otto Bock Healthcare GmbH 15 Duderstadt, Germany

4.3 Satisfaction with prostheses

Levels of dissatisfaction with the prosthesis, technological progress and the financial resources devoted to prosthetic development are shown below in figure 4.4.

Figure 4.4. Levels of dissatisfaction with the prosthesis in relation to prosthetic budget and technological development. Graphs based on studies undertaken in Europe and the United States [Zahedi 2007].
One major difficulty in designing a lower limb prosthesis is that it has to be able to adapt to a large number of changing functional situations. The frequencies of six common daily activities are listed in table 4.1 [Zahedi 2007].

Table 4.1. Average daily frequency of five common activities
Adapted from [Zahedi 2007].

<table>
<thead>
<tr>
<th>Activity</th>
<th>Frequency</th>
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<tbody>
<tr>
<td>Changes walking speed</td>
<td>437 times</td>
</tr>
<tr>
<td>Stumbles</td>
<td>108 times</td>
</tr>
<tr>
<td>Stop and stands</td>
<td>1450 times</td>
</tr>
<tr>
<td>Sits</td>
<td>48 times</td>
</tr>
<tr>
<td>Descends stairs</td>
<td>23 times</td>
</tr>
<tr>
<td>Descends ramps</td>
<td>38 times</td>
</tr>
</tbody>
</table>

A further challenge is that an amputee who was previously very active prior to the limb loss will want to return to the previous quality of life [Weisshaar 2004]. Activities may include dancing, hurdling, climbing, playing rugby, diving, sailing, paragliding and skiing. There is currently no multi-purpose prosthesis available that permits the amputee to satisfactorily accomplish these various actions and also adapts to the different climatic conditions.

Walking is arguably the function that is best managed by current technology. This study will therefore focus exclusively on the activity of walking and in particular on the stance phase of the prosthetic limb. Stance is biomechanically very significant since both stability of the supporting limb and forward propulsion of the centre of mass have to be maintained. In an email communication with Dr. Hans Dietl, Chief Technology Officer of Otto Bock HealthCare, 2004, it was emphasised by Dr. Dietl that in the TF amputee, control of the knee is most critical during the stance phase.

A standard prosthetic limb constrains normal gait patterns because it receives no prior signal regarding the intentioned movement of the individual nor does it offer direct feedback to modulate the consequential movements. Additionally, the prosthetic limb has in most cases no power source of its own to move its joints. Instead, it relies on forces transmitted through it generated by movements of body
segments as a result of contracting muscles. Further factors include the design of the prosthesis itself and the attachment method to the residual limb.

4.4 Epidemiology

TF amputation in the United Kingdom is most frequently performed because of vascular changes due to diabetes. The National Amputee Statistical Database (2007) reports that 67% of lower limb amputations in the UK are undertaken because of dysvascularity with only 9% of amputations being due to trauma and 3% due to neoplasia. The cause of amputation is age dependent with trauma accounting for 28% of amputations in the 16 – 54 age group but only 2% in the over 75 age group. Conversely, dysvascularity is the cause of amputation in 41% of the 16-54 age group but 75% in the over 75 age group. The annual number of TF amputations performed in the UK has remained relatively constant over the last nine years with the number of TF amputations performed in 2005/2006 recorded as 1761. In times of conflict, however the number of amputations grossly increases. The First World War resulted in an estimated 54,953 amputations of the lower limb in German soldiers [Fineman 1999]. This devastation to human limbs led to developments in prosthetics and novel surgical techniques being introduced.

The profile and incidence of lower limb amputees varies considerably between countries. The precise number of amputations that are performed worldwide is not known. Generally, the epidemiology of limb loss is better reported in countries with a sophisticated health system [Ephraim et al. 2003]. In 2001, the International Committee of the Red Cross (ICRC) fitted a total of 3985 prostheses in Afghanistan and 2139 in Burma. The overwhelming reason for loss of a limb was landmine trauma. There are estimated to be more than 110 million mines in over 70 countries. Limb loss is therefore likely to be a major health concern in the countries afflicted for some considerable time. The victims have a different age and economic profile than amputees in Western Europe and the United States. On average, they are younger and it takes an estimated ten years for an amputee to earn sufficient money to pay for a basic prosthesis [Walsh & Walsh 2003]. There is therefore a need for continuing need for research and development into prostheses.
4.5 Muscle surgery in TF amputation

4.5.1 Conventional TF amputation

In a TF amputation, many of the muscles crossing the hip joint are transected (see table 6.1). These include the hamstrings (semi-membranosus, semitendinosus and biceps femoris) which are extensors of the hip joint and flexors of the knee joint. The major extensor, gluteus maximus, although not cleaved, has its line of action affected by the transection of tensor fasciae lata. The principal flexor of the hip, iliopsoas is unaffected in a TF amputation with only the weak flexors, sartorius and rectus femoris, being cut. Both adductor magnus and adductor longus are severed thus diminishing considerably the power of the adductors. In contrast, the abductors remain intact with only TFL being transected. The hip rotators are minimally compromised in a transfemoral amputation. Following an amputation, the subject is therefore not only left with diminished muscle power to manoeuvre the prosthetic limb but also an imbalance in the muscle forces with, in particular, the abductors being stronger than the adductors.

The remaining muscle power is also influenced by the choice of surgical technique applied to the muscles. In order to provide an effective moment on a joint the muscle must have a firm anchorage to both the proximal and distal parts of the joint. Cleaved muscles that are ineffectively fixed will result in inadequate muscle power to propel the body forwards and hence an over reliance on the intact limb for propulsion. The two common surgical methods applied to muscles during a standard TF amputation are myodesis and myoplasty. Myodesis involves attaching the cut muscle to drill holes in the femur (see figure 4.5b). Myoplasty is a procedure whereby the fascia of the agonist muscles is attached to the fascia of the antagonist muscles. Gottschalk (1999) conducted a study investigating the difference in muscle force generation resulting from a myoplasty or myodesis. This study reported decreased femoral abduction and side lurch in twenty patients with myodesis of adductor magnus compared to a comparable number of patients in whom a myoplasty had been performed to the adductors.
A further effect that the type of muscle fixation technique may have is on muscle structure. Jaegers et al. (1995a) undertook an investigation into changes in hip muscles following a TF amputation. The measurements were made using 3-dimensional reconstructions from transverse magnetic resonance images (MRI) of the thigh and hip. The study was based on twelve TF amputees who had undergone amputations at least 2 years previously due to trauma or osteosarcoma. The investigators found between 10%-73 % atrophy in the hip muscles of the residual limb compared to the intact limb in addition to the presence of fatty degeneration. Greater atrophy was observed in the cleaved muscles than in the intact muscles, with the greatest atrophy occurring in the bi-articular muscles. For example, semitendinosus was found to have atrophied by 73% compared to 12% for adductor brevis. The investigators reported that fixation of cleaved muscles was essential in reducing atrophy and maintaining muscle functioning. A further observation made in this study was that the amount of atrophy was related to the length of the residual limb, with a shorter residual limb resulting in greater muscle atrophy.

The method of muscle surgery has significance not only for the structural and functional behaviour of the muscles but also for the bone density of the femur. Studies on bone density of the femur have reported that bone density is reduced by 10% – 15% on the amputated side compared to the intact side [Kulkarni et al. 1998; Leclercq et al. 2003]. The decreased density is the result of disuse atrophy as well as the decreased mechanical load placed on the femur by the contracting cleaved
Chapter 4. Background material to transfemoral amputation and prostheses

muscles [Jaegers et al. 1995a]. Following surgery, the position of the femur is often changed relative to the intact side with the femur in varying degrees and combinations of flexion, abduction, and external rotation. An important factor in femoral alignment has been reported to be surgical technique rather than socket shape or prosthesis alignment [Gottschalk 1990]. An altered femoral alignment will affect the amount of pelvic tilt and symmetry of gait.

4.5.2 Osseo-integrated TF amputation

Osseo-integrated prostheses represent a new development in the rehabilitation of amputees with the first surgery having been performed in the United Kingdom in 1997 [Sullivan et al. 2003]. This procedure has also been carried out in Australia, Canada, Sweden and Germany [Staubach 2001; Bränemark et al. 2001]. This type of prosthesis allows the prosthetic limb to be directly linked to the bony skeleton thus avoiding the discomfort TF amputees frequently suffer due to pressure from the socket on the skin [Hagberg et al. 2004]. The linkage system between bone and prosthesis consists of a fixture anchored into the bone and an abutment that penetrates through the skin and provides a point of attachment for the prosthesis (see figures 4.6 and 4.7).

![Figure 4.6. Schematic representation of an osseointegrated prosthesis.](image1)

![Figure 4.7. Photograph of a subject fitted with an osseointegrated prosthesis.](image2)
In the United Kingdom osseo-integrated prostheses are currently being used on subjects who have encountered problems with conventional prostheses. The eligibility for the suitability for the procedure to be undertaken is listed in subsection 6.2.1. The surgery involves two stages. During the first stage, the residual limb is opened and a titanium rod inserted into the medullary cavity of the femur. A period of rest follows during which bone growth occurs around the rod firmly anchoring it in place. The second stage of surgery involves insertion of the abutment. The muscles of the residual limb are transected perpendicular to the femur and the cut end is covered with a thin layer of skin. The transected muscles are not fixed but instead muscles are sutured to adjacent tissues.

Two mechanical features of an osseo-integrated prosthesis that distinguish it from a conventional prosthesis are firstly that during locomotion forces pass directly from the ground through the prosthetic limb along the titanium rod and into the femur. In the case of a conventional prosthesis forces pass from the socket into the muscular cuff of the residual limb and hence indirectly into the skeletal system. As a consequence of the rod being fixed in the bone, bone anchored prostheses have been reported to provide more proprioceptive information than conventional socket prostheses [Jacobs et al. 2000]. The additional proprioceptive input is probably the result of the titanium rod stimulating interosseous and possibly periosteal receptors. A second mechanical feature is that the cleaved muscles are not fixed to the femur or antagonist muscles but instead are sutured to surrounding fascia. The force acting on the residual limb when the amputee contracts the cleaved muscles will therefore be different than the force produced in a conventional residual limb.

4.5.3 Direct muscle-prosthetic link surgery

Before concluding this section, mention must be made of a novel approach taken to muscle surgery in amputees. Biesalski during the First World War developed a surgical method of connecting the musculature of the residual limb directly with the prosthesis (see figure 4.8). Pulleys were connected between canals created in the muscles and the prosthesis. The success of this procedure is not known nor has the infection rate been reported.
4.6 Effects of amputation on muscle and nerves

An above knee amputation results in severe disturbance to the structure of the muscle and its peripheral innervation. Severance of a peripheral nerve will interrupt the efferent impulses passing along the alpha and gamma motor neurones from the spinal cord and the afferent impulses being transmitted from the muscle to the spinal cord. Amputation may also destroy the innervation point of a muscle. The innervation point is generally described as being located near its mid point although variations may occur [Loeb & Gans 1986]. A high TF amputation may therefore obliterate the innervation point of the long hip muscles such as the hamstrings, adductor magnus and adductor longus. Some or all of the fibres within a motor unit may be affected. In the event of muscle fibres losing contact with the motor neurone new contacts may be established with severed motor neurones [Wu & Kaas 2000]. Additionally, intact motoneurones may make contact with the denervated muscle fibres, which may not necessarily be part of their motor unit. Some motor units may have more and different types of muscle fibres than prior to the trauma. The altered motor units should be detectable by assessing their sEMG patterns through wire electromyography. An anticipated finding would be a changed order of motor unit
recruitment. The author is not aware of any studies having been undertaken investigating changed motor unit activity in amputated muscle.

Histologically it is possible for fast-twitch muscle fibres to transform into slow-twitch fibres following electrical stimulation [Kubis et al. 2002] and slow twitch fibres to transform into fast-twitch muscle fibres after spinal cord injury [Burnham et al. 1997; Round et al. 1993]. Disruption of the peripheral innervation to a muscle following amputation may result in alteration in its microstructure and function. Changes that have been reported in reinnervated muscle fibres include disturbed sarcoplasmic Ca$^{2+}$ uptake, different neural regulation and modification of the muscle fibre type [Zhou et al. 2006]. The time interval necessary for changes in structure to occur has been found to be dependent on the fibre composition of the muscle. Soleus, a muscle with predominantly type I fibres showed an decrease of 57% in the number of muscle fibre nuclei after 10 weeks of denervation compared to a decrease of only 17% in extensor digitorum longus which has a greater preponderance of type II fibres [Schmalbruch & Lewis 2000]. A study investigating the long-term effects of denervation of extensor digitorum longus however reported that although over a two month period there was only a 3% decrease in cross-sections not containing nuclei, by seven months of denervation the decrease had risen by about 30% [Viguie et al. 1997]. The temporal consequences of denervation on muscle fibre structure are related to the clinical observation that muscles denervated for periods of six to eight months do not regain full function. Disuse atrophy of the muscle will also occur in the amputee during the immediate recovery period after the surgery. The atrophy is the result of decreased protein synthesis and increased protein degradation [Zhang et al. 2007]. Changes in muscle structure and function will affect the manner in which the action potential is propagated along the muscle fibre and hence ultimately the recorded sEMG.

Very few studies appear to have been undertaken on the electrical activity of amputated muscle. One investigation was carried out by Devetag Chalaupka and Bernardi (1999) who reported a case of spinal myoclonus in the adductors and vastus medialis in the residual limb. The EMG potentials from these muscles using needle electrodes had amplitude of 50-200 $\mu$V, an activity burst frequency of 1.3 Hz to
1.7 Hz and duration of 210ms to 480ms. The spontaneous activity was triggered by tapping the affected muscle of the residual limb. The burst of activity would spread to the same muscle on the contra-lateral side. Movement of the contra-lateral limb interrupted the spontaneous activity. Details as to whether a myoplasty or myodesis was performed were not given. Pain and phantom limb sensation preceded the onset of myoclonus. The theory proposed by Devetag Chalaupka and Bernardi (1999) was that increased afferent stimulation to the spinal cord segments from the cut muscle increased alpha motor neurone activity hence producing myoclonus in these muscles. The proposed altered synaptic activity within the spinal cord segments might then affect the contraction of the muscles on the contra-lateral side. Thiele et al. (1973) investigated the sEMG in quadriceps femoris in twelve TF male amputees. Large polyphasic action potentials were observed which were concluded to occur because of the reinnervation. O'Neill et al. (1994) measured sEMG in residual and intact upper limb muscles during a three second sustained contraction in 32 subjects with above elbow (AE) or below elbow (BE) amputations. No statistically significant spectral difference was found between the intact and cleaved muscles. This experimental result is in conflict with the changes that one would theoretically predict given the altered muscle morphology and disrupted innervation with consequential histological and physiological changes to muscle fibres as described earlier. The lack of significant spectral changes in the O'Neill study can be explained by a lack of specificity in the methodology. Firstly, the study compared different muscles (wrist flexors in BE amputees and biceps brachii, deltoid or triceps brachii in AE amputees) and used different electrode location sites. Secondly, the subjects included both male and female covering a wide age range from 9 to 73 years old. A third over generalisation was that the cause of the deficiency varied between congenital (thirteen subjects) and acquired (nineteen subjects). On visual inspection, spectral differences were apparent when subjects were viewed individually.

Afferent information from the musculoskeletal system provides feedback for the nervous system and thus modifies the signals generated [Zehr & Stein 2000]. Any change in the musculoskeletal system can therefore cause functional change in the nervous system. Functional changes in the central nervous system following
amputation have reported to occur in the thalamus and cerebral cortex. Florence et al. (2000) have found evidence of functional reorganisation of the thalamus and cortex following an upper limb amputation several years earlier in two monkeys. Roricht et al. (1999) reported functional alteration in the motor cortex of subjects who had had arm amputations many years previously. Functional reorganization is likely to lead to a change in locomotion control patterns and an altered sEMG signal in certain muscle groups during locomotion.

**4.7 Prostheses**

There are many different types of prostheses available to the TF amputee. The mass, type of material used, design of the knee and ankle joint, type of socket and positioning of the socket on the residual limb may vary as follows:

- **Mass**
  Prosthetic limbs are of variable mass with the majority of designs aiming for a lightweight structure. Selles et al. (1999) however in a review of the effect of prosthetic mass on gait reported that there was no theoretical framework to support this aim.

- **Material**
  Traditional prosthetic limbs have aluminium tubes connecting the prosthetic socket to the prosthetic foot. Deformable connectors are currently being developed that will bend slightly at heel-strike [Sukhanov et al. 2005].

- **Joints**
  The knee unit within a prosthetic limb may have a single or polycentric axis, and the movement may be mechanically, pneumatically or hydraulically controlled. Different types of prosthetic feet include the single axis foot, the multiaxis foot, the flexible forefoot foot and the energy return foot [Radcliffe 1994].

- **Sockets**
  There are two main types of sockets for transfemoral amputees. These are the older quadrilateral socket and the more recently developed ischial containment socket (see figure 4.9). Ischial containment sockets have been reported to be more successful on short fleshy unstable residual limbs whereas quadrilaterals are better for longer firmer residual limbs [Schuch & Pritham 1999]. The imbalance between the
abductors and adductors has been recognized by prosthetists and some sockets have been designed to overcome the abducted femur [Gottschalk et al. 1990]. A conventional socket for TF amputees will frequently have a narrow mediolateral profile. The reported advantage of this construction is that it will improve function of the hip abductors thereby aiding stability of the pelvis [Czerniecki 1996]. Boonstra et al. (1994) did not however report any correlation between socket design and abduction deformity.

![Types of socket](image_url)

**Figure 4.9.** Types of socket [North Western University 2007].

- **Positioning**

Positioning of the prosthesis in a position of flexion at least five degrees greater than the residual limb helps control the knee flexion moment at heel strike [Schuch & Pritham 1999].

In addition to the prostheses described above a recent development is the prosthesis incorporating a microprocessor controlled knee joint. There are two types of controlled knee prostheses, namely actively actuated and passively controlled prostheses. In the former, the angle of the knee joint is actively altered whereas in the latter the knee impedance is regulated. The Power Knee™ (Ossur, Reykjavik, Iceland) is an actively actuated knee prosthesis currently fitted to about 40 TF amputees in the United States. Although a passively controlled TF prosthesis is not able to move the knee actively thus compensating for the diminished muscle power, it does offer a number of advantages compared to the conventional prosthetic knee [Zlatnik et al. 2002]. These include increased stability at early stance by locking or damping the knee mechanism, decreasing the resistance to knee flexion during late
stance and adjusting the resistance depending on walking velocity and walking surface. Artificial sensors, which are incorporated into ‘intelligent’ prostheses, do have limitations as presented in chapter 1. Natural sensors have the potential to enhance the information provided by the artificial sensors. This will be discussed further in section 4.9.

4.8 Gait in TF amputees

4.8.1 Gait parameters

The gait of a TF amputee differs from that of an intact subject, the main differences being reduced self selected walking speed, increased pelvic obliquity, altered joint kinematics and loss of symmetry. Table 4.2 lists the differences in intact versus transfemoral amputees for various parameters.

Table 4.2. Mean and standard deviation time-distance parameters for level walking for 20 intact subject and 8 TF amputees. Source: [Bae et al. 2007].

<table>
<thead>
<tr>
<th>Time-distance parameters</th>
<th>intact subjects (N=20)</th>
<th>transfemoral amputees (N=8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gait speed (m/s)</td>
<td>1.36 (0.99)</td>
<td>0.82 (0.15)</td>
</tr>
<tr>
<td>Cadence (step/min)</td>
<td>112.08 (1.68)</td>
<td>88.23 (8.92)</td>
</tr>
<tr>
<td>Cycle duration (s)</td>
<td>1.01 (0.03)</td>
<td>1.62 (0.20)</td>
</tr>
<tr>
<td>Stride length (m)</td>
<td>1.39 (0.10)</td>
<td>1.29 (0.16)</td>
</tr>
<tr>
<td>Stance phase (%)</td>
<td>61.14 (1.67)</td>
<td>58.91 (2.72)</td>
</tr>
</tbody>
</table>

Jaegers et al. (1995b), in a kinematic study of eleven TF amputees, reported that hip extension was greater at the end of the stance phase compared to intact subjects apart from in two amputees with very short residual limbs. The same study observed that flexion of the prosthetic knee did not increase and decrease during the loading phase in the amputees. The amputees maintained extension of the knee because of the decreased stability of a loaded flexed prosthetic knee. An additional finding was increased lateral flexion of the trunk towards the stance limb. The latter feature is
associated with the pelvic obliquity patterns characteristic of TF amputee gait. The swing side hip is raised above the stance side hip, a trait known as hip-hiking [Michaud et al. 2000]. Asymmetry between the prosthetic and intact limbs has been measured for time-distance parameters, kinetic parameters and kinematic parameters [Michaud et al. 2000; Nolan et al. 2003; Jaegers et al. 1995b]. Clinically increased loading on the intact side may result in pain and early degenerative change in the lower limb joints [Nolan et al. 2003].

The loss of much of the lower limb musculature leads to overuse and altered functioning of the lower limb and trunk muscles resulting in fatigue and anaerobic consumption of energy [Graupe 1989]. Energy consumption (millilitres of O₂ consumed per kilogram of body weight per minute) during level walking for TF amputees in general has been estimated to be 40% higher than in intact subjects for a given velocity [Boonstra et al. 1994]. The majority of TF amputees have been observed to slow down their gait so that they can maintain aerobic consumption of energy [Popovic & Kalanovic 1993]. The energy cost (millilitres of O₂ consumed per kilogram of body weight per metre travelled) of the traumatic amputees alone has been calculated to differ little from age-matched controls [Waters et al. 1976].

4.8.2 sEMG activity of trunk and lower limb muscles during walking in amputees

Jaegers et al. (1996) conducted the largest study on sEMG activity in TF amputees. They investigated the sEMG of superficial hip muscles bilaterally in eleven men with unilateral TF amputations and in three controls with intact limbs. The eleven hip muscles whose activity was measured were GMAX, GMED, tensor fasciae latae (TFL), RF, sartorius, adductor longus, AM, gracilis, BF, semimembranosus and semitendinosus. In addition, activity of the erector spinae muscles was measured. The electrode position was based on resistance tests and a three dimensional reconstruction of the musculature. Activity of muscles within the socket was measured using neonatal surface electrodes. The activity was recorded during two runs of 7m with the subject walking at their own comfortable walking speed. The sEMG activity for each muscle was full wave rectified and normalised as a percentage of the maximum activity for that particular muscle during a run. The
sEMG activity was averaged over at least three strides and the eleven different muscles were recorded over four successive sessions. Jaegers et al. (1996) did not investigate the characteristics of the frequency spectrum for the individual muscles nor apply pattern analysis to the data. The inter-stride repeatability of the sEMG patterns for individual subjects was not calculated nor was the variability of sEMG patterns between subjects provided. The ensemble sEMG for the intact limb and the residual limb of an individual TF amputee for GMAX, GMED, RF, AM and BF is shown in figure 10 together with the mean ensemble patterns from three intact subjects.

![Figure 4.10. Ensemble sEMG amplitude for 5 hip muscles in a TF amputee and intact subjects (n=3) during level walking at comfortable walking speed normalised to maximum per individual run and averaged over a minimum of 3 cycles per individual. Modified from Jaegers et al (1996)](image-url)
Jaegers et al. reported that the following conclusions about the mean activity pattern of TF amputees could be drawn when all eleven amputee patterns were observed:

**RF**
The intact limbs displayed two phases of activity during the gait cycle. The first occurred at the beginning of stance (0% - 25%) and the second at the end of stance and beginning of swing (45% - 80%). In contrast RF was active in the residual limb only during the first 30% - 35%. Amputees with long residual limbs additionally exhibited increased sEMG amplitude at the end of stance and beginning of swing. Short residual limbs displayed continuous activity on the amputated side.

**GMAX**
These muscles were active in the intact subjects just before heel strike and continued into early stance (0%-15%). In the amputees with a short residual limb, these muscles were active for a longer period, up to 40% of the cycle and throughout the stride in those subjects in whom the iliotibial tract was not fixed.

**BF**
In both limbs of the amputees and in the intact subject BF was active at the end of swing until the early stance phase. In two subjects with very short residual limbs BF was active throughout the cycle.

**GMED**
GMED exhibited activity in the intact subjects from 0-25% of the cycle. In the amputees this muscle was active for longer bilaterally (up to 53% of the cycle). In short residual limb amputees GMED was active on the intact side throughout the stride.

**AM**
A large variation in activity of the adductors was observed in the intact subjects. These muscles displayed biphasic patterns with the first phase of activity occurring in early stance (5%-30%) and the second during late stance/swing (50%-75/90%). The amputees displayed a similar pattern of activity as the controls but had a greater variation in activity of the intact side depending on residual limb length. On the amputated side, the second phase of activity remained active throughout the swing phase.
The aim of the study by Jaegers et al. (1996) was primarily to record the sEMG amplitude of individual hip muscles in the intact and residual limb of TF amputees and compare them with the patterns recorded in intact subjects. Two further studies assessing lower limb sEMG activity in TF amputees were conducted by Peeraer et al. (1990) and Jin et al. (2000). The aims of these investigations were to assess whether sEMG could determine terrain. Peeraer et al. (1990) recorded the sEMG of six muscles (RF, GMAX, GMED, adductor longus, TFL and the 'hamstring' muscles) in a TF amputee whilst the subject walked uphill, downhill and on level ground. Electrodes were inserted into the socket although the method of determination of location of the electrodes was not described. Normalisation of the sEMG was performed by averaging four consecutive maxima for each muscle prior to the recording. The sEMG linear envelope was calculated using a 50Hz smoothing filter. The subject was tested on a 5m long level walkway and a 6m ramp. The conclusion was that it was possible to determine slope incline using parameters from at least three muscles (GMAX, GMED and TFL) in addition to the ground reaction force. This conclusion was based on visual inspection of the sEMG patterns and no level of accuracy was offered. The type of prosthesis influenced the amount of muscular activity with the hydraulic system greatly increasing TFL activity and to a lesser extent gluteus medius. As in the Jaegers study, only the amplitude of the sEMG signal was assessed and not the frequency spectrum. Additionally the variability between gait cycles of sEMG patterns for the subject was not assessed.

The study by Jin et al (2000) measured sEMG from vastus lateralis, vastus medialis, RF, TFL, adductor longus, BF, semimembranosus and semitendinosus in TF amputees and non-amputees. The number of subjects participating was not recorded. Recordings were taken as the subjects walked upstairs and downstairs in addition to walking uphill, downhill and on the level. It is unclear how many gait cycles were analysed. The parameters derived from the sEMG data were the integral of the differential, moving average (MAV), median frequency (MDF) and mean frequency (MF). The conclusion drawn by Jin et al. (2000) was that it was possible to identify stair and incline walking using a selection of parameters extracted from the semimembranosus sEMG. Therefore, unlike the Peeraer study, only data from a
single muscle was necessary to identify terrain.

To conclude this section, the limited studies indicate that TF amputees have a cyclic pattern of sEMG activity in the residual limb muscles. The pattern of activity is broadly similar to that present in intact limbs and is dependent on the length of the residual limb. However, the repeatability of these signals has not been assessed in sEMG studies on TF amputees. Good repeatability is essential if sEMG from a single muscle is to be considered as a natural sensor. The two studies undertaken by Peeraer et al. (1990) and Jin et al. (2000) conclude that terrain can be identified from sEMG parameters. Although studies have not been conducted to identify phases of gait it is reasonable to assume that sEMG can be used to identify gait phases. The challenge is to extract the appropriate features from the sEMG and apply the necessary pattern analysis techniques. Types of features and pattern analysis will be discussed in chapter 5.

4.9 Natural sensors

The type of sensor used to record the signal generated by human tissue is referred to as a natural sensor as opposed to the ‘artificial’ sensors that are currently used in prosthetic lower limbs. The advantages of natural sensors is that they are well integrated within the human tissue and have evolved over millions of years to respond to changes in the external and internal milieu [Chan et al. 2000]. In addition to the greater range of information that the natural sensor carries, it also possesses a different temporal quality. The natural sensor records signals prior to the movement having occurred whereas the artificial sensor records the ensuing movement, force or pressure at the joint. Natural sensors additionally may have the potential of predicting patterns of movement due to the electro-mechanical delay (EMD). The delay is the consequence of time taken for development of the signal, time for force to develop within the muscle and time for movement of the joint to occur. The EMD for sEMG has been reported to range from 7-160ms [Muraoka et al. 2004; Loram et al. 2005]. This variation in delay times reflects the fact that EMD is the consequence of a number of different factors involving physiological factors, mechanical factors and signal processing methodology. This will be discussed further in the next section.
There are various methods of recording neural signals. Measurement of the action potentials present in a peripheral nerve, spinal cord or cerebral cortex represent direct methods of obtaining neuronal activity data. Jia et al. (2007) have investigated the feasibility of using neural signals recorded from an amputated upper limb to control a prosthetic hand. This study reported that the subject was able to control finger extension. However implanting an electrode into the central nervous system or a cuff electrode around a peripheral nerve is invasive. Indirect non-invasive measurements of neuronal activity involve recording the sEMG of a muscle. The sEMG reflects the underlying MUAPs, which in turn is related to the neural signals transmitted along the alpha motor neurones to the motor units. Frequency, scalar and amplitude parameters can be extracted from a simple sEMG trace. The only other surface signal that can be recorded from muscles in a non-invasive manner is the mechanomyogram (MMG). Upper limb prostheses have been developed which utilize MMGs as natural sensors [Silva et al. 2005]. However compared to sEMG, research into MMG is in its infancy and to date no commercial MMG controlled prostheses have been developed. The electroencephalogram (EEG) represents another non-invasive method to assess movement. The EEG has been used to assess muscle fatigue [Abdul-latif et al. 2004], navigation in a virtual environment [Pfurtscheller et al. 2006] and speech [Guan et al. 2004]. There has been a limited amount of research investigating cortical electrical activity and locomotion in cats [Mushahwar et al. 2006]. The phases of locomotion have not as yet been determined from EEG. Whilst EEG may well be the optimal sensor to control a prosthetic limb, research is in its early days. The study has therefore focused on sEMG as a natural sensor.

The sEMG of the hip joint muscles in intact subjects and in TF amputees has been recorded by a number of researchers as described in this chapter. The muscles display a cyclical pattern of activity during locomotion with varying levels of repeatability (see subsection 3.4.3). Jaegers et al. (1996) have undertaken the only significant analysis investigating sEMG in conventional TF amputees (see subsection 4.8.2). Smaller studies recording sEMG in TF amputees include those done by
Chapter 4. Background material to transfemoral amputation and prostheses

Peeraer et al. (1990) and by Jin et al. (2000). No reports have yet been published on sEMG in osseointegrated TF amputees.

The sEMG signal is highly complex, composed of many superimposed MUAPs with varying amplitudes and having a broad range of frequencies. Potentially, applying the appropriate signal analysis techniques, a large number of parameters can be extracted from a single sEMG. These parameters may reflect different gait events. Further information can be obtained by analysing the sEMG from a number of different muscles since the CNS operates on groups of muscles in order to achieve the desired movement.

During locomotion, humans are constantly detecting potential obstacles to gait through visual and auditory input and adjusting limb impedance accordingly [Prochazka 1993]. If a new motor task is encountered during gait, for example walking over a slippery surface, the neural control system will cause multiple muscle contractions. After familiarisation with the task, the muscles contracted will be fewer and specific to the task. The sEMG paradigm will therefore evolve over time as the CNS adapts to the required movement.

The disadvantages of utilising sEMG are many and include the requirement of multiple electrodes, low SNR as a result of skin movement relative to the muscle, incorrect positioning of surface electrodes, a low pattern recognition rate and long signal processing time [Chan et al. 2000]. In addition, in amputees there may be considerable fat accumulation around the superficial muscle to be monitored resulting in the need for substantial amplification [Peeraer et al. 1990]. Each individual will have a different output for the same muscle for a given function due to variables such as the differing thickness and composition of tissue between the electrode and muscle, different microstructure of the muscle, different temperature and different skin surface. The appeal of natural sensors is further diminished when one considers the relative simplicity of artificial sensors. Force transducers and magneto-resistive transducers produce signals that can be readily processed and calibrated and their output does not suffer from excessive noise. The sensors are incorporated into the prostheses in fixed locations and therefore do not display the considerable variability as is the case with natural sensors.

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However, a key motivating factor for harnessing the signals from natural sensors is that the information gained is different to that of artificial sensors. The sEMG is an indicator of the amplitude and frequencies of numerous MUAPs. These in turn are a reflection of the impulses being transmitted along the motor neurones, which are controlled by spinal neurones. The level of activity of the spinal neurones is influenced by signals descending from supraspinal nuclei, impulses travelling into the spinal cord from the periphery and from the self-generating postulated CPG neurones. The sEMG can therefore be regarded as a highly processed signal, influenced by both internal volitional input and external environmental input. By contrast, the artificial sensors are limited in information conveying only the current force being transmitted and the kinematics of the prosthetic limb.

4.10 Myoprocessors

Researchers have demonstrated that sEMG can be used to recognise different types and phases of movement. Different types of classifications have been made using parameters extracted from sEMG. The classifications include categorising specific body segment movements, determining patterns of movement, and phase identification within a cyclic motion. Most studies aiming to identify segment movement from sEMG have been conducted on the upper limb [Chan et al. 2000; Englehart & Hudgins 2003; Englehart et al. 2001; Englehart et al. 1999; Huang and Chiang 2000; Hudgins et al. 1993; Kuruganti et al. 1995; Kwon et al. 1996]. A limited number of studies have investigated the lower limb. These studies and the techniques used for classification will be discussed in Chapter 5.

The function of sEMG as an effective classifier has therefore permitted it to be incorporated as a myoprocessor in upper limb prostheses to select and modulate movements of multifunctional wrist joints [Parker et al. 2005]. Additionally sEMG signals from the trunk have been used for controlling functional electrical stimulation of the lower limb in paraplegics [Graupe 1989; Graupe 1995].

Myoprocessors have not however been successfully built-in to lower limb prostheses. The commercially available microprocessor controlled prostheses such as the Otto Bock C-leg use artificial sensors. The disparity in utilisation of the myoprocessor in
upper limbs compared to lower limbs is related to the function of the myoprocessor. In the arm the subject intentionally contracts a muscle which is detected by surface electrodes. Following classification of the signal a movement of the prosthetic limb is selected. However, the classifier in the lower limb prosthesis is required to select a gait phase from rapidly changing signals. Additional noise may be added to the signal arising from movements between the electrodes and the socket. A large number of muscles are involved in locomotion acting as prime movers, antagonists or synergists. Although kinematic patterns are highly repeatable, the underlying pattern of activity of individual muscles may be highly variable. As Winter (1987) stated 'it is quite possible to achieve the same movement, as measured kinematically, from a score of different combinations of muscle patterns'. A combination of a complex noisy signal with poor repeatability between gait cycles for individual muscles makes accurate phase identification a challenge.

Recent developments that make the use of natural sensors more attractive are the development of sophisticated signal processing and pattern classification techniques. The latter include artificial neural networks (ANNs) and fuzzy logic models. ANNs allow patterns in signals to be detected, which might not have been using conventional methods, and fuzzy logic makes allowances for the variability in sEMG data because of both noise and the individual variations due to stride. Additionally the development of the osseo-integrated prosthesis allows the user to have a bare residual limb thus reducing the noise problems associated with the prosthetic socket rubbing against the surface electrodes.

Jin et al. (2000) describes how a myoprocessor could be used to identify whether the subject is going up or down a slope, upstairs or downstairs and their current walking speed. The design is the same as the commercially available microprocessor controlled prosthesis with the additional input of sEMG parameters into the classifier. Following selection of a mode a signal would be transmitted to drivers controlling stepper motors to hydraulic and / or pneumatic piston and cylinder assemblies. In this way the resistance to flexion / extension of a prosthetic knee joint for a particular terrain or speed could be adjusted. Adjustment of the prosthetic knee resistance according to gait phase would be similar to mode adjustment but input from the
sEMG of several muscles would be necessary. The number of phases to be identified must be carefully considered since as the number of functions to be classified increases so does the complexity of the signal processing and the classification techniques [Pattichis et al. 1999].

A critical aspect of employing the myoprocessor in a lower limb prosthesis is that all calculations have to be performed in real-time. Whereas a maximum delay of 300ms might be acceptable for controlling a prosthetic upper limb [Englehart & Hudgins 2003], this is not the case for the lower limb. Different events are occurring in rapid succession so it is essential that the signals be processed, the classification made and adjustments to knee resistance undertaken in a short period of time. The time taken from heel strike to full weight bearing is only approximately 120ms. During this period, it is essential that there is resistance to knee flexion preventing the knee from flexing excessively. Adjustments to the knee have to be made as soon as possible within this time period of 120ms. Tang et al. (1998) reported that sEMG activity of anterior and posterior thigh muscles and leg muscles when contracting in response to forward movement of the floor were of relatively long duration, from 70ms to 200ms, and high amplitude of up to nine times the normal activity. These perturbations in sEMG occurred from 90ms to 140ms after the displacement. This suggests that the time it takes for the MUAPs to react to an external physical event is of the order of 100ms.

4.11 Conclusion

There have been considerable developments in prosthetics from the early wooden 'peg leg' designs to the current 'intelligent' models that are able to detect phases of the gait cycle through artificial sensors. However, from the user perspective the prosthesis could be further improved to minimise the energy expended whilst moving, improve control over the prosthesis, decrease the discomfort and improve the aesthetics. One way forwards is to investigate incorporating natural sensors into controlling the knee joint of the prosthesis. The type of natural sensor that has been selected for further consideration is sEMG since this signal has been extensively investigated in intact subjects, it is relatively simple to record and it is not invasive. The next chapter will report on signal analysis techniques applied to sEMG.
Chapter 5
Signal Analysis

5.1 Introduction
The sEMG is the cumulative sum of the action potentials from many different motor units that lie within the detection range of the electrodes. The contribution each motor unit makes to the sEMG will vary depending on such factors as the size and number of the muscle fibres within the motor unit, the distance between the motor unit and electrode, the histology of the intervening tissue and the rate of firing. The firing rate of each motor unit will change in a semi-random manner. The resultant electrical activity detected at the surface is therefore stochastic in nature. Both the amplitude and the frequency dependent properties of the MUAPs will be considerably attenuated and modulated at the surface of the skin.

In addition to the signal arising from the MUAPs, there will be noise and interference components which have been described in section 2.7. Adequate processing of the sEMG must therefore be performed before inferences about muscle activity patterns can be made. Some processing will take place within the hardware as described in chapter 2. However, a significant amount of processing must be undertaken externally using software algorithms. The sequence of processes applied to the signal picked up by the surface electrodes in order to classify patterns of movement incorporates four different stages. Amplification, hardware filtering and digitisation have already been discussed in section 2.6. Software processing includes further filtering, whitening, normalisation and ensemble averaging of time-dependent parameters, feature reduction and application of a pattern classifier. These stages are illustrated in figure 5.1.
Chapter 5. Signal Analysis

Figure 5.1. Flow diagram illustrating some common processes involved in analysis of a sEMG signals.

5.2 Stage 1 - Software digitisation and whitening

5.2.1 Software processing

This stage involves both hardware and software processing and prepares the signal for parameter extraction. Although the differential amplifier and the hardware filters will considerably reduce the noise in the sEMG output, there will still be some level of noise present. Further filtering by the application of software algorithms can eliminate much of the remaining noise. A further processing stage of whitening may be applied to the signal prior to feature extraction.

- Filters

Noise present in the sEMG can be divided into different types of signal with different characteristics depending on the source producing it as discussed in the previous chapter. The employment of a number of different filters may therefore be necessary
to reduce the total noise. The filters should be selected so that they result in minimal distortion of the true signal.

The three main types of noise are those resulting from movement, thermal noise and power line interference. Removal of the low frequency motion artefact can be achieved by applying a high pass filter, using a moving median or mean procedure or by the application of a wavelet filtering procedure. Conforto et al. (1999) reported that the best method for removing motion artefact without distorting the signal and retaining accurate muscle activation detection was using the wavelet method. High pass filters were reported to yield the poorest results. Thermal noise composed of higher frequencies can be reduced by a low pass filter. Power line interference will result in noise being produced at 50 Hz and multiples thereof. The interference can be removed using a notch filter but a proportion of the power of the signal is lost. A better method is to use an adaptive filter, which will retain a proportion of the 50 Hz signal [Clancy et al. 2001]. The proportion of noise will vary during a dynamic contraction with the muscle force modulating the higher frequency noise signal. In a rapidly changing sEMG bias is the main source of the estimation error. In contrast, in a ramp-like contraction where the contraction force steadily increases, variance is the main change [Park & Meek 1995]. Application of a time varying filter such as a Wiener adaptive filter may be appropriate to a rapidly changing dynamic signal.

The sEMG is a stochastic process, which should theoretically have a mean about zero. In practice there is likely to be a small direct current (DC) component [Loeb & Gans 1986]. This results from the ionic composition of the outer layers of the skin (see section 2.8). Since the skin PD varies over the surface of the body, the differential amplifier will not eliminate the DC component. The DC bias can be removed by applying a high pass filter or subtracting the mean value of the signal from each data point.

- **Whitening**

The recorded sEMG is sampled at minimally twice the Nyquist frequency resulting in contiguous samples being related which may affect statistical analysis. Whitening or decorrelation of the signal orthogonalises the data resulting in independent contiguous samples and an increased statistical bandwidth. Whitening however, only
reduces the variance part of the MSE which is present due to the random nature of the signal. The whitening process involves a number of stages. Firstly, the PSD of the sEMG is estimated. The shape of the whitening filter is the inverse of the square root of true PSD. The whitening filter is then applied to the sEMG. Clancy *et al.* (2002) describe three methods in which the whitening filter can be applied depending on the nature of the sEMG.

In a weak contraction, noise forms a greater proportion of signal than in a strong signal so becomes an important factor in shaping the whitening filter. The weak signal is therefore less effectively filtered by a conventional whitening filter [St-Amant *et al.* 1998]. A solution to filtering a weak signal is to use an adaptive whitening filter formed by applying a fixed whitening filter, an adaptive Wiener filter and an adaptive gain correction. The Wiener filter adapts depending on the sEMG amplitude. At high amplitude the Wiener filter is an all-pass filter whereas at low frequencies it becomes increasingly a low pass filter. Clancy and Farrow (2000) reported that estimates in tracking a signal at 0.25 Hz were improved by applying a whitening filter. This study involved fourteen subjects isometrically contracting their elbow flexors or extensors in an attempt to match a pursuit signal with a fluctuating 0.25 Hz target signal. The pursuit signal was either a single channel or multichannel sEMG signal, either unwhitened or whitened or the dynamometer signal. The subject was not informed as to the type of pursuit signal. The standard deviation tracking error was reduced for the multichannel whitened signal, being 6.35% (standard deviation (SD) 2.18%) compared to 7.09% (SD 2.09%) for the multichannel unwhitened. However, the tracking error was still greater than when the pursuit signal was from the dynamometer which was only 4.35% (sd 1.86%).

5.3 Stage 2 – Parameter selection

5.3.1 Introduction

Stage 1 prepares the signal by reducing unwanted components, amplifying it and increasing the bandwidth by whitening. The signal is thus ready for the next stage which involves extracting parameters which reflect the underlying activity of the motor units. The parameters selected depend on the type of muscle contraction (e.g. isometric, eccentric, concentric) since the statistical characteristics of an sEMG are dependent on the type of muscle contraction. The type of muscle contraction is
determined by the position of the body, the number of muscles contracting, the type and number of motor units activated and the firing rates of the motor units.

In an isometric, constant force contraction the sEMG signal is stochastic with Gaussian or Laplacian distribution of amplitudes and is stationary (mean, variance and autocorrelation constant) over a period of 0.5-2 s [Knaflitz & Bonato 1999]. However, slow non-stationaries may be present within a signal due to muscle fatigue. Factors affecting onset of fatigue include strength of contraction, type of muscle fibres, the presence of pathology and any musculoskeletal abnormality. In a non-isometric varying force contraction, the sEMG is a stochastic non-stationary signal.

The majority of the parameters that have been selected to investigate the sEMG during locomotion fall into five categories. They are time dependent, linear regressive, quadratic time frequency and parameters derived from the application of Fourier and wavelet transforms. Time dependent, linear regressive and Fourier analysis transforms are applicable to stationary signals but less to non-stationary.

Using inappropriate features may reduce pattern recognition. Chan et al. (2000) found for example that utilizing the slope sign change parameter resulted in some cases worsening of the classification results. Within a study different features may be used to describe various aspects of a movement. Jin et al. (2000) reported that the speed of walking, steps, level or sloping ground and uphill/downhill could be identified by mean frequency, integral of the differential, integral of absolute value and median frequency respectively. The following sections introduce the different types of parameters.

5.3.2 Time-domain parameters
Time-domain parameters include the full wave rectified value, mean absolute value (MAV), root mean square (RMS), number of zero crossings, integrated value and Willison amplitude. The latter parameter is the number of counts in the sEMG amplitude that exceeds a predefined threshold [Zardoshti-Kermani et al. 1995]. Time dependent parameters recommended by the SENIAM report includes both the MAV and the RMS [Freriks & Hermens 2000]. These two parameters will therefore be discussed in more detail. They are mathematically defined as follows:
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\[ MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \]  \hspace{1cm} (5.1)

\[ RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2} \]  \hspace{1cm} (5.2)

where: \( x_i \) is the value of sEMG at sample \( i \)

\( N \) is the number of samples

RMS is related to the mean power and the MAV to the area under the signal. The normalized root mean square is a function of the number of motor units firing, the frequency of firing, the area of the motor unit, the duration of the motor unit and the velocity of the signal [LeVeau & Andersson 1992].

A difference has been reported between these two parameters with RMS having higher values than MAV with both the noise and the true signal increased but no difference in the SNR [Freriks & Hermens 2000]. In contrast, studies by St-Amant et al. (1998) and Clancy et al. (2001) reported that the utilisation of MAV parameters yielded a higher SNR than RMS parameters. Theoretically RMS has been stated to be a better choice of parameter if the signal is Gaussian [Hogan & Mann 1980] and MAV better if the signal is Laplacian [Clancy & Hogan 1999]. The SNR is superior by 6.4% if the signal is Gaussian and a RMS processor is used compared to a MAV processor. However, if the signal is modelled as Laplacian, RMS processing is inferior by about 10.6% compared to MAV processing. Figure 5.2 illustrates the probability density estimates for a constant force, constant length contraction for biceps and triceps. Superimposed on the density curves are the Laplacian distribution curve and the Gaussian distribution curve. The experimental density curves lie between these two distributions although closer to the Gaussian distribution than the Laplacian. However, despite the signal being closer to the Gaussian distribution, the SNR was increased when the sEMG amplitude was processed using MAV [Clancy & Hogan 1999].
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Figure 5.2. Normalized experimental probability density estimates for constant-force, constant-angle, nonfatiguing, 50% MVC contractions. Experimental densities are the average of 266 recordings. Shaded regions indicate one standard deviation above and below the average. (a) flexion contractions (biceps muscles) (b) extension contractions (triceps muscles). [Clancy & Hogan (1999)]

A low pass filter is generally applied to the MAV to create a smooth linear envelope. The frequency of the low pass filter applied to produce a linear envelope varies. Winter (1990) recommended low pass frequencies of 3-6 Hz which represents window lengths of 166-333ms. Merletti (1999) reported that a filter with a time constant higher than 25ms, or a frequency below 6 Hz, produced delays and was not appropriate when seeking to define definite events. The SENIAM report [Freriks & Hermens 2000] suggests using a window length of 0.25s to 2s for sustained contractions and 25ms to 80ms for dynamic contractions. These recommended lengths for dynamic contractions with corresponding frequencies of about 12-40 Hz are sufficiently high to allow specific events to be determined and result in a low delay time. An algorithm has been developed by Clancy et al. (2001) to estimate the optimal window length, N, for a non-causal (midpoint moving average) signal s:

\[ N_{\text{noncausal}} = f \left( \frac{72}{g} \right)^{\frac{1}{5}} \left( \frac{S^2_{\text{Ave}}}{\sigma^2_{\text{Ave}}} \right)^{\frac{1}{5}} \]  

(5.3)
where:  
\[ f = \text{sampling frequency} \]
\[ s_{\text{av}}^2 \text{ is the average value of the square of the EMG amplitude} \]
\[ g \text{ is a constant dependent on the number of degrees of freedom, the number of channels and the type of detector} \]
\[ N_{\text{noncausal}} \text{ is the window length (number of samples)} \]

In a rapidly changing signal better results may be obtained by applying a varying length window [Clancy 1999].

The SNR is related to the length in seconds of the smoothing window, \( T \), the number of channels, \( L \), and the bandwidth \( B_s \) of the signal by the following relationship [St-Amant et al. 1998]:
\[
SNR = \sqrt{2.2 B_s L T}. \tag{5.4}
\]

A measure of this noise is provided by the mean square error (MSE) of the signal. The MSE of a signal is the sum of the variance and bias squared. The variance is due to the stochastic nature of the signal causing random fluctuations whereas the bias is the error in calculating the actual change in the signal. The variance \( \sigma^2 \) of a signal (see section 2.3.5) is related to the statistical bandwidth \( B_s \), number of EMG channels recorded on specific a muscle \( L \) and the length of the smoothing window \( T \) by the following algorithm [Clancy 1999]:
\[
\sigma^2(t) = \frac{f_s s^2(t)}{2 N g(B_s, L, D)} \tag{5.5}
\]

where  
\[ s(t) \text{ is the true amplitude value} \]
\[ N \text{ is the length of window in samples} \]
\[ g \text{ is a constant (dependent on statistical bandwidth } B_s, \text{ number of EMG channels } L \text{ and parameter selected } D \text{ (MAV or RMS))} \]
\[ f \text{ is the sampling frequency.} \]

The bias error is more complicated and involves derivatives of the amplitude value. Increasing the length of the smoothing window decreases the variance error but increases the bias error.

Clinically, time dependent features are most commonly used since the processing is fast and relatively simple. The variations of these features during a muscle contraction may be represented as linear envelopes or as 'on-off' lines (see figure 2.6).
There may be considerable variation in parameter values between individuals for the same muscle activity making inter-subject and intra-subject comparisons of values problematic. In order to overcome these variations, normalisation is frequently performed. Investigators have used several normalisation techniques which include the following:

- Normalisation to MVC of the muscle [Sutherland 2001].
- Normalisation to maximum walking signal [White and McNair 2002].
- Normalisation to mean of muscle activity [Olree and Vaughan 1995].
- Normalisation to contraction against a fixed weight [Ounpuu and Winter 1989].

The first method involves the subject performing an MVC. However, a MVC is dependent on the anatomical positioning of the body, the direction of resistance applied, physiological properties of the muscle and psychological state of the subject. If the MVC is not correctly controlled, the values may be as much as 20% to 30% less than those obtained following the recommended procedure [Merletti 1999]. All four normalisation methods are linear. However, the factors affecting the amplitude sEMG between individuals are not linear. Distortions of waveform may result from normalisation.

Yang and Winter (1982) investigated four different types of normalisation techniques applied to full wave rectified low pass filtered sEMG recorded from five lower limb muscles during level walking. They observed that the normalisation procedure selected affected the repeatability as determined by the CV. The best repeatability was obtained from normalising to ensemble maximum or to the mean EMG over the stride. The mean CV for the sEMG of the five lower limb muscles recorded was 36% when normalised to the maximum sEMG over the stride compared to a CV of 80% when the sEMG was normalised to 50% MVC. Therefore one can conclude that normalisation of the time dependent parameters is essential and the most acceptable method is normalisation to the maximum or mean over the stride.

5.3.3 Time-frequency / scalar parameters

Time-domain parameters are derived from the amplitude of the signal which is the sum of the individual MUAPs. Analysis of time dependent parameters does not yield any information on the types, numbers or firing rates of motor units involved in the production of the sEMG. This may not be significant in the case of a low force
isometric contraction. However, in the case of a force varying dynamic contraction important information may be missed. Time frequency representations offer more information on the characteristics of the signal and possible links with the underlying physiology. Von Tscharner and Goepfert (2003) found time-frequency changes occurred prior to amplitude changes. Several studies have extrapolated details of the muscle fibre type composition from the time-frequency parameters [Kupa et al. 1995; Zwarts & Stegeman 2003]. Time-frequency parameters can be derived from the raw sEMG signal using a variety of techniques which include the fast Fourier transform (FFT), short-time Fourier transform (STFT), Choi-Williams distribution (CWD), wavelet transform (WT) and the wavelet packet transform (WPT). 

- **Fourier transform**

Application of Fourier transforms is one of the simplest methods of time-frequency analysis. However since the sEMG is sampled at a particular frequency and therefore consists of discrete data points the continuous Fourier transform cannot be used for analysis. Instead the discrete-time Fourier transform (DFT) or FFT must be applied. The FFT and DFT however produce outcomes that are different to the continuous Fourier transform as a result of aliasing (see section 2.3.4), leakage and the ‘picket fence’ effect [Denbigh 1998]. Windowing in the time domain introduces false ripple known as leakage. Instead of using a rectangular window function, a window function with lower side-lobes such as a Hamming or von Hann window can be used. The addition of zeros to the data set, a procedure known as zero-padding, can remove the ‘picket fence’ effect. The resolution is however the same. Welch’s method is a special application of the FFT to a stationary signal. The signal is divided into several sections with some overlap. Each section is windowed and the FFT is applied to the signal sections. The periodograms for all of the sections are averaged.

The sEMG from muscles that have changing length and varying forces of contraction are not stationary signals therefore the PSD function from such signals does not correspond to the Fourier transform of its autocorrelation function [Bonato et al. 1996]. One commonly applied method of analysing the frequency content of a non-stationary signal is by application of the STFT. FFT is used on segments of the signal $x(t)$ to obtain the periodograms for different times. The energy (magnitude squared modulus of STFT) of the signal in time and space is represented by the
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spectrogram. Figure 5.3 illustrates a spectrogram for the sEMG recorded from adductor magnus for a subject walking at a comfortable walking speed. The changes in the intensity of frequency can be observed from the spectrogram. However, both the temporal and frequency resolution are poor. The frequency resolution is equal to the reciprocal of the duration of the segment. Therefore for a 64ms segment the resolution is approximately 16 Hz.

In order to achieve better resolution of frequency other techniques must be applied. Quadratic time-frequency representations (QTFRs) and wavelet analysis are two techniques suitable for non-stationary signals which resolve both the frequency and temporal components.

- **Quadratic time frequency representations**

  QTFRs represent the time-frequency energy distribution of a signal. QTFRs that have been applied to sEMG data include the Wigner-Ville transform (WVT) and the CWD [Bonato et al. 1996; Bonato et al. 2001] both of which belong to the Cohen class of transforms. Cohen transforms are particularly suited to time-frequency representations of non-stationary stochastic processes.

  The WVT is the most well known and can be defined time for $t$ and frequency $\omega$ for a sEMG signal $x(t)$ as:

  $$WV(t,\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} x(t/2)x^*(t/2)e^{-j\omega \tau} d\tau$$  \hspace{1cm} (5.6)

  where $x^*$ is the complex conjugate of $x(t)$

  $\tau$ is the time interval
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The WVT however is not best suited for processing multiple frequency signals such as sEMG because of interference terms generated. A more appropriate distribution is the CWD. The CWD has the property of being time and frequency shift invariant which means that if a signal is shifted in time or frequency its time-frequency representation will also be shifted by the same amount [Hlawatsch & Boudreaux-Bartels 1992]. This property makes the CWD 'extremely desirable for correlating the signal characteristics to phenomena that take place in the system that generates it' [Bonato et al. 1996].

The CWD is defined at time $t$ and frequency $\frac{f}{f}$ for a sEMG signal $x(t)$ as:

$$CWD(t, f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x(t + \tau/2)x^*(t' - \tau/2)g(\theta, \tau)e^{-j2\pi \theta(t-t')}e^{-j2\pi f\tau} \, d\theta \, d\tau$$  (5.7)

where $g(\theta) = e^{-\theta^2}$

$x^*(t)$ is the complex conjugate of $x(t)$

$\theta$ is the frequency-lag

$\tau$ is the time-lag

$\tau'$ is the auxiliary variable

The value of sigma in the algorithm is subjectively chosen depending on the signal. The higher the value of sigma the better the resolution but the poorer the interference term suppression [Karlsson et al. 2000]. At high values of sigma the CWD effectively becomes the WVT. An adaptive Choi-Williams distribution (ACWD) algorithm has been developed by Gomes (1999) that uses a time varying sigma. The value of sigma is calculated such that entropy is minimised.

Bonato et al. (2001) and Knaflitz et al. (1999) have applied Cohen class time-frequency transforms to sEMG to calculate the instantaneous median and mean frequencies. Bonato et al. (2001) reported that the CWD resulted in a smaller estimation error compared to the Born-Jordan and WVD. Although quadratic time frequency representation provides very good frequency resolution they are too demanding in computer time to be used in real time. A comprehensive discussion of quadratic time-frequency representations is provided by Hlawatsch and Boudreaux-Bartels (1992).
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- **Wavelet transforms**

An increasing number of studies are using WTs to analyse sEMG. WTs provide reasonable time-frequency resolution and are computationally less demanding in time than QTFRs. The basic concept of WT is that a signal can be represented as a linear combination of wavelet transforms obtained by dilating and shifting a mother wavelet. The wavelet transform $T(a,b)$ is a convolution of the signal $x(t)$ with the mother wavelet $\psi(t)$:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t-b}{a} \right) dt$$  \hspace{1cm} (5.9)

where $a$ is the dilation parameter

$b$ is the translation parameter.

$\psi^*$ is the complex conjugate of the wavelet transform

The mother wavelet must satisfy 3 criteria [Addison 2002] as follows:

i. The wavelet must have finite energy

$$E = \int_{0}^{\infty} |\psi(t)|^2 dt < \infty$$  \hspace{1cm} (5.10)

where $\psi(t)$ is the wavelet function.

ii. The wavelet must have no zero frequency component

$$C_s = \int_{0}^{\infty} \left| \hat{\psi}(f) \right|^2 df < \infty$$  \hspace{1cm} (5.11)

where $C_s$ is known as the admissibility constant dependent on the wavelet $g$

$\hat{\psi}$ is the Fourier transform of $\psi(t)$.

iii. In the case of complex wavelets the Fourier transform must be real and not present for negative frequencies.

![Figure 5.4. Four different types of wavelets (a) Mexican hat 2 wavelet. (b) Morlet wavelet (real). (c) Daubechies 4 wavelet. (d) Symlet 4 wavelet](image)

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Many different types of mother wavelets are available for analysis. Complex Gaussian, Mexican hat, Daubechies, Symlets, Coiflets, Morlets and non-linearly scaled wavelets are some of the wavelets that have been applied to sEMG [Bertrand et al. 1994, De Stefano & Allen 2003; Laterza & Olmo 1997; Panagiotacopulos et al. 1998; von Tscharner 2000]. Figure 5.4 illustrates four types of these wavelets.

There is currently no consensus as to which type of wavelet is most appropriate for sEMG analysis. Laterza and Olmo (1997) compared analysis of sEMG signals with a Mexican hat wavelet to a Morlet wavelet. They concluded that the former wavelet achieved better decomposition of the signal particularly in the presence of noise. The explanation provided was that the Mexican wavelet bears a closer resemblance to the MUAP (see figure 2.1). However, whilst the shape of the MUAP might be significant with regard to wire or multi-array electrode EMG, it is likely to be less so in the case of sEMG. This is because the individual patterns of the MUAPs are distorted by filtering effect of the soft tissue, the added noise and the interference of the individual MUAPs (see chapter 2).

Complex wavelets hold the advantage over wavelets consisting only of real numbers in that they allow separation of phase and amplitude. The Morlet wavelet is an example of a complex wavelet and its waveform, \( \psi(t) \), is represented in the simple form [Addison 2002] by:

\[
\psi(t) = \frac{1}{\pi^4} e^{j2\pi f_0 t} e^{-t^2/2}
\]  

(5.12)

where \( f_0 \) is the centre frequency.

Signals with strong transients have been reported to be best analysed with the Morlet wavelet [Jaffard et al. 2001]. Strong transients are present in the sEMG recorded from rapidly contracting muscles.

Non-linearly scaled wavelets have been developed which have been applied to simulated signals, sEMG from seven muscles of the lower limb during cycling and five muscles of the lower limb during running [von Tscharner 2000; von Tscharner 2002; von Tscharner et al. 2003]. Unlike linear wavelets, there are a greater number of oscillations present in the wavelet. as the scale increases which allows better time-resolution of muscle activation events.
Hostens et al. (2004) investigated fatigue in brachioradialis and biceps applying a STFT (Hamming window) and a WT (Daubechies 5) in both dynamic and isometric contractions. The instantaneous mean frequency (IMPF) and mean power frequency (MPF) were averaged over 256 ms. Analysis of variance (ANOVA) revealed no significant difference between the MPF and the IMPF. The dynamic contraction was however performed at slow rate therefore producing a semi-stationary signal.

Panagiotacopulos et al. (1998) compared the muscle contraction onset time of the erector spinae calculated using time dependent features and three different types of wavelets (Daubechies, Symlets, Coiflets) in twelve patients. The researchers concluded that wavelet analysis gave more precise and reproducible information than using time dependent parameters although no detailed statistical analysis was provided in the paper. Two of the twelve subjects displayed noisy sEMG signals which prevented full analysis. De Stefano et al. (2003) applied wavelet transforms to the sEMG of gastrocnemius and tibialis anterior measured during walking in two subjects with cerebral palsy and two control subjects. Complex Gaussian wavelets were used of the order 3 and scales 1 to 20 with 0.5 intervals. The authors concluded that the indices derived from the wavelet transform were able to divide the subjects into three groups although the number of subjects was very small and therefore no statistical analysis was undertaken.

The scalogram (see figure 5.5) displays the distribution of energy of the signal in a time-scale plane in a similar manner to the spectrogram (see figure 5.4).
The scalogram is different to the spectrogram in that they are not comparable representations [Rioul & Vetterli 1991]. This difference is due to scales having better time resolutions for lower values whereas in a spectrogram the time resolution is equal across all the frequencies. Scale is related to frequency by the following algorithm [Wang et al. 2005]:

\[ f_a = \frac{f_0}{a \Delta t} \]  \hspace{1cm} (5.13)

where \( a \) is the scale

- \( f_a \) is the pseudofrequency at scale \( a \)
- \( f_0 \) is the centre frequency
- \( \Delta t \) is the sampling interval

The greater the value of \( a \), the greater is the dilation of the wavelet and the lower is the frequency of the wave. A Morlet wavelet has a central frequency of 0.849 [Addison 2002]. A scale of 30 using a Morlet wavelet of a signal sampled at a 1000 Hz therefore is equivalent to a frequency of about 28 Hz whereas a scale of 2 is equivalent to about 425 Hz.

5.4 Stage 3 - Feature processing of parameters

5.4.1 Introduction

The previous section described parameter extraction methods. Another feature of sEMG is that an individual may display variations in sEMG activity patterns between cycles. The data is therefore often subjected to ensemble averaging in order to obtain a representative average activity pattern for a cycle. The following two sections will discuss normalisation and ensemble averaging.

5.4.2 Time normalisation

Previous studies investigating sEMG locomotor patterns have used different lengths of time normalisation. Davis and Vaughan (1993) used 50 points per gait cycle, Wootten et al. (1990) time-normalised to 32 points, and Shiavi and Griffin (1987) to 16 points.

5.4.3 Ensemble averaging

Ensemble averaging involves averaging the values at specific time intervals across a number of different cycles. This technique carries with it the assumption that the pattern of muscle activity is similar for each cycle, that is there is a condition of
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cyclostationarity. This presumption is not valid in the case of gait analysis for two main reasons. Firstly, muscle fatigue may develop depending on the duration of walking, the force involved and any pathology or abnormal anatomy present in the subject (see section 2.3). Secondly, there will be minor variations in recruitment of muscles between gait cycles. This is based on the theory that the locomotor control system regulates a movement as a whole rather than additional muscles (see subsection 3.4.3). Additional factors which question the validity of using ensemble averaging are changes in the positioning of the electrodes relative to the underlying muscle fibres between cycles and fluctuating noise levels (see subsection 2.3.5).

Overall, the effect of ensemble averaging for the sEMG activity of a particular muscle is to temporally elongate the activity [Bogey et al. 1992]. Figure 5.6 illustrates how ensemble averaging elongates the sEMG of soleus for four gait cycles. Bogey et al. (1992) has developed two alternative methods to ensemble averaging namely the intensity filtered average and packet analysis. The former removes rectified averaged sEMG with intensities less than 5% of the maximum muscle test value and those sEMG with duration of less than 5% of the gait cycle. The value of 5% appears to be arbitrarily selected. The packet method uses linear interpolation to relate individual linear envelopes to each other. Bogey et al. (1992) reported that the intensity-filtered average was the preferable form of averaging.

Inter-subject ensemble averaging of sEMG gait cycles is frequently undertaken to obtain a representative pattern of activity. However, individuals have their own
unique locomotor strategies as mentioned in section 3.2. Ensemble averaging will lose information regarding locomotor control typologies. This is illustrated in a study by White and McNair (2002) who recorded the sEMG activity of three abdominal muscles and the erector spinae in thirty eight adults during gait. They reported that rectus abdominis displayed minimal activity during the gait cycle when the ensemble average of the group was calculated. However, when the group was divided into two through the application of cluster analysis, a distinct peak of activity could be identified close to each foot-strike for one of the groups.

In summary, an individual will display variability in sEMG parameters between gait cycles in addition to having an average sEMG pattern which differs from other subjects. Ensemble averaging is useful in observing an individual's average gait pattern however, this process does lose that gait descriptor of variability. Techniques that allow all the individual gait cycle data to be assessed will be discussed in the next chapter.

5.5 Stage 4 – Feature reduction and application of a pattern classifier

5.5.1 - Introduction

The majority of clinical applications will not require this fourth stage. However, the application of sEMG as a myoprocessor as discussed in section 4.10 will generally require feature reduction techniques and pattern classifiers to be applied.

5.5.2 Feature reduction

Locomotion involves the synchronised activation of a large number of muscles. Many different parameters can be extracted from each single raw sEMG resulting in potentially vast amounts of features to describe a gait cycle. Although it is advantageous to utilise several several features an excess number can adversely affect the performance of pattern classification. A method to reduce the dimensionality of the data should be employed. Englehart et al. (1999) emphasize the importance of dimensionality reduction and state 'a classifier with fewer inputs has fewer adaptive parameters to be determined, leading to a classifier with better generalization properties'. Reduction in parameters may be achieved by using a feature selection method to obtain the best subset or a feature projection method to obtain the best combination of parameters. Englehart et al. (1999) compared a
Euclidean class separability method (CS) for feature selection with components PCA for feature projection. PCA was reported to be vastly superior to CS for parameter reduction. CS differs from PCA in that it is a supervised method where features are ranked using *a priori* information whereas PCA is unsupervised making no assumptions about the features. The latter is a more appropriate method for sEMG since the data for locomotor sEMG is limited.

PCA ‘describes the variation of a set of multivariate data in terms of a set of uncorrelated variables, each of which is a particular linear combination of the original variables’ [Everitt & Dunn 2001]. Superfluous data can therefore be removed if there is correlation between the variables. In locomotion there is considerable co-activation of muscles occurring resulting in repetition of information. PCA is therefore an ideal tool to remove the replicated information. Additionally the variability of sEMG during gait which is a feature in itself is not lost if all the different cycles are incorporated into the analysis matrix. The first PC accounts for most of the variance, the second accounts for the next greatest amount of variance and this pattern is repeated for all the remaining PCs. Each PC is orthogonal to the next. The number of PCs necessary to describe the multivariate data will be less than the number of PCs if there is correlation present. Different criteria have been employed to determine the number of PCs which accurately reflects the features and can reproduce the original data:

- Total variation accounted for by the PCs is a minimum of 70% to 90% [Everitt & Dunn 2001].
- PCs extracted from a correlation matrix whose eigenvalues are less than 0.7 [Everitt & Dunn 2001].
- Scree diagram – number corresponding to the ‘elbow’ on a scree diagram [Everitt & Dunn 2001].
- Retaining an additional PC results in an increase of cumulative power greater than 1% [Shiavi & Griffin 1981].

The PCs can be derived from the covariance or correlation matrix of the raw data or standardised raw data. Standardisation is important if the variables are in different units or if there is significant variance of the columns. It ensures that the variables have equal weighting, although this may not be necessarily a desirable property if one variable should have more influence than another.
A small number of studies investigating phasic patterns of sEMG during walking have been undertaken. Wootten et al. (1990) measured ten lower limb muscles in thirty five subjects. In total 27 gait cycles were recorded over 3 days. The raw sEMGs were rectified, smoothed, normalised to respective maximal area and time normalised to 32 points per gait cycle. An ensemble average was then calculated for each subject. The 32 point vectors were appended for all subjects forming a 32 (time-points) x 35 (number of subjects) matrix. Principal components were then computed from the correlation matrix of the 32 x 35 point matrix. The principal components showed phasic patterns. Adductor magnus and the hamstring muscles needed 5 features to reconstruct the signal compared to only 3 features for gluteus maximus indicating a more variable pattern of activity for the former.

Principal component analysis has been applied to gait parameters to identify gender and hip pathology. Gender identification from the sEMG of five lower limb muscles of the right lower limb during running on 40 male and 41 female runners has been investigated by von Tscharner et al. (2003). The analysis involved deriving multi-muscle principal patterns from non linear wavelets. A 95% correct classification of gender was reported. The significance of the difference in frequency spectra between male and females was tested using ANOVA. Yamamoto et al. (1983) applied PCA to identify subjects with hip disease and to monitor their subsequent progress. They measured five gait parameters in 211 patients with hip disease. Principal components were then calculated using 10 input variables. 3 PCs were identified which accounted for most of the variance. The plot of the factor score of each patient against the first two principal components approximately categorised the hip pathology. Four subjects had their factor scores tracked over a period of up to 16 months post-surgery allowing evaluation of recovery of normal gait.

Walking velocity and stride-length has been analysed from sEMG. Patla (1985) applied the PCA using the correlation matrix expansion to the sEMG recorded from 7 or 8 muscles to two groups of subjects. The first group of 6 subjects were asked to walk at seven different speeds and 7 muscles were measured whereas the second group of 7 subjects were asked to walk at normal speed but changed their stride length 3 times and 8 muscles were measured. A minimum of four features were needed to reproduce the muscle patterns for the different speed and stride-length conditions.
Shiavi and Griffin (1981) measured sEMG from 8 lower extremity muscles in 25 normal subjects walking at normal speed for a total of 10 gait cycles. The gait cycle was divided into 16 parts. PCA was applied to reduce the feature set. The PCAs derived from the covariance and correlation matrix were compared. Covariance matrix accounted for a greater proportion of variance (the first two eigenvectors accounted for 68% of variance compared to 59% for the correlation PCs).

PCA of the sEMG during a gait cycle cannot be used in real-time since the feature vector for the entire cycle must be determined prior to analysis. However it is a useful method that enables analysis of correlations in variables, investigation of the different contributions of variables during the gait cycle and assessment of the variability of individual gait cycles. The next sequence in pattern recognition is selection of a pattern classifier and feeding the reduced data into it.

5.5.3 Pattern classification

Different types of classifications have been made using parameters extracted from sEMG. The classifications include categorising specific body segment movements and moments, determining patterns of activity, and phase identification within a cyclic motion [Atsma et al. 1996; Chan et al. 2000; Hillstrom & Moscowitz 1992; Sepuldeva et al. 1993; Shiavi & Griffin 1981; Zhang et al. 1991]. Various methods of pattern recognition have been applied to sEMG to establish classifications. Factor analysis, multi-dimensional scaling (MDS), linear discriminant analysis (LDA), cluster analysis and ANNs are techniques that have been employed by researchers.

- Factor Analysis

Factor analysis is similar to PCA in that it reduces a number of correlated features. However the differences between PCA and factor analysis is that whereas PCA only explains variances of variables factor analysis explains correlations and co-variances of variables and postulates a model [Everitt & Dunn 2001]. Davis and Vaughan (1993) applied factor analysis to EMG data from the 16 muscles measured by Winter (1987). Four factors were necessary to reproduce the sEMG. They found in both cases 4 factors that could account for 91.5% of the variance. Three of the factors were found to represent different phases of gait namely heel strike, loading response and propulsion whilst the fourth corresponded to muscles that displayed biphasic activity. Olree and Vaughan (1995) also used factor analysis to analyse sEMG
during locomotion. Eight muscles were recorded bilaterally in ten subjects. Five factors were needed to describe the original data. The first two factors related to the loading phase, factors three and four to the propulsive phase and the fifth factor to the co-ordinating phase.

- **Linear discriminant analysis**

  LDA finds a linear combination of features that separates out 2 or more classes. The technique uses *a priori* knowledge about the features and a transformation formula to find the minimum difference between a pair of group means and the variance within the groups to identify groups. Hillstrom and Moscowitz (1992) used LDA (Gaussian Bayesian reference model) on 9 different above knee muscles to predict flexion and extension. The subjects were intact and their ankle/foot was placed in a cast. The percentage of correct classifications was not stated in the paper. Von Tschamer (2003) used LDA on the sEMG of five lower limb muscles to divide 81 runners into male and female. Correct classification of gender was made in over 95% of cases.

- **Multi-dimensional scaling**

  MDS is a technique that detects underlying features that allows one to explain the similarity or dissimilarity between objects. Davis and Vaughan (1993) applied an MDS procedure to Winter’s gait data in addition to factor analysis previously described. Four regions were identified which corresponded to the four factors calculated by factor analysis.

- **Artificial neural networks**

  Factor analysis and multidimensional scaling techniques however have the disadvantage that no allowance is given to the imprecise nature of the EMG data. The signal pattern for a given muscle will not be replicated precisely for a particular phase in every stride and will also vary between individuals. Robust classification techniques allow for imprecision in data. ANNS are a robust classification technique and are ideally applied when imprecision in data is present and the data is non-linear. This is the case for locomotor sEMGs where the signal pattern for a given muscle will not be replicated precisely for a particular phase in every stride and will also vary between individuals. Currently artificial neural networks are being used extensively for pattern recognition of sEMG (Graupe 1989; Graupe & Kordylewski 1995; Huang & Chen 1999; Hudgins *et al.* 1993; Kwon *et al.* 1996; Sebelius *et al.* 1999; Sepuldeva *et al.* 1993). ANNs do not require a specific algorithm or
specific rules. Instead, during the training process the ANNs will alter the weights of each neuron following repeated exposure to data. A large number of signals may be required for training. Huang et al. (1999) used 2 channels to predict 8 types of upper limb movements. An ANN was used with back propagation and the parameters selected were the integrated sEMG, variance, zero crossings, waveform length, Willison amplitude and second order autoregressive parameters. The on-line classification accuracy was 71%. Sepuldeva et al. (1993) used data from Winter (1987) to map the sEMG from 16 muscles onto joint moment and joint angle at 5% segments of the gait cycle. The predicted joints were the knee, ankle and hip. The classifier was an ANN with back-propagation. Classification of the joint angles and moments occurred after 54,000 and 98,000 iterations respectively. A study by Prentice et al. (2001) used an ANN with kinematic data as the input to predict the sEMG amplitude of 8 lower limb muscles during the gait cycle with 12 different conditions being investigated. The majority, 91 out of 96, muscle/gait conditions had a correlation above 0.80. Popovic and Kalanovic (1993) used a radial basis function neural network to determine the hip and ankle angles during locomotion. The knee angle was used as input and 19 strides in an able bodied subject were recorded. The cross-correlation for the ankle and hip was 0.94 and 0.95 respectively.

A problem with the classification method employed by Hudgins (1993) is that the segments are presented to the network simultaneously thus temporal structure within the record will be lost. A finite impulse response neural network allows for inclusion of temporal features [Atsma et al. 1996; Englehart et al. 1995]. Kwon et al. (1996) proposed combining a hidden Markov model (HMM) and an ANN to find temporal patterns in sEMG data. An HMM is a statistical model based on a stochastic process conditionally independent of past states [Rabiner 1989]. The HMM makes the assumption that data segments within the gait cycle are independent. The ANN selected by Kwon et al. (1996) was a standard 2-layer algorithm. Only one subject was used in the study and six types of elbow joint movements were assessed which were repeated thirty times each. The error rate in recognising movements with this hybrid model varied from approximately 3% for pronation to 23% for supination.

The disadvantage of ANNs is that the neural network algorithms are not easily defined and therefore it is difficult to obtain an insight into the control variables.
Chapter 5. Signal Analysis

The hidden layers have been compared to a black box [Nauck et al. 1997]. So although ANNs allow one to extract patterns, they give no information as to why these patterns arise. Combining fuzzy logic with ANN into neuro-fuzzy technique gives one the advantages of both techniques and provides information about the control variables. In fuzzy logic the concept of an object either belonging to a set or not is redundant. Instead, the idea of partial membership is introduced. This concept is ideally suited to the sEMG signal when one considers the numerous distortions and modulations it has undergone. Chan et al. (2000) compared using a fuzzy logic approach for classification of elbow joint movements with an ANN method in four subjects. Two electrodes were placed over the biceps brachii and triceps muscles with a single differential channel. Each sEMG signal selected was 240ms long and divided into 40 ms segments. Four different time dependent parameters were derived from the sEMG. The basic ISODATA algorithm was used for clustering and the fuzzy rules were trained with a back propagation algorithm. They concluded that the classification results were similar but that the fuzzy method produced ‘slightly higher recognition rate; insensitivity to overtraining; and consistent output demonstrating higher reliability’.

- Cluster Analysis

Cluster analysis is a classification scheme that divides observations into groups. It is an internally based scheme involving no a priori information. Two main types of clustering are hierarchical and iterative partitioning methods. Hierarchical clustering involves observations being partitioned at different levels. Different algorithms are available depending on how the distance is measured and what type of algorithm is selected to determine the distance between clusters. Methods of distance measurement between the observations include Euclidean, cityblock and cosine. Single linkage (minimum distance), average linkage, complete linkage (maximum distance), within groups and Wards (sum of squares) are algorithms frequently applied to determine distances between clusters. The dendrograms provide graphical representation of groupings.

Iterative partitioning methods include k-means and iterative self-organizing data analysis techniques (ISODATA) clustering. K-means clustering divides the data into k number of clusters, with each observation within a cluster being as close as
possible to each other and characterised by its centroid. Each centroid is as far away as possible from other centroids. A global optimisation method is used to reassign objects to different clusters or move the position of the centroids. ISODATA clustering is a more sophisticated method of clustering than k-means since the number of clusters is not fixed.

Locomotion is a cyclic movement with each gait cycle being divided into stance and swing phases each of which can be divided into sub-phases (see figures 3.1 and 3.2). This hierarchical structure of locomotion would suggest that a hierarchical algorithm is more appropriate for analysis of sEMG than an iterative algorithm.

Both types of clustering have been used for analysis of sEMG. Most of the studies have been based on dividing subjects into groups rather than applying the clustering algorithm to sEMG to determine natural divisions in the sEMG activity during the gait cycle. White and McNair (2002) have applied cluster analysis to sEMG recorded from the abdominal and erector spinae during walking. Two different hierarchical clustering algorithms (Wards and Furthest neighbour) and the iterative K-means clustering were selected. All three algorithms identified two different cluster groups with the same subjects for the internal oblique and rectus abdominis and 3 clusters for the erector spinae with identical subjects. Two groups were identified for the external oblique with different groupings according to the algorithm selected. Cluster analysis was also the technique selected by Shiavi and Griffin (1981) who divided 25 subjects into five to ten different groupings according to the pattern of sEMG of 8 lower limb muscles during gait. A hierarchical clustering algorithm was applied to the first three principal components to form the groups. Significance of resulting clusters was tested using Hotellings T2 statistic which showed that the patterns formed were significantly different with a significance level of less than 0.02. The conclusion was that in a ‘normal’ subject group there are profoundly different patterns of individual sEMG patterns during level walking. Zhang et al. (1991) applied iterative K-means clustering technique to 20 subjects with anterior cruciate ligament injury and 26 subjects with uninjured knees during free speed and fast walking. Six different groups were identified from the DFT parameters of vastus lateralis for both speeds of walking. The majority of the uninjured subjects fitted into two groups during free speed walking. No statistical
significance was however given for the level of clustering. The study additionally compared the classification accuracy of using parameters obtained from an auto-regressive (AR) model with those from a discrete Fourier transform. The AR model was reported to be very poor in describing a linear envelope resulting in very different sEMG linear envelopes being partitioned by clustering analysis into the same group.

A statistical method of analysing how well the cluster groups represent the original data is to calculate the cophenetic correlation coefficient (CCC). This compares the height of the linkages between any 2 points with the distance between the points with the original data distance. A value above 0.8 is considered significant [Everitt & Dunn 2001].

5.6 Conclusion

One of the aims of the study as outlined in section 1.2 was to investigate the potential of using sEMG as a natural sensor. This assumes that the sEMG patterns are a reliable indicator of the underlying MUAP patterns. However, sEMG is not a direct measurement like height or temperature but rather an indirect measurement of an electrical process occurring some distance away and distorted by the intervening tissues and electrical environment. The signal thus has to undergo significant processing before a representation can be attained of the underlying events. An analogy can be made with Plato’s cave. The colourful three-dimensional moving characters are perceived by the prisoners as grey two dimensional shadows. This can be likened to the representation by a single digital signal of the motor units firing at different frequencies and originating from different locations within the muscle. The correct application of signal analysis techniques and the awareness of its limitations is therefore essential in order to make accurate suppositions about the underlying muscle activity.

The conclusions that can be drawn from this chapter is that firstly there are numerous processing methods that can be applied to the sEMG. The simplest and most frequently derived parameters are time-dependent, in particular RMS and MAV. However, both experimentally and theoretically these parameters do not satisfactorily describe non-stationary signals such as the sEMG recorded during
dynamic movements. For this type of signal, time-frequency parameters are more appropriate such as the ACWD and WT parameters. A variety of mother wavelets have been used in the WT including the Morlet wavelet which has the advantage of providing information about phase. Repeatability studies for the sEMG recorded during the gait cycle report high variability compared to other gait parameters. Ensemble averaging removes this variability at the cost, however, of losing individual gait cycle information. PCA is a method whereby all the gait cycle data can be utilised and has been applied in a number of sEMG studies. Relatively little pattern classification of sEMG during locomotion has been undertaken and none that the author is aware of to identify different phases of stance. Cluster analysis represents a simple method of pattern classification and has been applied in several sEMG studies. However, information from several muscles should be included for the cluster analysis since locomotion involves control of groups of muscles to achieve a desired joint movement rather than control of individual muscles. Chapter 6 will present the methodology chosen for the study with section 6.8 providing further details of the signal analysis and the algorithms selected.

Methods of signal analysis that will be selected and will be described in detail in the next chapter include the following:

- Extraction of four different types of parameters (MAV, STFT, ACWD, WT)
- Normalisation of MAV to maximum recorded during the stance
- Time normalisation of stance to 30 points
- Feature reduction using PCA
- Pattern classification using cluster analysis

Certain analysis techniques such as whitening or applying adaptive filters have not been selected. The rationale for this exclusion is that if the sEMG is to be processed in real-time, minimising the time on processing the signal is essential. The next chapter will elaborate on the processing techniques used.
Chapter 6
Materials and Methods

6.1 Introduction
The previous chapter discussed the different types of signal analysis techniques that have been employed in investigation of sEMG. This chapter now presents the procedure and the methods of analysis in achieving the aims of the study set out in chapter 1.

Sections 6.2 and 6.3 discuss the subjects selected and the ethics. This is followed by a description of the muscles recorded and methods used to place the electrodes and markers. Section 6.5 covers the apparatus used in the study. The procedure used for the pre-trial and trial recordings is detailed in sections 6.6 and 6.7. The final parts of this chapter outline the methods of analysis chosen for the study and the conclusion.

6.2 Subjects
6.2.1 Subject groups
Two groups of subjects were involved in the study, the amputee group A and the intact group B. The first group, group A represented the main study group and extensive parameter extraction and pattern analysis was applied to this group’s sEMG. Group A consisted of five subjects who had undergone TF amputations and were fitted with osseo-integrated prostheses. The eligibility criteria for osseo-integrated surgery provided by Integrum AB, the Swedish company that has pioneered osseo-integrated surgery are as follows [Integrum-AB 1999]:

i. The patient must be a transfemoral amputee or must be undergoing uni- or bilateral transfemoral amputation.

ii. The patient must have present problems or must be expected to have problems with conventional socket prosthesis.

iii. The patient must have undergone pre-operative radiographic assessment including Computer Tomography imaging.

iv. The patient’s skeletal maturation must be completed.
v. The patient must have normal skeletal maturity.
vi. The patient must not be over 70 years of age.
vii. The patient’s body mass must be less than 100kg.
viii. The patient must be suitable for surgery based upon medical history and physical examination.
ix. The patient must not have severe vascular disease, diabetes mellitus with complications, skin diseases involving the amputated limb or other diseases that could affect the suggested treatment negatively.
x. The patient must not be or must not have been treated with systemically administrated corticosteroids, chemotherapy drugs or other drugs in a way that could affect the suggested treatment negatively.
xi. The patient must not be pregnant.
xii. The patient must be likely to comply with treatment and follow up requirements.
xiii. The patient must have given written informed consent to participate in the clinical investigation.

In addition to the criteria necessary for subjects in group A to have undergone osseo-integrated surgery, two further criteria were included for participation in this study. They were:

i) They must all have completed the rehabilitation procedure and were able to walk unaided.

ii) Males subjects only.

Only males were investigated since at the commencement of the study only male subjects had been fitted with osseo-integrated prostheses at the UK centre study base. The second group, group B consisted of ten healthy male students and represented the reference group. Data analysis was limited to time-dependent parameter extraction and assessment of repeatability. The importance of this group was that it allowed comparison with the results of previous locomotor sEMG studies and thus offered some validity to the measuring and analysis techniques employed in this study. The inclusion criteria were as follows:
Chapter 6. Materials and Methods

i) Must be in good medical health

ii) Must not have any pathology, significant congenital abnormality, sustained any trauma or undergone surgery that has affected their gait pattern.

iii) Must not be clinically obese (BMI >30kgm⁻²).

iv) Must be male

v) Must be between 10 and 65 years of age.

A restriction was placed on the BMI on the subject since obese patients have been observed to have altered lower extremity kinematics during walking [DeVita & Tortobágyi 2003]. In addition, subjects with a high BMI will have a thicker adipose layer and therefore there will be a greater filtering effect on the MUAPs. Male subjects only were recruited in group B since group A consisted of only male subjects. Differences in gait have been observed between the genders with females exhibiting greater hip internal rotation and adduction in addition to greater gluteus maximus activity. A restriction on age was imposed since in healthy subjects, the influence of age on gait is important above the age of 65 and below the age of 10 [Chester et al. 2006; Riley et al. 2001]. In the older subject increased limitation of hip extension alters gait patterns. In the child the immature musculoskeletal system and developing locomotor control pathways results in a gait different from the typical adult gait. TF amputees with conventional prostheses were not recruited due to the problems associated with the friction of the socket over the residual limb whilst recording the sEMG and the movement artefact that would have arisen.

6.2.2 Sample sizes

The sample sizes for both groups A and B were small being only five and ten respectively. The five amputees represented the maximum number of subjects who were willing to participate in the study at the time of their annual assessment at the Gait Laboratory at Queen Mary’s Hospital, Roehampton. The aim of the study was to examine individual patterns of sEMG rather than to determine a statistically significant pattern for all individuals. Sample size is therefore necessary only to have sufficient to represent different individual locomotor patterns for group A. Two of the studies described in subsection 5.5.3 report that the sEMG activity fall into two patterns whereas a third study estimated between five and ten patterns of sEMG.
activity during locomotion. Five subjects will therefore not be sufficient to identify all types of locomotor patterns reported in previous studies. Ten intact subjects were recruited to participate in the study. This number is sufficient to create an ensemble average for sEMG with which to compare with previous studies. Since individual patterns of sEMG activity are being investigated, the number of stances available for analysis is more critical than the subject number. The minimum number of stances that has been recommended to minimise variability is twenty (see subsection 3.4.3).

6.3 Ethics

The Wandsworth LREC at St. George’s Hospital, Tooting, London gave approval for the study. All subjects were volunteers and were provided with an information sheet (see Appendix 1) and signed a consent form (see Appendix 2).

6.4 Placement of electrodes and kinematic markers

6.4.1 Number of muscles recorded

A constraint was placed on the number of electrodes utilised by the total maximum sampling frequency of the Biometrics Datalink system, which was set at 8000 Hz. This permitted a maximum of five electrodes at the sampling rate of 1000 Hz.

Table 6.1. List of muscles acting on the hip joints (adapted from Spence (1990)).

<table>
<thead>
<tr>
<th>Flexion</th>
<th>Extension</th>
<th>Adduction</th>
<th>Abduction</th>
<th>Lateral rotation</th>
<th>Medial rotation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iliopsoas</td>
<td>Gluteus maximus</td>
<td>Adductor longus</td>
<td>Gluteus maximus</td>
<td>Gluteus maximus</td>
<td>Gluteus maximus</td>
</tr>
<tr>
<td>Sartorius</td>
<td>Biceps femoris</td>
<td>Adductor magnus</td>
<td>Gluteus medius</td>
<td>Obturator internus</td>
<td>Obturator externus</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>Semimembranosus</td>
<td>Adductor brevis</td>
<td>Piriformis</td>
<td>Gemelli sup &amp; inf</td>
<td>Adductor longus</td>
</tr>
<tr>
<td>Pectineus</td>
<td>Piriformis</td>
<td>Pectineus</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adductor longus</td>
<td>Pectineus</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quadratus femoris</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1 Cleaved muscles. 2 Altered line of action. TFL – tensor fasciae latae. *Muscles spanning two joints. Shaded muscles are muscles selected in study for recording.
(see subsection 2.6.4) to be used. Although small, this number does allow for a range of muscles to be assessed, which individually can produce all the types of movement present in the hip joint (see table 6.1). However, as discussed in subsection 3.4.3, the same movement of a joint can be produced by a range of muscles contracting in a variable number of ways. Since only a small number of muscles are being assessed not all these patterns of contraction will be detected.

6.4.2 Muscles selected
The three criteria used to determine which five muscles should be selected for recording were that the muscles must be superficial, they must act on the hip joint and each muscle must have a different action on the hip joint. Superficial muscles were selected since the range of the sEMG is only about 15 mm from the skin. This precludes the recording of deeper muscles such as iliopsoas. Only hip joint muscles were included for the trial recordings although other muscles such as iliocostalis lumborum demonstrate well-defined cyclical sEMG during gait [Pantall 2004]. The reason for focussing on the hip joint was that there is high reproducibility of kinematic data for the hip for an individual’s gait cycle. Movement of the hip joint is achieved by varying amounts of contraction of hip joint muscles in addition to some contraction of the trunk muscles. Underlying the cyclical pattern of hip joint kinematics one would anticipate a repeatable pattern of hip joint multi-muscle activity. Reproducible patterns of activity are essential for a myoprocessor. A second reason for selecting only the hip joint muscles is that future recordings may involve the use of a cuff containing sensors. This would be positioned around the residual limb and gluteal region. The final inclusion criterion was that in their combined actions, the selected muscles must account for all the movements possible at the hip joint as shown in table 6.1. This is linked to the CPG theory as outlined in section 3.3 that locomotor control aims to reproduce movement of a joint rather than activation patterns of individual muscles.

The muscles that were selected were from the left side for the intact group and the residual limb side for the amputees. The choice of the left side was arbitrary. There is no evidence that a difference in activity exists between the dominant and non-
dominant side (see subsection 3.2.3). Therefore it is not significant which side is selected. The muscles which were finally chosen were gluteus maximus (GMAX), gluteus medius (GMED), rectus femoris (RF), adductor magnus (AM) and biceps femoris (BF). These five muscles when contracted produce varying forces and moments during the gait cycle. Figure 6.1 shows forces that have been predicted for seven lower limb muscles during the gait cycle.

![Figure 6.1. Prediction of muscle force during the gait cycle [Fang et al. 2007].](image)

### 6.4.3 Placement of electrodes

The subjects were asked to wear shorts during the measurement procedure. The skin was cleaned with alcohol, but the area was not shaved. The site that was selected for placement of electrodes for GMAX and GMED for group A and group B was in the location recommended by SENIAM project [Freriks & Hermens 2000]. The electrode position for GMAX was located with the subject lying prone on a table. The electrodes were placed halfway along a line from the middle of the sacrum to the greater trochanter. The electrodes were orientated in the direction of this line. The muscle was clinically tested by the subject extending the lower limb against manual resistance. The subject lay on the side for determination of the electrode position for GMED. The electrodes were placed 50% on a line from the crista iliaca to the greater trochanter and oriented in the direction of the line from the crista iliaca to the greater trochanter. The position was clinically tested by the subject attempting to abduct his lower limb against manual resistance. The location of the electrodes for the intact group for RF and BF was determined according to the recommendations made by the SENIAM report. In the case of placement of the RF electrode, the intact subject lay supine and the electrode was positioned mid-way between the anterior superior iliac spine and the superior border of the patella. The position was clinically tested by the
subject attempting to extend the knee against resistance. The BF electrode was placed, with the intact subject lying prone, on the posterior aspect of the thigh midway between the ischial tuberosity and the lateral femoral epicondyle. The position was clinically tested with the subject attempting to flex the knee against resistance. The location selected for the AM electrodes for group B was one third along a line from the ischiopubic ramus to the adductor tubercle. The position was tested with the subject supine attempting to adduct the lower limb against resistance.

The position suggested by the SENIAM project and Winter & Yack (1987) for RF and BF could not be used for the amputee group. This group had all undergone high TF amputations therefore the recommended positions are located distal to the residual limb. The problem of identifying muscles where the insertion point has been removed can be overcome by using MRI scans [Jaegers et al. 1996]. However, MRI scans in the amputee group were taken only prior to the stage 1 surgery. These images will be of little value at the time of the study since the muscles will have atrophied, there may be fatty infiltration and the direction of the muscle fibres will have changed. Further MRI scans were not possible for both practical and financial reasons. Instead, a combination of careful palpation of the muscle outline followed by palpation of the isometrically contracting muscle was undertaken. The muscle outline of RF, AM and BF was approximately determined by locating the origin of the muscle and visually projecting distally to the insertion point (see table 6.2).

Table 6.2. Origin and insertion of rectus femoris, adductor magnus and biceps femoris as stated in Gray’s Anatomy [Warwick & Williams 1973].

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Origin</th>
<th>Insertion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectus femoris</td>
<td>Straight head</td>
<td>Superior border of patella</td>
</tr>
<tr>
<td></td>
<td>Anterior inferior iliac spine</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reflected head</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Superior acetabular rim</td>
<td></td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>Ischiopubic ramus</td>
<td>Linea aspera (medial lip)</td>
</tr>
<tr>
<td></td>
<td>Ischial tuberosity</td>
<td>Medial supracondylar ridge</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Adductor tubercle</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>Long head</td>
<td>Fibular head</td>
</tr>
<tr>
<td></td>
<td>Ischial tuberosity</td>
<td>Tibial lateral condyle</td>
</tr>
<tr>
<td></td>
<td>Short head</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Linea aspera (lateral lip)</td>
<td></td>
</tr>
</tbody>
</table>
Palpatory changes felt in contracting muscle included increased hardness of the muscle in addition to movement of the muscle belly as the diameter increased. Kleissen et al. (1997) used a similar procedure in which the experimenter palpated the contracted muscle and placed the electrode on the most prominently contracting part. Further confirmation of correct placement was obtained from the sEMG recorded during isometric contraction of the muscles. Electrodes were placed on the skin overlying the muscle bulk parallel to the muscle fibres as shown in figures 6.2a and 6.2b.

**Figure 6.2a.** Superficial muscles of the anterior thigh. Adapted from Spence (1990)

**Figure 6.2b.** Superficial muscles of the posterior thigh. Adapted from Spence (1990)

Figure 6.3 illustrates a transverse section of the right thigh. Gluteus medius is not included in this diagram since the section is inferior to the insertion point of gluteus medius. The site of attachment of three of the electrodes is shown in figure 6.4.
Figure 6.3  Schematic illustration of superior view of a transverse section of the right lower limb 2cm inferior to the ischial tuberosity [Radcliffe 1955]. Muscles shaded red indicate recorded muscles.

Figure 6.4. Photograph of an intact subject with electrodes attached. Gluteus maximus, gluteus medius and rectus femoris electrode placements visible.

6.4.4 Placement of kinematic markers

In addition to the sEMG electrodes the amputee group also had retro-reflective markers placed on their lower limbs and trunk in locations specified by the modified Helen-Hayes system (see table 6.3). Figure 6.5 shows an amputee subject with the markers applied.
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**Table 6.3.** Modified Helen-Hayes marker system for the lower limb [Centre for Biomedical Engineering, University of Surrey 2008]

<table>
<thead>
<tr>
<th>MARKER</th>
<th>Marker placement</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIS</td>
<td>Placed over the ASIS</td>
</tr>
<tr>
<td>Sacrum</td>
<td>Placed mid-way between posterior superior iliac spines</td>
</tr>
<tr>
<td>Thigh wand</td>
<td>Wand placed midway between greater trochanter and knee marker or for a short residual limb marker placed directly on prosthesis distal to greater trochanter.</td>
</tr>
<tr>
<td>Knee</td>
<td>Placed on lateral joint line</td>
</tr>
<tr>
<td>Shank wand</td>
<td>Wand placed over midway between lateral knee joint and lateral malleolus</td>
</tr>
<tr>
<td>Ankle</td>
<td>Placed on lateral malleolus</td>
</tr>
<tr>
<td>Forefoot</td>
<td>Between the 2nd and 3rd metatarsal heads.</td>
</tr>
</tbody>
</table>

![Osseointegrated amputee with lower limb markers attached according to the modified Helen-Hayes marker system.](image)

**Figure 6.5.** Osseointegrated amputee with lower limb markers attached according to the modified Helen-Hayes marker system.

### 6.5 Equipment

The sEMG signal was collected using the Biometrics DataLINK DLK800 system (Biometrics Ltd, Gwent, UK) comprising a Base Unit, Subject Unit and surface electrode pre-amplifier type SX230 (see figures 6.6 and 6.7). The equipment conformed to the Medical Device Directive 93/42/EEC [Biometrics Ltd. 2003b].

The specifications of the electrodes are as follows [Biometrics Ltd. 2004]:

- Very high input impedance- about $10^{15}$ ohms.
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- A high pass 3rd order filter comprising a linear 13 Hz 2nd order high pass Bessel type in series with a simple linear 13Hz 1st order high pass Butterworth.
- A low pass switched-capacitor 8th order 1.2 elliptic filter, cut-off 460 Hz which provides a transition ratio of 1.2 and a typical stop band rejection of 60 dB.
- Gain of 1000.
- A low noise instrumentation amplifier front-end with a common mode rejection rate of greater than 96 dB.
- Noise< 5 µV

Figure 6.6. sEMG electrode type SX230 [Biometrics Ltd. 2004]

The electrodes were composed of silver- silver chloride, which electrically are very stable [Clancy et al. 2002]. Figure 6.7 illustrates the basic structure of the electrode showing the pre-amplifier, low, and high pass filters.

Figure 6.7. Schematic illustration of sEMG electrode type SX230 [Biometrics Ltd. 2004]

The Subject Unit performed the process of sampling and converting the analogue sEMG into digital values as well as amplifying the signal. The gain of the amplifier could be adjusted to x1, x10, x100 and x1000. In addition to the sEMG input, there
was also a digital input from the contact switch signal. The Base Unit was the interface between the Subject Unit and the personal computer (see figure 6.8). The settings for recording the sEMG and CSS were configured using the Biometrics Datalink software. All the sEMG signals were recorded with a sampling frequency of 1000 Hz. This is the minimum frequency necessary to eliminate aliasing (see subsection 2.6.4). The sampling of the digital contact switch was 100 Hz. The channel sensitivity and full-scale value were varied depending on the amplitude of the signal. The TF amputees had weaker signals recorded from the cleaved muscles therefore increased channel sensitivity was necessary and a lower full-scale value.

**Figure 6.8.** Schematic diagram of equipment CSS – contact switch signal. sEMG – surface electromyography. PC1 – First personal computer. PC2 – Second personal computer. PC3 – Third personal computer.

Kinematic data were recorded using a six-camera MacReflex 60 Hz marker detection system (Qualisys Medical AB, Partille, Sweden). Ground reaction forces were collected using a 3.3m dual – platform walkway developed at the Gait Laboratory [Hynd *et al.* 2000] with a sampling rate of 2000 Hz.

Synchronisation of the force data and the sEMG data was achieved using a contact switch which led into the Biometrics Base Unit via the Biometrics Subject Unit. The digital contact signal was sampled at 100 Hz resulting in an accuracy of +/- 10ms. From here, a cable connected to the computer (PC2) receiving the force walkway data and another cable connected to the computer (PC1) receiving the sEMG data (see figure 6.8). The kinematic data was transmitted to the computer (PC3) which was synchronised with the force data entering PC2.

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6.6 Pre-trial recordings

The purpose of the pre-trial recordings was firstly to gain familiarity with the sEMG equipment, the force platform and sEMG analysis. A second intention was to improve palpatory skills of muscle locations and ensure that the electrode application was not too invasive or uncomfortable for the subjects. Another aim was to establish that clear signals could be obtained from the muscles with visibly little noise and interference and could be readily exported into and processed in the MATLAB environment. The effects of changes in walking speed on the sEMG were observed in these early recordings. A further intention was to ensure that the procedure ran smoothly and there was not a problem with trailing cables or electrodes becoming displaced. In total six different muscles were recorded namely GMAX, GMED, RF, AM, BF and iliocostalis lumborum. The following subsections describe the four pre-trial recordings.

6.6.1 November 2003 – One intact subject

These pre-trial recordings involved one intact subject performing isometric contractions of the GMAX, GMED, RF, AM and BF against weights of 9.8N, 19.6N and 49N. The sEMG of these muscles was recorded. The subject then walked a distance of 5m at three different velocities. Contact switches were placed underneath the heel and forefoot to record heel-strike and toe-off.

6.6.2 June 2004 - Four intact subjects

Four intact subjects walked at three different speeds, comfortable walking speed, fast speed and slow speed. The muscles recorded were GMAX, GMED, RF, AM and iliocostalis lumborum. A routine was written in MATLAB to divide the walks into stance and swing and calculate the squared magnitude for stance sEMG (see figure 6.9). Further details of these pre-trial recordings are contained in Appendix 3.
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2.5

stance — 2nd stance — 3rd stance — 5th stance

Figure 6.9. Squared magnitude of adductor magnus sEMG signal for 6 stances for one subject [Pantall 2004].

6.6.3 June 2004 – One osseointegrated TF amputee

This trial was undertaken to determine that electrodes could be positioned accurately on the residual limb. The muscles recorded were GMAX, GMED, RF, AM and BF. Resisted muscle tests were performed and the techniques adjusted for the amputee since force could not be applied distal to the residual limb. The subject was then asked to walk at three different speeds.

6.6.4 Results from pre-trial recordings

All subjects were comfortable with having the electrodes attached to their skin. The amputee subject was able to perform the isometric contractions well. An assistant was required to ensure that the trailing wires did not interfere with the subjects path. Data from the pre-trial recordings were not subjected to statistical tests since there was insufficient data. Instead, a visual inspection was made of the raw data and the derived parameters. Conclusions drawn regarding the results were as follows:

- Accurate electrode placement could be performed on both the intact subjects and amputee. Partial verification of this was that there was increase in the amplitude of the sEMG during isometric contraction of the recorded muscle.
- There was a cyclical pattern of activity of the sEMG for all 6 muscles recorded during locomotion for the intact subjects and amputee.
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- The cyclical patterns of activity were similar for the 3 walking speeds.
- There was minimal evidence of noise and interference present in the signal.
- The contact switches were not robust enough to function for extended periods.

Based on these pre-trial recordings it was decided to record activity from the 5 hip muscles - GMAX, GMED, RF, AM and BF. Only one walking speed namely comfortable walking speed was selected for the trial. The decision was made to use a force platform for determining the stance phase of gait rather than contact switches.

6.7 Trial recordings

Trial recordings on the five amputee subjects and ten intact subjects took place between November 2004 and March 2006. The following four subsections cover aspects of the methods used.

6.7.1 Types of contractions recorded

The sEMG was recorded from both isometric and dynamic contractions. The isometric contractions were performed to indicate that the electrode was correctly positioned. An increase in amplitude whilst the subject was contracting a muscle against a specific resistance suggests that the muscle is being activated. This will support the first hypothesis listed in section 1.3. No increase in amplitude implies that either the electrode is incorrectly placed or that the muscle and nerve structure is severely disrupted so no MUAPs can be generated. Another reason for recording isometric contractions was to observe the frequency spectrum through application of Welch's averaged periodogram method. This technique cannot be applied to a non-stationary signal such as the sEMG recorded during locomotion. Any obvious noise like 50 Hz mains noise will show in the periodogram as 50 Hz peaks and multiples thereof. The static and dynamic procedures will now be described in more detail.

6.7.2 Isometric contraction

Recordings took place whilst the subject was lying supine and then either on their intact lower limb side for group A or on their right side for group B. Thirty seconds of data were collected from the relaxed muscles. The subjects were then asked to resist extension, flexion, adduction and abduction of the hip joint for approximately
10 seconds. The force applied to the prosthetic limb in group A or the left lower limb in group B was either the maximum force that the subject was comfortable with or the maximum that the experimenter could apply. The sEMG trace was checked in real-time and adjustments were made to the amplification for both groups and position of the electrodes where necessary for the amputee group.

6.7.3 Walking
The subject was then asked to walk along a 10 m long walkway at their normal walking speed. The comfortable walking velocity will be less for a TF amputee than for an intact subject. However, as described in subsection 4.8.1, the energy cost for TF amputees has been reported to be equal to the energy cost for subjects with intact limbs when walking at their self-selected speed. Prior to commencement of the walk the subject was asked to press the contact switch. The walk was repeated a minimum of ten times resulting in approximately 20 stances for analysis. Twenty stances have been reported to be the minimum necessary to obtain a representative pattern (see subsection 3.4.3). The subjects were requested to keep their hands free during walking since arm position has been found to affect gait [Tang et al. 1998]. During each of the walking trials, data was recorded from the sEMG electrodes, the contact switch, and the force walkways and in the case of the amputees the reflective markers.

6.7.4 Repeat measurements
A key question relates to the constancy of the sEMG pattern. A successful myoprocessor requires that the patterns are repeatable over long periods. Two of the amputees and the entire control group had the procedure repeated at between two months to one year later. The procedure was the same as initially except that no kinematic data was collected for the amputees.

6.8 Analysis of trial recording data
6.8.1 Review of aims
The criteria used to select appropriate analysis techniques for the sEMG was based on the aims of the study. In order to answer the first hypothesis presented in section 1.3, namely that the muscles of the residual limb display increased activity during
contraction, a simple determination of sEMG amplitude, mean frequency and median frequency for relaxed and isometrically contracting muscles was made. A Wilcoxon signed rank test was applied to the sEMG data to determine whether there was any change in amplitude or frequency as the muscle contracted. Analysis of the locomotor patterns and stance modes involved techniques that were more complex. These included additional parameter extraction, assessment of repeatability, and application of PCA and cluster analysis. The following sections present a detailed account of the methods of analysis.

6.8.2 Viewing and export of raw data

The raw sEMG and contact switch signals were viewed using Biometrics version 3.0 software (Biometrics Ltd. Cwmfelinfach, Gwent, UK). The data (log) files were then exported into Microsoft Excel. Any files, which had no valid contact switch signals or displayed excessive noise, were deleted. The customised software Gait 3_04 developed at the Gait Laboratory was employed to analyse the force walkway data. Plots of the vertical ground reaction force and the contact switch signals were made (see figure 6.10).

![Figure 6.10. Plot of vertical ground reaction force and contact switch signal for one walk](image)

A schematic outline of the algorithms written and data files generated is provided in figure 6.11.
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**BIOMETRICS DATALINK**

(*.log)
sEMG data files + Contact data files
1000 Hz 100 Hz

Import into Excel
*emg.txt files

**FORCE WALKWAY**

(*.gdf)
force files
2000 Hz

(*.gdf)
contact files
2000 Hz

Import into Excel
*.csv files
Shorten force files to start contact data
*forcesync.csv

*rawzeroforceemg.m
synchronises and concatenates force and emg data. Removes dc component from emg data. Plots graphs of force&emg.

*rawzeroforceemg.mat
(forceemg timstartemg)

*mav.m
divides files into stance and swing phases. Applies moving average filters (10-filifilt). Pchip function to obtain 30 points per stance. Graphs plotted

*MAV.mat

*MAVstats.m
calculates mean, sd, var, cov, r & pcoeffs for stance.

*mavstats.mat
(*mavstats)

*_sl_sw.mat
heel strike and toe-off read from force graphs

*sl_sw.mat
heel strike and toe-off

*gait_times.m
calculates stance and swing times, means and sd

*gait_times.mat
(*st_sw meantime sd)

**Figure 6.11. Schematic diagram of analysis of time-dependent feature of sEMG.**
The force walkway was composed of a right section and a left section. Walking trials were removed if the trace indicated that a subject’s foot straddled over the two sections or if there was not a clear signal from the contact switch. The data (.gdf) files were then exported into Microsoft Excel. MacReflex 3.42f2 PPC software was used to track the position of the retro-reflective markers on the amputee group during their first recording session. The data (.tsv) files were converted to data (.c3d) files and the kinematic data was analysed by the software Visual 3D version 3.13.0 (C-Motion Inc. USA).

The subject’s height, mass, knee width, ankle width and foot width for each subject were entered into the Visual 3D version 3.13.0 (C-Motion Inc. USA) software. The knee width and ankle width were measured at the same level as the markers for recording knee flexion/extension and ankle plantarflexion/dorsiflexion respectively. The foot width was measured from the marker to the centre of the foot. Reports containing information regarding gait-times and kinematics of the hip, knee and ankle joints were produced for the five TF amputees. Since the study was investigating the sEMG of the hip joint muscles, only the hip joint kinematics were further analysed. The data (.c3d) files containing hip angle positional data about the vertical, medio-lateral and antero-posterior axes were exported to Microsoft Excel. This was then imported into the MATLAB environment where algorithms were applied and the variability of this kinematic data estimated (see subsection 6.8.5).

**6.8.3 Resting and isometric muscle contraction analysis**

Analysis of the sEMG from the resting and isometrically contracting muscle was undertaken to obtain an estimate of the noise present, to verify the electrode placement and establish the potential of the residual limb muscles to display activity. The resting sEMG contains electrical noise, physiological noise and some background activity of motor units. The data (.log) files were imported into MATLAB where firstly the dc offset was removed followed by calculation of the mean rectified amplitude and variance and estimation of the frequency spectrum. Since the signals were stationary, the frequency spectrum could be estimated by application of the Welch method. The MATLAB signal processing toolbox `pwelch` routine was used with a Hamming window of size 500 and overlap of 250 (see
subsection 5.3.3). A Hamming window was selected rather than a rectangular window since as discussed in subsection 5.3.3 using a window with smaller sidelobes reduces leakage. The choice of a Hamming window as opposed to a von Hann, Kaiser or other type of window is based on the type of windows previous studies have selected. The author was unable to find any research comparing the power spectral densities obtained from applying different windows. The length of the window was selected to reduce variance of the MDF and MNF [Farina & Merletti 2000]. The frequency peaks for the signals generated by the resting and contracting muscles were recorded. Any sharp peaks at 50 Hz and multiples thereof represent electrical noise. The mean and median values were calculated from the frequency spectrum. The change in the mean amplitude, mean frequency and median frequency estimated during the resisted contraction to that estimated whilst the subject was resting was calculated for each muscle for each subject.

6.8.4 Dynamic sEMG analysis

All the data recorded during the walking trials was initially imported into Microsoft Excel. The time at which the contact switch signal was detected by the force walkway PC was determined and the force and kinematic data truncated to coincide with the contact switch. Heel-strike and toe-off were determined from the GRF applying a threshold of 5N. A data matrix *st_sw.mat was exported to MATLAB containing timings of these gait events. All subsequent analysis was conducted in MATLAB. A routine, rawzzeroforceemg.m, was written in MATLAB which imported the raw sEMG (1000 Hz sampling frequency), contact switch data (100 Hz sampling frequency) and the synchronised force walkway data (2000 Hz sampling frequency) and where available the kinematic data (60 Hz sampling frequency) for the hip joint angles (see Appendix 4). The routine synchronised the sEMG, force and kinematic data. The sEMG and force data was concatenated into a single matrix for each subject. The DC offset in the sEMG was removed by subtracting the mean sEMG for each trace. The *st_sw.m algorithm was applied to the data matrices to subdivide each matrix into stance and swing sections. Four different parameters were then extracted from all the stance sEMG signals by the application of filters and transforms for group A subjects. Group B, the reference group, only had the time-
dependent features analysed for reasons provided in subsection 6.2.1. The following four sections describe the parameters and methods of calculation.

**6.8.4.1 Time-domain parameters**

Subsection 5.3.1 discussed the time-domain parameters and emphasised that this type of parameter is not appropriate for analysis of a non-stationary stochastic signal such as that recorded during locomotion. However, in this study a time-domain parameter was included since firstly the processing is quick and secondly, there have been many previous studies of patterns of locomotor time-domain parameters. The latter point is important since it allows comparison of this study’s results with those of previous investigations. Both the RMS and MAV are commonly derived parameters. There is no overwhelming evidence from studies of sEMG during locomotion that either carries more advantages than the other does. The MAV parameter was therefore selected and calculated using the MATLAB forward / reverse `filtfilt` function to obtain linear envelopes (see Appendix 5). The `filtfilt` function filters the input data in the forwards direction. The filtered data is then reversed and filtered again resulting in output data with zero-phase distortion. Five different length windows were initially applied to the rectified sEMG to determine the most appropriate length for the filtering window. The filtered sEMG was then divided into stance and swing sections and interpolated to 100 points. Figure 6.12 illustrates the patterns obtained by applying the five different filters to the sEMG for one stance cycle.

![Figure 6.12](image.png)

**Figure 6.12** Five different length filters applied to single stance sEMG of adductor magnus of TF amputee. Filter lengths 25 ms, 50 ms, 100 ms, 200 ms and 300 ms applied. MATLAB function `filtfilt` used to calculate MAV.
The similarity between stances was assessed for different length windows using the MATLAB `corrcoef` function (see Appendix 6). This function calculates the correlation coefficients between successive 30-point stances. The percentage of stances where the p-value was less than 0.05 was then determined. The list of the percentages is given in table 6.4.

**Table 6.4.** Percentage of stances with p value < 0.05 for five hip muscles averaged across five TF amputees. Number of stances = 18 – 23.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>MOVING AVERAGE FILTER (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>GMAX</td>
<td>29.8</td>
</tr>
<tr>
<td>GMED</td>
<td>21.9</td>
</tr>
<tr>
<td>RF</td>
<td>15.1</td>
</tr>
<tr>
<td>AM</td>
<td>38.8</td>
</tr>
<tr>
<td>BF</td>
<td>30.7</td>
</tr>
</tbody>
</table>

The length of the window selected was 100ms. The choice of window length was a compromise between having too long a window with resultant over smoothing and loss of key events (see figure 6.12) or too short a window with poor repeatability (see table 6.4). The window length, equivalent to a frequency of 10 Hz is below the SENIAM recommended frequency of 12 Hz – 40 Hz for dynamic contractions but above the minimum frequency reported by Merletti (1999) (see subsection 5.3.2).

The smoothed sEMG amplitude was then normalised according to the method used by Davis and Vaughan (1993) and reported by Yang and Winter (1982) to minimize the inter subject variability (see subsection 5.3.2). The normalised MAV, $x_{\text{norm}, j, k, t}$, is calculated as:

$$x_{\text{norm}, j, k, t} = 100 \times \frac{x_{j, k, t} - x_{\min, j, k}}{x_{\max, j, k} - x_{\min, j, k}}$$

where $x_{j, k, t}$ is the MAV for muscle j during kth stance at time t

$x_{\min, j, k}$ is the minimum MAV for muscle j during kth stance

$x_{\max, j, k}$ is the maximum MAV for muscle j during kth stance
The MATLAB routine for normalisation is contained within the algorithm in Appendix 5. The disadvantage of normalizing relative to the maximum signal during the gait cycle is that no indication is given as to how strongly a muscle is contracting as a percentage of the maximum muscle force. However, since the aims of the study are to assess patterns of sEMG activity during the stance cycle rather than to relate the sEMG to muscle force, this is not a consideration.

6.8.4.2 Time-frequency and time-scalar parameters

Time-domain parameters are limited in their ability to describe a dynamic sEMG signal. Time-frequency and time-scalar parameters offer information about the underlying frequencies present in the signal. In this study three types of these parameters were extracted which were the short time Fourier transform (STFT), adaptive Choi-Williams distribution (ACWD) and the wavelet transform (WT). The rationale for selecting these three types is that they have each been applied in several sEMG studies and each has its own particular advantage as outlined in subsection 5.3.3. The details about the algorithms will be provided in the following sections.

The STFT was applied using the MATLAB signal processing toolbox routine `specgram` with a Hamming window of length 64ms and overlap of 36ms. A Hamming window was selected for the reasons provided in subsection 6.8.3. A window length of 64ms was selected since although a window length of 128ms gives better correlations between stances (see table 6.5), there will be a time difference of up to 128ms plus processing time between an event occurring and the estimated STFT parameter. This delay may not be appropriate for real-time applications such as myoprocessors. Additionally, a window length of 128ms may be too long to detect short duration events such as initial loading. The overlap of 36ms was selected since this corresponds to windows being sampled every 28ms and therefore will allow for sEMG changes to be detected over a short time-period. A routine was written in MATLAB to estimate the MNF and MDF according to the following algorithms [Clancy et al. 2004]:

\[
\text{MNF} = \frac{\sum_{f=1}^{f<500} fS(f)}{\sum_{f=1}^{f<500} S(f)}
\]  

(6.2)
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\[ \text{MDF} = \frac{\sum_{f=1}^{\text{f=500}} (f - \bar{f})S(f)}{\sum_{f=1}^{\text{f=500}} S(f)} \]  

(6.3)

where \(S(f)\) is the PSD of the signal at frequency \(f\)

\(\bar{f}\) is the mean frequency

The mean frequency (MNF) yielded improved correlations compared to the median frequency (MDF) hence MNF was chosen.

Table 6.5. Percentage of stances with p value < 0.05 for STFT derived parameters from five hip muscles averaged across five TF amputees. Number of stances = 18 – 23. MDF – median frequency. MNF – mean frequency.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>MDF (32,4)</th>
<th>MNF (32,4)</th>
<th>MDF (64,36)</th>
<th>MNF (64,36)</th>
<th>MDF (128,100)</th>
<th>MNF (128,100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMAX</td>
<td>50.5</td>
<td>57.1</td>
<td>60.5</td>
<td>64.7</td>
<td>71.4</td>
<td>77.7</td>
</tr>
<tr>
<td>GMED</td>
<td>53.5</td>
<td>59.9</td>
<td>72.0</td>
<td>83.1</td>
<td>84.6</td>
<td>88.3</td>
</tr>
<tr>
<td>RF</td>
<td>44.2</td>
<td>48.9</td>
<td>51.0</td>
<td>54.0</td>
<td>65.9</td>
<td>73.3</td>
</tr>
<tr>
<td>AM</td>
<td>41.9</td>
<td>48.8</td>
<td>52.0</td>
<td>59.2</td>
<td>68.2</td>
<td>76.0</td>
</tr>
<tr>
<td>BF</td>
<td>48.4</td>
<td>56.1</td>
<td>58.3</td>
<td>69.4</td>
<td>73.8</td>
<td>84.5</td>
</tr>
</tbody>
</table>

The signals were then further analysed using the ACWD algorithm \texttt{tfracwd} [Gomes 1999].

The vector of sample sigmas ranged from 1 to 100, the length of performance window was 100 and the number of frequency points was 256. Previous studies applying the CWD to sEMG data have used a value of 1 for sigma [Bonato \textit{et al.} 1996; Bonato \textit{et al.} 2001; Karlsson \textit{et al.} 2000]. However, the ACWD algorithm varies the value of sigma so that entropy is minimised (see subsection 5.3.3). The number of frequency points was based on that selected in previous studies [Bonato \textit{et al.} 1996; Karlsson \textit{et al.} 2000; Knaflitz and Bonato 1999]. The performance window of 100 was chosen for the same reasons as the filter window selected as described in subsection 6.8.4.1. A routine was written in MATLAB to estimate the MNF according to Equation 6.2.

The \texttt{scalog.m} function in the Wavelet Toolbox Version 3.0 (1-Jun-96) developed by the Universidad de Vigo was applied to calculate the wavelet parameters. This algorithm uses a Morlet wavelet. There is no clearly identified best choice mother
wavelet for dynamic sEMG analysis (see subsection 5.3.3). However, the characteristics of Morlet wavelet make it a suitable option to analyse the transients present in the stance sEMG [Jaffard et al. 2001]. The scales were calculated from 2 to 30 at 0.5 intervals, representing a frequency band of 28 Hz to 425 Hz (see subsection 5.3.3). This is a greater range than that selected by Stefano et al. (2003) who selected scales 1 – 20 with an interval of 0.5. The sampling frequency of 1000 Hz in the author’s study was too low to permit a scale of 1 to be applied. Increasing the scale to 30 allowed more of the low frequency components to be analysed. A routine was written in MATLAB to calculate the mean scale (MNS) for each stance using the following algorithm:

\[ \text{MNS} = \frac{\sum_{s=2}^{30} sP(s)}{\sum_{s=2}^{30} P(s)} \]  

where \( P(s) \) is the PSD of the signal at scale \( s \).

6.8.4.3 Temporal normalisation

The piecewise cubic Hermite interpolating polynomial (MATLAB function \textit{pchip}) was used to temporally normalise the stance and swing into approximately thirty and twenty segments respectively. Normalisation of time was undertaken to allow matrices containing consecutive sEMG data to be constructed. As described in subsection 5.4.2, time normalisation varies between studies. However, since 50 points per cycle has been frequently applied in previous studies, this normalisation has been selected. This number of points is sufficiently large to detect gait events, such as initial loading present in only the first 10% of stance (see subsection 3.2.1). However, too many points will result in poor repeatability of patterns. The decision was therefore made to normalise the stance data to 30 points and the stance data to 20 points. This is also equal to the operational frequency of the Otto Bock C-leg [Otto Bock 2007]. Only the stance data was further analysed since the stance phase of the knee is the most critical to monitor since any slight alteration in the stability during this phase has to be rapidly compensated for.

6.8.5 Calculation of interstance parameter variability

The use of single channel sEMG as a natural sensor requires that there is good repeatability between stances. The variability of the sEMG during the stance phase
between trials and between days was calculated using the CMC for the four different parameters derived from the sEMG data. This method has been used previously as described in subsection 3.4.3.

The calculation of the CMC between trials according to Kadaba *et al.* (1989) is:

\[
CMC = \sqrt{1 - \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{t=1}^{T} (x_{ijt} - \bar{x}_{it})^2}{MT(N-1)}}
\]

where \( M \) is the number of trials

\( N \) is the number of stances

\( T \) is the number of time-points

\( x_{ijt} \) is the value at the \( t \)th time-point of the \( j \)'th stance on the \( i \)th day.

The CMCs were additionally calculated for the force walkway data and the hip joint angles recorded from the initial session of the amputee group. The purpose of this was to assess if variability in sEMG data was related to variability in kinematic or force walkway patterns during stance. The value of the CMC lies between 0 and 1, with 1 indicating similarity of waveforms and 0 indicating dissimilarity of waveforms. The closer the value of the CMC is to 1, the higher is the similarity between waveforms. Although Vickers *et al.* (2008) have defined good repeatability between waveforms when the CMC lies between 0.73 - 0.90, this is not based on tests of statistical significance. Interpretation of the CMC should therefore be described in relative terms with higher CMCs indicating better repeatability than lower CMCs.

### 6.8.6 Coherence

The coherence between the force walkway data and the sEMG data was estimated using the MATLAB signal processing toolbox `cohere` routine for the amputee group. This routine estimates the coherence between two signals using Welch's average periodogram method. A repeatable pattern of sEMG between stances should result in a high coherence of close to 1 at the walking frequency of about 1 Hz.
6.8.7 Principal components analysis

PCA was the method selected for feature reduction of sEMG data for the amputee group. This method has been used extensively in previous studies and provides better results than the class separability method [Englehart et al. 1999]. This is in part due to the correlation present between the muscles. Principal component analysis was applied to reduce the feature set for each of the four groups of variables (MAV, STFT, ACWD and WT).

The princomp function in the MATLAB statistics toolbox was used to calculate the principal components, the representation of the signal in principal component space, the variances and Hotellings $T^2$ statistic. Since the data was all in the same units and already normalised it was not necessary to standardise the data using the princomp(zscore) function. Principal components were derived from three different sEMG matrices:

- A STANCE matrix 30 x 5 in size for each stance representing the 30 time points and 5 muscles.
- A MUSCLE matrix 150 x n in size where n was the total number of stances for that individual. The 150 point vector was composed of the stacked individual 30 point muscle vectors.
- A DATA matrix 30 x 5 n in size where n was the total number of stances for that individual, 30 represents the time points and 5 are the muscles.

The minimum number of PCs necessary to reflect the data was taken to be that which accounted for at least 80% of the variance (see subsection 5.5.2). The PCs were then loaded into a cluster analysis algorithm to determine patterns of sEMG during gait.

6.8.8 Cluster analysis

Hierarchical cluster analysis was selected as being the most appropriate method to identify patterns in the reduced sEMG feature set of the amputee group for the reasons set out in subsection 5.5.3. The cluster routine in the MATLAB statistics toolbox was applied to the first three to four principal components derived from the sEMG features. A number of data sets were taken from the amputee group and different choices of distances and linkage methods were applied to determine which
Chapter 6. Materials and Methods

particular choice provided the clearest clustering (see subsection 5.5.3). Cosine was selected as the most appropriate measurement of distance and average was chosen as the method of linkage. The maximum number of clusters within the cluster routine was set at 8. This assumes that the number of sEMG phases present during stance is no greater than eight. The number of functional divisions of the stance phase as shown in figure 3.2 is five. Therefore, the selection of eight maximal divisions should be sufficient to distinguish these different phases.

The routine cophenet was applied to the clusters to determine the cophenetic index which is a statistical measure as to how well the clusters fit the input data. Graphical illustration of the clustering was provided by a dendrogram using the MATLAB function dendrogram. This MATLAB routine colour coded the clusters according to the default threshold which is equal to 0.7 times the maximum linkage distance.

6.9 Conclusion

The study has been constrained by both the small number of osseo-integrated subjects available for analysis in the United Kingdom and the budget for equipment. Therefore, ideally, more subjects would be selected and all the superficial muscles acting on the hip joint would be investigated. However, the five muscles selected for sEMG recording represent a selection of muscles, which together perform all possible actions on the hip joint. The sEMG was recorded for isometric contractions of the muscles and during locomotion. Isometric contractions were performed to validate placement of electrodes, to determine the noise content and to establish the presence of muscle activity. The sEMG measured during locomotion was divided into stance and swing sections and only stance sEMG was further analysed.

Whitening, which is a technique that can enhance tracking events from sEMG data was not undertaken (see subsection 5.2.1). The reason for this is that the amplitude of sEMG recorded from cleaved muscles was low reducing the effectiveness of whitening. Although improved filtering can be obtained by applying a fixed whitening filter, an adaptive Wiener filter and an adaptive gain correction this processing will add to the complexity and processing time of the signal. It was therefore decided not to whiten the signal. Four different types of parameter were extracted from the stance data. Each parameter reveals a somewhat different facet to
the sEMG. The majority of studies investigating locomotor sEMG in TF amputees have only assessed time-domain parameters. PCA and cluster analysis was then applied to the sEMG data. Figure 6.13 summarises the stages involved in the analysis of the four types of sEMG parameters.

Figure 6.13. Stages in processing of sEMG variables from raw stance signal
Chapter 7
Results and Discussion – Part 1

7.1 Introduction
This chapter presents and discusses results regarding subject groups, analysis of the sEMG recorded from isometric contractions, the gait parameters and kinematic and force-plate stance parameters. Subsection 7.2.1 introduces the subject data. This is followed by subsection 7.2.2, which gives the results from resting muscle and isometric muscle contraction. The gait parameters, ground reaction force, kinematic data and variability are presented in subsection 7.2.3. A discussion of the results presented in this chapter is contained in section 7.3 and its subsections. Chapters 8 and 9 are concerned with coverage of the stance sEMG and its subsequent pattern analysis.

7.2 Results
7.2.1 Subject data
In total, five subjects in group A and ten subjects in group B were selected. Two of the group A subjects and all ten group B subjects had repeat measurements taken on a different day. There were therefore seven group A datasets and twenty group B datasets available for analysis. The five group A subjects were coded A1 to A5 and the ten group B subjects were coded B1 to B10. Data sets were named after the subject’s codename and repeat measurement and consisted of the subject’s codename followed by the postfix rep. Tables 7.1 and 7.2 list the mean age, height, mass and body mass index (BMI) for the amputees in group A and for the intact subjects in group B. The two groups are not comparable for these variables since the mean age and BMI are less for group B than for group A.

All the amputee subjects underwent the original amputation more than ten years previously due to major traumatic injuries to the lower limb. The traumas involved were motorcycle accidents, crushing by an HGV and a shotgun injury. All the subjects had been fitted with the osseo-integrated prosthesis at least 18 months previously. Subjects A1, A3 and A4 had a right-sided prosthesis whereas subjects A2 and A5 had a left-sided
prosthesis. The types of prosthesis fitted were not standard, with subjects wearing prostheses with different knee joints and ankle joints.

### Table 7.1. Age, mass and height for group A

<table>
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<th>Height (m)</th>
<th>Body mass index</th>
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### Table 7.2. Age, mass and height for group B

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<th>Height (m)</th>
<th>Body mass index</th>
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<td>1.81 (0.08)</td>
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#### 7.2.2 Analysis of sEMG from resting and contracting muscles

The sEMG was recorded from both group A and group B subjects from five muscles whilst they were relaxed and then isometrically contracting (see subsection 6.4.3).

Figure 7.1 shows a typical raw sEMG for isometrically contracting BF for dataset A1. A typical raw sEMG for isometrically BF for intact dataset B2 is shown in figure 7.2. Appendix 7 contains the sEMG traces for the remaining muscles datasets A1 and B2. The amplitude of the sEMG increased for all subjects as they contracted the muscle. The pattern of the raw sEMG trace however differed between the two groups with the intact subjects demonstrating a more consistent increase in amplitude during the contraction compared to the amputees.
Chapter 7. Results and Discussion – Part I

Figure 7.1  sEMG of biceps femoris during resisted hip extension for Dataset A1

Figure 7.2  sEMG of biceps femoris during resisted hip extension for Dataset B2.

The PSD for both the resting sEMG and isometrically contracting muscle for group A was estimated by application of the Welch method to a section of the signal (see subsection 6.8.3). The PSD of the sEMG of isometrically contracting muscles of the group B subjects was not analysed for two reasons. Firstly, since group B consisted of healthy subjects it was assumed that contraction of their muscle fibres would generate a ‘normal’ sEMG. Secondly, the SENIAM recommendations for electrode placement could be applied since the insertion points of the muscles of group B were intact. The length of the signal used was 4 seconds for resting muscle and varied between 2 to 4 seconds for contracting muscle. Figures 7.3a to 7.3g illustrate the PSD profiles for the seven amputee data sets.

Figure 7.3a  PSD Estimate for Dataset A1 for isometric contraction

Figure 7.3b  PSD Estimate for Dataset A2 for isometric contraction
Chapter 7. Results and Discussion – Part I

Figure 7.3c. PSD Estimate for Dataset A3 for isometric contraction

Figure 7.3d. PSD Estimate for Dataset A3rep for isometric contraction

Figure 7.3e. PSD Estimate for Dataset A4 for isometric contraction

Figure 7.3f. PSD Estimate for Dataset A4rep for isometric contraction
Peaks at specific frequencies are clearly visible for dataset A3 in figure 7.3c. These peaks represent mainly mains noise since the initial peak is at a frequency of 50 Hz. The remaining data sets do not exhibit significant peaks and would therefore not appear to be notably affected by mains noise.

Table 7.3 lists the amplitude, mean frequencies and median frequencies calculated for resting and isometrically contracting muscle for the seven amputee data sets. Percentage change is shown for the parameters of mean amplitude, variance, mean frequency and median frequency from contracting muscle to the resting state. The variance of the amplitude is related to the number of motor units firing as described in chapter 2. All the muscles revealed increased mean amplitude when contracting compared to their resting state. However, the amount of change in the mean amplitude varied between subjects and between muscles. The greatest increase in amplitude occurred for GMAX, which increased by an average of 2181% compared, to the least change for RF with only an average 439% increase (see table 7.4). The maximal increase was for dataset A4 with a rise in sEMG of 1475% compared to the least increase for dataset A5 of only 185% (see table 7.5). The distribution of variance change was similar to that of mean amplitude with GMAX and dataset A4 exhibiting the greatest changes and RF and dataset A4 exhibiting the smallest changes (tables 7.4 and 7.5).
Table 7.3. Amplitude, mean and median frequencies as determined by Welch method for resting (R) and isometrically contracting muscle (C) for the 7 amputee data sets. Percentage change shown for the parameters of mean amplitude, variance, mean frequency and median frequency from contracting muscle to resting muscle.


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<tr>
<th>MUSCLE</th>
<th>R mean ampl (mV)</th>
<th>C mean ampl (mV)</th>
<th>C var /R var (%)</th>
<th>R mnf (Hz)</th>
<th>C mnf / R mnf (%)</th>
<th>R mdf (%)</th>
<th>C mdf (%)</th>
<th>C mdf / R mdf (%)</th>
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</tbody>
</table>
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Table 7.4. Mean increase in amplitude and variance of sEMG from contracting muscle to resting muscle for 5 hip muscles for group A. Standard deviation in brackets.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Mean percentage amplitude increase from relaxed state to contracting state (%)</th>
<th>Mean percentage variance increase from relaxed state to contracting state (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>2181 (1695)</td>
<td>57620 (76496)</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>651 (648)</td>
<td>8194 (16275)</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>439 (198)</td>
<td>2717 (2062)</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>746 (610)</td>
<td>9757 (12398)</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>933 (701)</td>
<td>16321 (23502)</td>
</tr>
</tbody>
</table>

Table 7.5. Mean change in amplitude and variance of sEMG from contracting muscle to resting muscle for seven group A data sets. Standard deviation in brackets.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Mean percentage amplitude increase from relaxed state to contracting state (%)</th>
<th>Mean percentage variance increase from relaxed state to contracting state (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>1346 (949)</td>
<td>22858 (16954)</td>
</tr>
<tr>
<td>A2</td>
<td>1294 (1772)</td>
<td>37691 (77163)</td>
</tr>
<tr>
<td>A3</td>
<td>397 (189)</td>
<td>23374 (2875)</td>
</tr>
<tr>
<td>A3rep</td>
<td>822 (586)</td>
<td>12177 (16930)</td>
</tr>
<tr>
<td>A4</td>
<td>1475 (1101)</td>
<td>41437 (53188)</td>
</tr>
<tr>
<td>A4rep</td>
<td>1428 (1534)</td>
<td>38354 (67454)</td>
</tr>
<tr>
<td>A5</td>
<td>185 (67)</td>
<td>450 (299)</td>
</tr>
</tbody>
</table>

Overall, there was no clear pattern in changes in sEMG median or mean frequencies from the resting state to the isometrically contracting state for individual muscles or individual datasets within the group A. In certain datasets such as A1 and A3, the frequency decreased with contraction of the muscles whereas in datasets A4rep and A5 the frequencies tended to increase with contraction of muscle. There was no clear pattern of change for the repeat data sets for A3 and A4. GMAX decreased in frequency for five of the seven datasets whereas BF increased in frequency for five of the seven datasets.

Table 7.6. p-values at 0.05 significance level for Wilcoxon signed rank test applied to sEMG recorded from relaxed and contracted GMAX (gluteus maximus), GMED (gluteus medius), RF (rectus femoris), AM (adductor magnus) and BF (biceps femoris) in group A subjects.* = reject null hypothesis

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Mean amplitude</th>
<th>Mean frequency</th>
<th>Median frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMAX</td>
<td>0.016*</td>
<td>0.078</td>
<td>0.031*</td>
</tr>
<tr>
<td>GMED</td>
<td>0.016*</td>
<td>0.571</td>
<td>0.688</td>
</tr>
<tr>
<td>RF</td>
<td>0.016*</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>AM</td>
<td>0.063</td>
<td>1.000</td>
<td>0.813</td>
</tr>
<tr>
<td>BF</td>
<td>0.016*</td>
<td>0.938</td>
<td>0.562</td>
</tr>
</tbody>
</table>

130
A Wilcoxon signed rank test was applied to the mean amplitude, mean frequency and median frequency to determine any significant change in these parameter when the muscle contracted. The desired level of significance was set at 0.05. The p-values are given in table 7.6. Only GMAX showed a significant change in mean frequency.

7.2.3 Results from walking
The second group of measurements were recorded whilst the subject was walking along the walkway. The subjects in group A and group B were asked to walk along the walkway until approximately twenty good stances had been recorded. The number of walks varied between a minimum of ten for dataset A4 to a maximum of twenty-three for dataset B8. Figure 7.4 illustrates the raw sEMG and force platform trace for dataset A2 for walk 33.

Figure 7.4 Raw sEMG and force platform trace for dataset A1 for walk 33.

A cyclical pattern can be ascertained for the raw sEMG traces of four of the five muscles shown in figure 7.4, the exception being RF. The coherence was estimated using the
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MATLAB signal processing toolbox function *cohere* which has been described in subsection 6.8.6. The coherence between the force platform data and the sEMG data shows a peak frequency occurring at 0.94 Hz. Figure 7.5 illustrates the coherence diagram between GMAX and the prosthetic limb force data for walk 33. This is similar to the gait frequency of this walk calculated at 0.91 Hz.

![Figure 7.5. Coherence diagram for dataset A1, walk 33, gluteus maximus](image)

### 7.2.3.1 Quality of sEMG signals

The raw sEMG recorded from the five muscles from both the group A and group B subjects were visually assessed for the presence of irregular, high amplitude signals. These types of signals are suggestive of noise or interference. Only one dataset, A2, displayed consistently irregular, high amplitude signals in the GMAX sEMG trace (see figure 7.6). The author was aware of the poor quality signal during the recording and did attempt to improve the quality by fixing the cables and taping the GMAX electrode more firmly to the skin. The amplifier gain was also adjusted. Although additional filtering could have improved the signal, it was decided to discard subject A2’s GMAX sEMG signal.

![Figure 7.6 Raw sEMG for gluteus maximus for dataset A2. High amplitude signals indicate noise.](image)
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7.2.3.2 Number of stances and gait parameters

The raw sEMG data was then split into individual stance and swing sections using heel strike and toe-off data from the force platform. Table 7.7 for group A and table 7.8 for group B list the dates when sEMG was recorded for each dataset and the number of stances successfully acquired. The repeat measurements for B1 and B8 were not successfully recorded due to problems saving the force platform data. A variable number of stances ranging from 18 to 27 were subsequently available for analysis.

Table 7.7 Dates of sEMG measurements and number of stances accurately recorded for group A

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Date of measurement</th>
<th>Number of stances</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>18.11.04</td>
<td>19</td>
</tr>
<tr>
<td>A2</td>
<td>10.11.05</td>
<td>23</td>
</tr>
<tr>
<td>A3</td>
<td>09.12.04</td>
<td>21</td>
</tr>
<tr>
<td>A3rep</td>
<td>10.11.05</td>
<td>24</td>
</tr>
<tr>
<td>A4</td>
<td>02.12.04</td>
<td>20</td>
</tr>
<tr>
<td>A4rep</td>
<td>10.11.05</td>
<td>27</td>
</tr>
<tr>
<td>A5</td>
<td>16.11.04</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 7.8 Dates of sEMG measurements and number of stances accurately recorded for group B

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Date of measurement</th>
<th>Number of stances</th>
<th>DATASET</th>
<th>Date of measurement</th>
<th>Number of stances</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>04.08.05</td>
<td>25</td>
<td>B6</td>
<td>04.08.05</td>
<td>20</td>
</tr>
<tr>
<td>B1rep</td>
<td>16.02.06</td>
<td>n/a</td>
<td>B6rep</td>
<td>19.12.05</td>
<td>22</td>
</tr>
<tr>
<td>B2</td>
<td>04.08.05</td>
<td>34</td>
<td>B7</td>
<td>19.12.05</td>
<td>21</td>
</tr>
<tr>
<td>B2rep1</td>
<td>17.11.05</td>
<td>34</td>
<td>B7rep</td>
<td>16.02.06</td>
<td>26</td>
</tr>
<tr>
<td>B3</td>
<td>07.11.05</td>
<td>28</td>
<td>B8</td>
<td>19.12.05</td>
<td>34</td>
</tr>
<tr>
<td>B3rep</td>
<td>19.01.06</td>
<td>30</td>
<td>B8rep</td>
<td>16.01.06</td>
<td>n/a</td>
</tr>
<tr>
<td>B4</td>
<td>19.12.05</td>
<td>22</td>
<td>B9</td>
<td>12.01.06</td>
<td>27</td>
</tr>
<tr>
<td>B4rep</td>
<td>16.02.06</td>
<td>20</td>
<td>B9rep</td>
<td>19.01.06</td>
<td>30</td>
</tr>
<tr>
<td>B5</td>
<td>04.08.05</td>
<td>28</td>
<td>B10</td>
<td>04.08.05</td>
<td>17</td>
</tr>
<tr>
<td>B5rep</td>
<td>07.11.05</td>
<td>21</td>
<td>B10rep</td>
<td>07.11.05</td>
<td>21</td>
</tr>
</tbody>
</table>

The gait parameters for group A and group B are listed in table 7.9. The mean gait cycle is longer for the amputees than for the intact subjects, being 1150ms compared to 1070ms. The percentage of the cycle accounted for by stance is 59.5% for group A compared to 62.5% for group B. The percentage of the gait cycle accounted for by the stance phase and the mean speed of walking for the five amputee subjects is shown in table 7.10. There is a moderate variation in percentage accounted for by the stance phase, ranging from 57.0 to 63.6% and a high range in walking speed, from 1.06m/s to 1.34m/s.
Table 7.9 Mean gait parameters calculated for group A (n=5) and group B (n=10).

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Group A</th>
<th>Group B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean stance (ms)</td>
<td>681.0</td>
<td>667.7</td>
</tr>
<tr>
<td>Standard deviation of stance (ms)</td>
<td>19.9</td>
<td>22.1</td>
</tr>
<tr>
<td>Mean swing (ms)</td>
<td>464.0</td>
<td>401.2</td>
</tr>
<tr>
<td>Standard deviation of swing (ms)</td>
<td>11.5</td>
<td>14.3</td>
</tr>
<tr>
<td>Mean gait cycle (ms)</td>
<td>1150</td>
<td>1070</td>
</tr>
<tr>
<td>Mean percentage cycle stance (%)</td>
<td>59.5</td>
<td>62.5</td>
</tr>
<tr>
<td>Range stance (ms)</td>
<td>580 - 757</td>
<td>714 - 855</td>
</tr>
<tr>
<td>Range swing (ms)</td>
<td>404 - 508</td>
<td>346 - 479</td>
</tr>
</tbody>
</table>

Table 7.10. Mean gait cycle accounted for by stance and mean speed for amputee subjects.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>% Gait cycle = Stance</th>
<th>Speed(m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>57.1</td>
<td>1.34</td>
</tr>
<tr>
<td>A2</td>
<td>53.4</td>
<td>1.20</td>
</tr>
<tr>
<td>A3</td>
<td>57.0</td>
<td>1.21</td>
</tr>
<tr>
<td>A4</td>
<td>60.2</td>
<td>1.25</td>
</tr>
<tr>
<td>A5</td>
<td>63.6</td>
<td>1.06</td>
</tr>
</tbody>
</table>

7.2.3.3 Group A joint kinematics

All five group A subjects had kinematic data of the pelvis and lower limb recorded during their first set of measurements. The methodology for acquiring the data was described in subsection 6.5.4. Kinematic reports were prepared for all five subjects (see Appendix 8). The hip and knee angles in the sagittal plane during the gait cycle are illustrated in figures 7.7a-e and 7.8a-e.
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Figures 7.7a – 7.7e Graphs illustrating position of knee joint in sagittal plane for gait cycles for group A subjects. Red dashed line indicates individual gait cycles and blue line shows +/− one standard deviation.

Figures 7.8a - 7.8e. Graphs illustrating position of hip joint in sagittal plane for gait cycles for group A subjects. Red dashed line indicates individual gait cycles and blue line shows +/− one standard deviation.

Low inter-stance variability was displayed for all subjects with the exception of hip flexion for subject A2. Differences in knee and hip flexion patterns were apparent during stance between the five subjects. These differences can be quantified by
selecting the timing of two kinematic events. These events are firstly the time instant at which knee flexion commences during the second half of the stance phase and secondly the time when hip flexion commences during pre-swing. Table 7.11 lists the timings.

Table 7.11 Time at which knee flexion commences during the second half of stance and hip flexion commences during pre-swing for group A subjects.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Onset of knee flexion</th>
<th>Onset of hip flexion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% gait cycle</td>
<td>% stance phase</td>
</tr>
<tr>
<td>A1</td>
<td>33.3</td>
<td>58.4</td>
</tr>
<tr>
<td>A2</td>
<td>35.2</td>
<td>65.9</td>
</tr>
<tr>
<td>A3</td>
<td>50.9</td>
<td>88.9</td>
</tr>
<tr>
<td>A4</td>
<td>39.4</td>
<td>65.4</td>
</tr>
<tr>
<td>A5</td>
<td>40.4</td>
<td>63.5</td>
</tr>
</tbody>
</table>

Dataset A3, unlike the other four datasets, does not display a small amount of flexion of the knee joint during the loading response. Instead, it extends slightly during the loading response and mid-stance (see figure 7.7c). Subject A2 shows small fluctuations of the knee joint during loading and mid-stance (see figure 7.1c). Observation of the hip joint kinematics in the sagittal plane reveals smooth hip extension until pre-swing when the hip joint commences to flex. Datasets A1, A2 and A3 show small amounts of hip extension just prior to toe-off. The hip joint of dataset A5 extends smoothly until approximately mid-stance when it decelerates for a short period (see figure 7.8e). The hip joint then accelerates into extension to resume its former angular velocity until hip flexion commences at 58.7% of the gait cycle.

7.2.3.4 Ground force reaction (GRF)

The GRF data recorded from the force platforms were exported and the mean GRF for each subject was calculated (see subsection 6.8.2). Figures 7.9a – g show the mean GRF for the seven data sets with standard deviation bars included. Similar to the kinematic traces, small variations can be ascertained between subjects for the GRF patterns.
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Figures 7.9a-g. Ground reaction forces for the prosthetic limb for group A datasets.

These variations can be quantified by measuring the timing of the two peaks. Table 7.12 contains the percentage times of the gait cycle at which the first peak and the second peaks are reached and the bodyweight percentage recorded at this peak.

**Table 7.12.** Timing and amplitude of first and second peaks of mean vertical GRF for amputee group.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>FIRST PEAK</th>
<th>SECOND PEAK</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% stance phase</td>
<td>% bodyweight</td>
</tr>
<tr>
<td>A1</td>
<td>15</td>
<td>99.9</td>
</tr>
<tr>
<td>A2</td>
<td>22</td>
<td>97.0</td>
</tr>
<tr>
<td>A3</td>
<td>27</td>
<td>99.9</td>
</tr>
<tr>
<td>A4</td>
<td>25</td>
<td>103.0</td>
</tr>
<tr>
<td>A5</td>
<td>27</td>
<td>99.3</td>
</tr>
</tbody>
</table>
7.2.3.5 Kinematic and force walkway parameter repeatability

The repeatability of the hip kinematic data was assessed by determining the CMC (see subsection 6.8.5). Overall, the repeatability for the group A vertical GRF and kinematic data was high, with a CMC above 0.8, with the exceptions of the hip angle in the coronal plane for dataset A4 and in the transverse plane for dataset A5 (see table 7.13).

Table 7.13. CMCs calculated for first group A measurements for between stance same measurement set for kinematic and GRF variables.

<table>
<thead>
<tr>
<th>ANGLE (sagittal plane)</th>
<th>Subject A1</th>
<th>Subject A2</th>
<th>Subject A3</th>
<th>Subject A4</th>
<th>Subject A5</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hip angle</td>
<td>1.00</td>
<td>0.86</td>
<td>1.00</td>
<td>0.84</td>
<td>0.99</td>
<td>0.94 (0.08)</td>
</tr>
<tr>
<td>Hip angle (coronal plane)</td>
<td>0.86</td>
<td>0.99</td>
<td>0.83</td>
<td>0.22</td>
<td>0.83</td>
<td>0.73 (0.30)</td>
</tr>
<tr>
<td>Hip angle (transverse plane)</td>
<td>0.95</td>
<td>0.84</td>
<td>0.94</td>
<td>0.81</td>
<td>0.67</td>
<td>0.84 (0.11)</td>
</tr>
<tr>
<td>GRF (vertical)</td>
<td>0.99</td>
<td>1.00</td>
<td>1.00</td>
<td>0.99</td>
<td>1.00</td>
<td>0.996 (0.005)</td>
</tr>
</tbody>
</table>

7.3 Discussion

7.3.1 Discussion on subject data

The group A subjects were on average older, heavier and shorter in height than the group B subjects (see tables 7.1 and 7.2). The reported effect of increased weight on intact subjects’ gait is to produce a slower walk with a shorter step length [DeVita & Tortobágyi 2003]. There is also likely to be increased hip extension and decreased knee flexion present during stance [DeVita & Tortobágyi 2003]. Subjects in both groups were within the age range in which a typical gait pattern is displayed as discussed in subsection 6.2.1. Age in this study is therefore unlikely to be a factor in producing differences in gait characteristics. Additional factors that are likely to produce variations in gait between the group A subjects are the onset and nature of the trauma, surgical techniques and types of prostheses fitted. Each of these factors has a strong influence on gait. One would therefore anticipate the amputees to exhibit a variety of gait patterns.

7.3.2 Discussion on resting / isometrically contracting muscle

The method used to produce an isometric contraction was based on the subject resisting to their maximal ability or to that of the experimenter, a force that the experimenter applied manually to the thigh (see subsection 6.4.3). A flaw in this procedure was that
the magnitude of force applied was not measured objectively, therefore it varied between subjects. However, the aim of the subject performing isometric contractions was to provoke activation of the muscle rather than assess the strength of the muscle. The purpose of recording these contractions was firstly to assess whether the electrodes were correctly positioned and secondly to investigate the frequency spectrum. The methodology was therefore sufficient to satisfy these two purposes.

All the muscles for the group A subjects displayed an increase in their mean amplitude and variance during isometric contraction (see table 7.4) indicating an increase in force of the recorded muscle [Lippold 1952; Schultz et al. 1982]. The greatest change in these parameters was shown by GMAX, a non-cleaved muscle, and the smallest change by RF, a cleaved bi-articular muscle (see table 7.6). Dataset A5 had the smallest mean increase in amplitude across the muscles of only 185% compared to the maximum of 1475% for dataset A4. This minor increase in sEMG may relate to the trauma subject A5 sustained. Subject A5, unlike the other amputees whose cause of amputation was through road traffic accidents, received a shotgun injury to his lower limb. There was therefore likely to have been significant disruption to the structure of the muscle fibres of subject A5 with adhesions present and destruction of muscle fibrils in addition to lesioning of the nerves and neuromuscular junctions [Bowyer & Rossiter 1997; Ordog et al. 1988].

An assessment of the frequency spectrum was made on the isometric sEMG. The group A subjects were unable to maintain an isometric contraction for 10 seconds of time, which generated a signal with fluctuating amplitude. The signal therefore did not strictly satisfy the criteria necessary to perform a STFT on (see subsection 5.3.3). The Welch method assumes that the signal is stationary (signal mean, variance and PSD remains constant through the signal section). A section of the signal was selected where the amplitude was observed to be as near constant as possible. The runs test, reverse arrangements test or modified reverse arrangements test was however, not applied to test for stationarity [Beck et al. 2006]. Results from the PSD estimation indicated that there was no consistent pattern of change in median or mean frequency (see table 7.3). Previous studies have not demonstrated any conclusive change in mean or median frequency (see subsection 2.10.1) as the force of contraction increases. Possible
explanations for this lack of consistency in frequency change include individual differences in recruitment strategy of muscle fibres and variations in the thickness and morphology of the tissues between the recorded muscle and surface electrode. The latter factor will affect the properties of the volume conductor with ensuing changes in conductivity and permittivity (see section 2.2). Skin fold thickness acts as a low pass filter and can significantly distort the sEMG frequency spectrum [Bilodeau et al. 2003]. Although the thickness was not measured, all five subjects had a BMI above 26kg/m² (see table 7.1) and are therefore likely to have a substantial subcutaneous layer thus significantly modulating the signal. Further causes in the amputee group that affect the PSD include a possible decrease in the number of type II fibres, changes in morphology of muscle fibres, early onset of fatigue and the presence of mains noise at 50 Hz. The latter factor was likely to have been a significant issue for dataset A3 (see figure 7.3c).

7.3.3 Discussion on gait parameters

The number of stances available for analysis was reasonable, ranging from 18 to 27 for the amputee group and 17 to 34 for the intact group. The minimum number of stances recommended to reduce variability is 20 (see subsection 2.4.3). The gait cycle is longer for amputees with a shorter percentage of 59.5% devoted to stance compared to the 62.5% for the intact group. The percentage of the gait cycle accounted for by the stance phase in the intact group is similar to that reported in the literature [Inman et al. 1994; Perry 1992; Sutherland et al. 1994]. Likewise the percentage of the gait cycle accounted for by the stance phase in the amputee group is comparable to that measured by Jaegers et al. (1995b) reported to be 58.4%.

7.3.4 Discussion on kinematic data

A CMC above 0.8 was obtained for most of the kinematic and kinetic measurements despite the lack of proprioceptive feedback from the knee, ankle and foot joints and an absence of input from the cutaneous foot receptors. Walking in these amputees is therefore a well-controlled event. The subjects had very fine control of activation of muscle groups in order to reproduce accurately the hip joint angle for successive stances indicating the presence of a possible CPG. The mean CMC of the hip kinematic variables was lower that reported by Kadaba et al. for intact subjects (see tables 7.13 and
7.14). This finding is consistent with the expectation that subjects with an intact musculoskeletal and neurological system would have a higher level of neuromotor control and therefore repeatability.

Table 7.14. List of interstance CMCs reported for hip kinematic data for intact subjects during level walking

<table>
<thead>
<tr>
<th>ANGLE</th>
<th>Kadaba (1989)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(SD)</td>
</tr>
<tr>
<td>Hip angle (sagittal plane)</td>
<td>1.00 (0.003)</td>
</tr>
<tr>
<td>Hip angle (coronal plane)</td>
<td>0.96 (0.03)</td>
</tr>
<tr>
<td>Hip angle (transverse plane)</td>
<td>0.89 (0.06)</td>
</tr>
</tbody>
</table>

An additional observation from the residual limb kinematic patterns was inter-subject differences in patterns. This can be explained by factors including the range of prostheses fitted, varying lengths of residual limbs, a difference in muscle and nerve lesioning, natural variations in morphology and different modes of neuromuscular control mechanisms.

7.3.5 Discussion on force walkway data

The ground reaction force graphs represent the manner in which an individual loads the lower limb as it makes contact with the ground and subsequently applies force to the ground to push the COM forwards. The pattern will be dependent on the activity of the lower limb and trunk muscles, flexibility of the lower limb and vertebral joints and movements of the upper extremities. The inter-stance reproducibility for the vertical component of the GRFs for the first set of measurements of the group A subjects was high with a CMC of 1.00 for subjects A2, A3 and A5 and 0.99 for subjects A1 and A4. This is similar to the low variability reported in the literature, with CVs reported of below 3% [Giakas & Baltzopoulos 1997; Masani et al. 2002]. The inter-subject variations in GRF patterns that were observed in figures 7.9a-g were consistent with the variations reported between osseo-integrated amputees for the loads measured from transducers placed in the prosthesis limb just distal to the stump [L. Frossard 2006, personal communication].
7.4 Conclusion

Although the number of subjects were small for both groups, the number of stances available for analysis was satisfactory. The subjects in group A were on average older and had a higher BMI than those in group B. The five subjects in group A differed in terms of the nature of trauma sustained, type of prosthesis fitted and the side of prosthetic limb. These factors may partially account for the diversity of findings between the group A subjects. All the amputees demonstrated an increase in sEMG amplitude in the five residual limb muscles recorded during isometric contraction. There was however, no consistent change in the MNF or MDF during an isometric contraction compared to the resting state. This finding may be due to the different properties of the volume conductor in addition to differing motor unit activation patterns that the five amputee subjects possess. Only one dataset, dataset A3, had significant mains noise within the signal recorded from isometric contraction of the five muscles. Amputees were able to reproduce both their hip joint movements in the sagittal plane and the vertical component of the GRF for the stance phase to a high level. The inference can be made that there is an underlying CPG co-ordinating muscle group activity. The next chapter will present the results from analysis of the sEMG recorded from the group A and group B subjects during walking and discuss these results.
Chapter 8

Results – Part II

8.1 Introduction

This chapter presents the parameters calculated through application of a moving average filter, a STFT, an ACWD and a WT for the stance phase of locomotion for group A. Only time-dependent parameters have been calculated for group B (see subsection 6.2.1). Large amounts of data and graphical representations have been generated by the application of various signal analysis techniques. A small proportion of this has been included in the body of the chapter.

Sections 8.2, 8.3, 8.4 and 8.5 present the MAY, STFT derived mean frequency, ACWD derived mean frequency and WT mean scale parameters respectively. Each subsection contains graphs of the selected sEMG parameter for the five muscles for representative dataset A1 for walk 33. This is followed by graphs illustrating the mean for each stance with standard deviation bars drawn on. All group A datasets have had moving average filters, STFT and WT applied. Only the sEMG of datasets A1, A3, A4 and A5 were analysed with ACWD due to the length of time required for processing. Assessment of the repeatability of stance for the four different parameters was made by calculating the CMC. This is described at the end of each subsection. A comparison of all the different parameters for each subject and each muscle is contained in section 8.6. A discussion of the results is presented within each subsection. Comparison with previously published results was only undertaken for the MAV parameter since there was a lack of published studies on patterns of STFT, ACWD and WT parameters during gait.

8.2 Moving average value (MAV)

8.2.1 MAV parameters

All the MAVs for both datasets in group A and group B were calculated using the MATLAB $\texttt{filtfilt}$ routine with a 100ms window. Figures 8.1a to 8.1e show the linear envelopes obtained for Dataset A1 for walk 33. All the five hip muscles displayed a cyclical pattern of activity with the largest peaks occurring during the swing phase. The amplitude of the peaks however varied between gait cycles.
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Figure 8.1a. Linear envelope for sEMG of gluteus maximus for Dataset A1 for walk 33 applying 100ms window. ▲ -Point of heel-strike

Figure 8.1b. Linear envelope for sEMG of gluteus medius for Dataset A1 for walk 33 applying 100ms window. ▲ -Point of heel-strike.

Figure 8.1c. Linear envelope for sEMG of rectus femoris for Dataset A1 for walk 33 applying 100ms window. ▲ -Point of heel-strike.

Figure 8.1d. Linear envelope for sEMG of adductor magnus for Dataset A1 for walk 33 applying 100ms window. ▲ -Point of heel-strike.

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Force platform (N)

Body weight (846.6N)

Figure 8.1e. Linear envelope for sEMG of biceps femoris for Dataset A1 for walk 33 applying 100ms window. ▲ -Point of heel-strike.

The walks were then separated into stance and swing phases. The stance phases were time normalised to 30 points and amplitude normalised to the maximum per stance (see subsection 5.3.2). Figures 8.2 to 8.6 depict the ensemble MAV graphs for GMAX, GMED, RF, AM and BF for the datasets in group A with the standard deviation (SD) bars included. Only six datasets were available for GMAX since the GMAX for A2 was discarded as discussed in subsection 7.2.3.1.

Figures 8.2a –8.2e. The mean moving average values for gluteus maximus for six datasets in group A with error bars of +/- one standard deviation shown. Length of smoothing window = 100ms.
Figures 8.3a – 8.3g. The mean moving average values for gluteus medius for seven datasets in group A with error bars of +/−one standard deviation shown. Length of smoothing window = 100ms.

Figures 8.4a – 8.4g. The mean moving average values for rectus femoris for seven datasets in group A with error bars of +/−one standard deviation shown. Length of smoothing window = 100ms.
Figures 8.5a – 8.5g. The mean moving average values for adductor magnus for seven datasets in group A with error bars of +/- one standard deviation shown. Length of smoothing window=100ms.
Chapter 8. Results – Part II

Figure 8.6g

Figures 8.6a – 8.6g. The mean moving average values for biceps femoris for seven datasets in group A with error bars of +/- one standard deviation shown. Length of smoothing window = 100ms.

The mean amplitude for GMAX and GMED tended to be maximal at the beginning of stance, decreased then attained a smaller peak during the second half of the stance phase. The RF, AM and BF did not exhibit a specific pattern. There was variability in the size of the SDs between datasets with datasets A1 and A4 having the largest and dataset A3 having the smallest SDs. GMED and AM had overall the smallest SDs whereas RF had the largest. There was additionally a change in the magnitude of the SDs during the cycle although there was no part of the cycle that consistently showed a greater or lesser SD.

Figures 8.7a-e and 8.8a-e show the mean ensemble MAVs for the five muscles for group A and group B. The general trend was for the mean to decrease from the beginning of stance and then rise again to reach a peak during the final 25% of the stance. There was no obvious difference in the size of the SDs between both groups.

Figure 8.7a.

Figure 8.7b.

Figure 8.7c.

Figure 8.7d.

Figure 8.7e.

Figures 8.7a – 8.7e. The mean moving average values for group A for all five muscles with error bars of +/- one standard deviation shown. Length of smoothing window = 100ms. n=5.
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Figures 8.8a – 8.8e. The mean moving average values for group B for all five muscles with error bars of +/- one standard deviation shown. Length of smoothing window = 100ms.  

8.2.2 Group B parameters and previous literature

GMAX and GMED

Group B traces for GMAX and GMED were similar to those reported in previous studies (see subsection 3.4.2) with peak activity occurring at the beginning of stance and then declining towards mid-stance.

RF

The sEMG pattern for RF showed good correspondence with results obtained by Olree and Vaughan (1995) and Jaegers et al. (1996) with increased activity at the beginning of stance (0% - 25%). During the loading response, contraction of the knee extensors is necessary to prevent excessive knee flexion.

AM

The AM activity pattern was in broad agreement with that reported by Olree & Vaughan (1995) and Jaegers et al. (1996), being biphasic with the first peak occurring during early stance and the second during late stance.

BF

The sEMG pattern for BF differed somewhat from that found by Jaegers et al. (1996) and Winter & Yack (1987) who reported that the sEMG increased during the first half of stance then decreased, remaining at a low amplitude during the latter part of stance. The pattern of activity of BF was however similar to that reported by Kadaba et al. (1989) and Shiavi et al. (1987) for the medial hamstrings. The difference in
findings between studies was probably related to the varying positions of electrode placements and subjects groups.

8.2.3 Group A MAV stance patterns and previous literature
The main previous study of sEMG in TF amputees during walking is by Jaegers et al. (1996) (see subsection 4.8.2). There are a number of differences between the findings of their investigation and that of the author’s. The former’s study analysed sEMG averaged over only a minimum of three complete strides and heel-strike and toe-off timings were extracted from kinematic data. Jaegers et al. (1996) applied different analysis techniques to obtain the linear envelope with the muscle activity being full wave rectified, filtered at 25 Hz and the output sampled at 200 Hz. A comparison of the results from the two studies now follows.

**GMAX**
When TFL was fixed, Jaegers et al. (1996) reported GMAX as being active during the first 40% of the stride cycle (equivalent to about 70% of the stance phase) and active throughout stride when TFL was not fixed. None of the osseointegrated subjects involved in the author’s study had their TFL fixed. However, in the author’s study the pattern of GMAX activity showed increased activity during the loading phase of stance with a subsequent decrease during mid-stance.

**GMED**
Jaegers et al. (1996) described GMED as being active throughout the stride in subjects with a short residuum and up to 53% of the gait cycle (about 90% of stance phase) in subjects with longer ones. The present study reported a different pattern of activity with the MAV high during the loading phase, decreasing during mid-stance and then increasing to another peak during terminal stance. The increased activity in GMED found in this study may be related to the more pronounced lateral trunk-bending present in osseointegrated TF amputees [Sullivan et al. 2003].

**RF**
RF was reported by Jaegers et al. (1996) to be active during the first third of the stance phase with some subjects having an increased episode of activity at the end of the stance phase. Datasets A3, A3rep and A5 had a similar pattern to this. A different pattern was exhibited by dataset A1, A2 and A4, all of which showed a peak at 60% to 70% of stance.
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AM
Dataset’s A1, A3 and A3rep MAV patterns for AM were similar to that described by Jaegers et al. (1996). The remaining four datasets however had different patterns.

BF
Datasets A4 and A4rep showed relatively constant activity which Jaegers et al. (1996) had observed in amputees with short residual limbs. The remaining datasets had patterns broadly in agreement with Jaegers et al.’s (1996) study, with the MAV high at the beginning or early part of stance, declining and then reaching another peak.

8.2.4 Group A and B MAV patterns
Overall resemblances in patterns can be observed between the mean group A and group B MAV sEMG traces (see figures 8.7a – 8.7e and figures 8.8a – 8.8e). During mid-stance, there was a dip in activity of all five muscles for both groups with the minima occurring at about 50% of the stance phase for group A and from 50% to 70% for group B. At this point of the cycle, the lower limb is vertical and there is only a small torque arising from the upper body segments about the hip joints. The earlier onset of the minima occurring for the group A subjects may be related to differences in kinematics between the 2 groups. The average onset of knee flexion for group A was 68% of the stance phase (see table 7.11) compared to an average of 81% of the stance phase for subjects with intact limbs [Perry 1992].

GMAX and GMED
The group A traces for these two muscles both displayed a maximum at the beginning of stance, decreasing to a minimum midway through stance and then peaking again at 70% to 80% of the stance phase. A comparable pattern can be observed for group B although with a later onset and less pronounced peak for GMED. During initial contact, there is an increase in the hip flexion moment, which must be counterbalanced by a hip extension moment arising from the contracting hip extensors. The increased activity in terminal stance for the amputees prior to double stance seen in GMAX and GMED produces increased extension and abduction of hip joint prior to the swing phase. This increased activity of GMED in group A subjects may be associated with the hip hiking that is commonly present in the amputees’ gait [Michaud et al. 2000]. Hip hiking and swinging the lower extremity laterally assists with toe clearance during the swing phase. The maxima of the peak for GMED for
group A occurred at about 75% of the stance phase which represents the time at which unloading commences (see figures 7.9a to 7.3g).

**RF**

A similar pattern to the intact group was found for the amputees with increased amplitude during the first half of stance and an additional increase during the latter part of the stance phase. There was not a very large change in amplitude for group A, with a maximum of about 60% and a minimum of about 40% of the mean normalised maximum value.

**AM**

The group A AM trace decreased from heel-strike to a minimum at 45% of the stance phase then sharply rose to a peak at about 87% of the stance phase (see figure 8.7d). The pattern of activity differed from that of the mean group B whose amplitude increased during the loading phase, declined during mid-stance and had a smaller secondary peak at about 80%. An explanation for the increased activity of group A during the pre-swing phase is that AM may be assisting GMAX in hip extension. Adductor magnus has been described as a major stabiliser of the femur [Gottschalk 1999]. High levels of activity of AM would therefore be anticipated during challenging tasks involving loading and unloading phases of the limb.

**BF**

Both group A and group B graphs for BF showed large SDs, which have also been reported by Patla (1985). The mean in both graphs decreased from initial contact to mid-stance and then increased during the second half of stance. In the case of the group A mean value, the amplitude plateaued at about 75% of the stance phase whereas for the group B the mean value steadily increased with a sharp rise during pre-swing as the knee flexed. The biceps femoris muscle differs from the other muscles recorded in that it possesses two heads. The two heads of BF are innervated separately by the two divisions of the sciatic nerve indicating their development from both the hip flexors and extensors and therefore have two different actions [Perry 1992; Warwick & Williams 1973]. The TF amputees only retain that part of the BF muscle originating from the ischial tuberosity and thus the actions of BF during stance are different to that found in intact subjects.
8.2.5 Inter-stance repeatability of MAV data

The CMC was calculated to assess the variability of sEMG parameters between stances and between measurement days for individual datasets. Table 8.1 lists the CMCs for the sEMG between stances for group A datasets and table 8.2 contains the CMCs for the sEMG between stances for the group B datasets.

Table 8.1 CMCs calculated for group A datasets for between stance same measurement set for sEMG MAV variables. n/a=not available

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Dataset</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>0.40</td>
<td>n/a</td>
<td>0.85</td>
<td>0.92</td>
<td>0.11</td>
<td>0.08</td>
<td>0.42</td>
<td>0.46</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.33</td>
<td>0.29</td>
<td>0.69</td>
<td>0.83</td>
<td>0.43</td>
<td>0.42</td>
<td>0.69</td>
<td>0.53</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.21</td>
<td>0.41</td>
<td>0.90</td>
<td>0.89</td>
<td>0.23</td>
<td>0.26</td>
<td>0.36</td>
<td>0.47</td>
<td>(0.30)</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>0.77</td>
<td>0.34</td>
<td>0.74</td>
<td>0.85</td>
<td>0.16</td>
<td>0.76</td>
<td>0.83</td>
<td>0.64</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.47</td>
<td>0.69</td>
<td>0.85</td>
<td>0.90</td>
<td>0.37</td>
<td>0.23</td>
<td>0.67</td>
<td>0.60</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>0.44</td>
<td>0.43</td>
<td>0.81</td>
<td>0.88</td>
<td>0.26</td>
<td>0.35</td>
<td>0.59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

There was intra-subject and inter-subject variation in the CMC for different muscles. Three of the five amputees displayed repeatability with a CMC above 0.75 for at least one of the hip muscles. Subject A3 had a CMC of above 0.80 for three muscles for the first set of measurements and for all muscles for the second set. Overall, the mean CMC was lower for the amputees than for the intact subjects. However, the subject across both groups with the best repeatability was Subject A3. Group B had a higher mean CMC for all muscles with the exception of BF.
8.2.6 Between measurement day repeatability of MAV data

Two of the five subjects in group A had the measurements repeated approximately eleven months later. All the group B subjects had the measurements repeated with periods varying between one week and six months between measurements. Two of the group B repeat measurement could not be analysed due to problems recording the force walkway data. The between day variability for the two subjects in group A and the eight subjects in group B are presented in table 8.3 and table 8.4 respectively.

Table 8.3. CMCs calculated for group A datasets for between dataset variability for sEMG MAV variables during stance.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Subject A3 n=21/24 336 days between recordings</th>
<th>Subject A4 n=20/27 343 days between recordings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>0.86</td>
<td>0.23</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.80</td>
<td>0.44</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.76</td>
<td>0.15</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>0.66</td>
<td>0.36</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.84</td>
<td>0.30</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>0.78 (0.08)</td>
<td>0.30 (0.11)</td>
</tr>
</tbody>
</table>

Table 8.4. CMCs calculated for group B datasets for between dataset variability for sEMG MAV variables during stance.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Subject B2 n=34/34 105 days between recordings</th>
<th>Subject B3 n=28/30 73 days between recordings</th>
<th>Subject B4 n=22/20 59 days between recordings</th>
<th>Subject B5 n=28/21 89 days between recordings</th>
<th>Subject B6 n=20/22 137 days between recordings</th>
<th>Subject B7 n=21/26 59 days between recordings</th>
<th>Subject B9 n=27/30 7 days between recordings</th>
<th>Subject B10 n=17/21 95 days between recordings</th>
<th>Mean (SD) of Group B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>0.25</td>
<td>0.54</td>
<td>0.48</td>
<td>0.38</td>
<td>0.31</td>
<td>0.54</td>
<td>0.66</td>
<td>0.60</td>
<td>0.47 (0.14)</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.54</td>
<td>0.50</td>
<td>0.76</td>
<td>0.56</td>
<td>0.66</td>
<td>0.73</td>
<td>0.62</td>
<td>0.75</td>
<td>0.64 (0.10)</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.55</td>
<td>0.37</td>
<td>0.44</td>
<td>0.21</td>
<td>0.61</td>
<td>0.38</td>
<td>0.48</td>
<td>0.52</td>
<td>0.45 (0.13)</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>0.46</td>
<td>0.62</td>
<td>0.51</td>
<td>0.66</td>
<td>0.69</td>
<td>0.81</td>
<td>0.72</td>
<td>0.62</td>
<td>0.64 (0.11)</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.63</td>
<td>0.37</td>
<td>0.42</td>
<td>0.32</td>
<td>0.43</td>
<td>0.50</td>
<td>0.49</td>
<td>0.63</td>
<td>0.47 (0.11)</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>0.49 (0.15)</td>
<td>0.48 (0.11)</td>
<td>0.52 (0.14)</td>
<td>0.43 (0.18)</td>
<td>0.54 (0.16)</td>
<td>0.59 (0.18)</td>
<td>0.59 (0.11)</td>
<td>0.62 (0.08)</td>
<td>0.53 (0.10)</td>
</tr>
</tbody>
</table>

Inter-day repeatability was low for both groups with the exception of subject A3 (see table 8.3) which had a mean CMC of 0.78.
8.2.7 Discussion of group B sEMG MAV repeatability

The CMCs for group B listed in table 8.2 were much lower than those calculated by Kadaba et al. (1989) (see table 8.5) with the exception of adductor magnus. Similarly, the inter-day repeatability listed in table 8.4 was poorer compared to Kadaba et al.'s results. A number of factors may account for these differences. Firstly as stated previously, the CMCs in this study were calculated only for the stance phase, which is likely to result in a lower CMC. Stance represents a more complex part of the cycle since muscles have to contract in such a way that equilibrium is maintained and the centre of mass moved anteriorly. Secondly, the preparation of the subjects was different since in this study the subjects' lower extremities were not shaved. The lack of skin preparation was in accordance with the advice provided in the Biometrics manual (Biometrics Ltd., Gwent, UK). A number of the volunteers had significant hair on the thighs, which was likely to result in distortion of the signal (see section 2.7). An additional factor is that five of the subjects had considerable muscle mass, in particular, of the quadriceps, which was observed to oscillate as the subject walked.

### Table 8.5.
Table listing the mean CMC values and standard deviations for inter-stance and inter-cycle MAV repeatability for same day and different measurement days for TF amputees from the author’s study and Kadaba et al.’s study.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>CMC (SD) Kadaba et al. (1989)</th>
<th>CMC (SD) Group B</th>
<th>CMC (SD) Kadaba et al. (1989)</th>
<th>CMC (SD) Group B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inter-cycle</td>
<td>Inter-stance</td>
<td>Same day</td>
<td>Same day</td>
</tr>
<tr>
<td>Gluteus maximus</td>
<td>0.85 (0.06)</td>
<td>0.57 (0.11)</td>
<td>0.82 (0.08)</td>
<td>0.47 (0.14)</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.85 (0.06)</td>
<td>0.79 (0.13)</td>
<td>0.84 (0.06)</td>
<td>0.64 (0.10)</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.86 (0.05)</td>
<td>0.62 (0.18)</td>
<td>0.82 (0.07)</td>
<td>0.45 (0.13)</td>
</tr>
<tr>
<td>Adductor (type)</td>
<td>0.75 (0.10)</td>
<td>0.76 (0.14)</td>
<td>0.66 (0.12)</td>
<td>0.64 (0.11)</td>
</tr>
<tr>
<td></td>
<td>longus</td>
<td>magnus</td>
<td>longus</td>
<td></td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.84 (0.07)</td>
<td>0.53 (0.16)</td>
<td>0.80 (0.09)</td>
<td>0.47 (0.11)</td>
</tr>
</tbody>
</table>

8.2.8 Discussion on group A sEMG MAV repeatability

Overall, the group A subjects displayed a very poor repeatability of sEMG for all four parameters and five muscles with the exception of subject A3 for the MAV parameter. There are no published data available on the reproducibility of sEMG in the residual limb muscles of TF amputees during locomotion that the author is aware of with which to compare these results.

In a TF amputee, there are fewer effectors with which to control the hip joint resulting in a smaller number of contraction patterns available to achieve a desired
hip angle compared to the intact subject. For example, in an intact subject, the amount of hip flexion is largely determined by the amount of contraction of the six agonists and five antagonists (see table 6.1). In a TF amputee the number of intact agonists is reduced to one (iliopsoas) and intact antagonists reduced to two (GMAX, piriformis). One might therefore have anticipated that TF amputees would have a more reproducible pattern compared to intact subjects given that there are fewer intact muscles involved. This however does not appear to be the case.

Subject A3 displayed high repeatability for the MAV parameter with mean CMC values of 0.81 and 0.88 for datasets A3 and A3rep respectively. This subject had the highest mass of 98.2kg and was also the youngest subject. The knee kinematics of subject A3 differed from that of other subjects in that the angle of the prosthetic knee remained constant during the loading phase and knee flexion commenced relatively late (see figure 7.7c). The percentage of stance phase taken to load subject A3’s prosthetic limb was long (27%). In summary, subject A3 had a stiff-legged gait, which he was able to reproduce well for successive stances.

8.3. Short time Fourier transforms

8.3.1 STFT parameters

The next method of analysis of the sEMG during stance was to apply a short time Fourier transform with a Hamming window of length 64 ms and overlap of 36ms. The STFT was applied only to the group A datasets for reasons described in subsection 6.2.1. Figures 8.9a to 8.9g illustrate the typical spectrograms obtained. All the spectrograms shown above display a cyclical pattern. However, the spectrograms for RF and AM contain a line running through at approximately 250 Hz. This artefact is likely to be a harmonic of the 50 Hz mains frequency. This artefact was not present in the spectrogram of isometrically contracting muscle (see figure 7.3a). The generation of this interference was probably therefore due to loops of wires moving through EM fields as the subject walked along the walkway (see section 2.7).
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Figure 8.9a. Spectrogram of gluteus maximus for Dataset A1. Walk 33. \( \uparrow \) Point of heel-strike

Figure 8.9b. Spectrogram of gluteus medius for Dataset A1. Walk 33. \( \uparrow \) Point of heel-strike

Figure 8.9c. Spectrogram of rectus femoris for Dataset A1. Walk 33. \( \uparrow \) Point of heel-strike

Figure 8.9d. Spectrogram of adductor magnus for Dataset A1. Walk 33. \( \uparrow \) Point of heel-strike
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**Figure 8.9e.** Spectrogram of biceps femoris for Dataset A1. Walk 33. - Point of heel-strike

The STFT was then applied to the sEMG for the individual stances and the mean frequency was calculated for each stance. The mean frequency points were time normalized to 30 points per stance (see subsection 6.8.4.2). The ensemble mean frequency for all the stances was then determined for each dataset for each muscle. Figures 8.10a to 8.14g show the ensemble mean frequencies for the five muscles and seven datasets with the SD bars included.

**Figure 8.10a**
**Dataset A1. Gluteus maximus**

**Figure 8.10b**
**Dataset A3. Gluteus maximus**

**Figure 8.10c**
**Dataset A4 rep. Gluteus maximus**

**Figure 8.10d**
**Dataset A5. Gluteus maximus**

**Figure 8.10e**
**Dataset A4 rep. Gluteus maximus**

**Figure 8.10f**
**Dataset A5. Gluteus maximus**

**Figures 8.10a – 8.10f.** The mean frequency for gluteus maximus for group A datasets with error bars of +/- one standard deviation showed. Hamming window of 64ms used with overlap of 36ms.
Figure 8.11a - 8.11g. The mean frequency for gluteus medius for group A datasets with error bars of +/- one standard deviation shown. Hamming window of 64ms used with an overlap of 36ms.

Figure 8.12a - 8.12g. The mean frequency for rectus femoris for group A datasets with error bars of +/- one standard deviation shown. Hamming window of 64ms used with overlap of 36ms.
Figure 8.13a - 8.13g The mean frequency for adductor magnus for group A datasets with error bars of +/- one standard deviation shown. Hamming window of 64ms used with overlap of 36ms.

Figure 8.14a - 8.14g. The mean frequency for biceps femoris for group A datasets with error bars of +/- one standard deviation shown. Hamming window of 64ms used with overlap of 36ms.
The mean frequency was generally variable between subjects with high magnitude of SDs displayed. Datasets A3 and A5 showed a similar mean frequency pattern during stance with a peak present at about 70% of stance for GMED. Subject A4’s two datasets in comparison revealed a trough at this point. Datasets A2 and A3rep also had a minima present at this point in the cycle. The mean frequencies for Subject A3’s datasets for RF were comparable in outline with peaks from about 25% to 80% of the stance phase. The BF mean frequency patterns had maxima at approximately 50% for datasets A3 and A4rep. However, the graphs for datasets A3rep and A4 did not repeat this pattern.

8.3.2 Discussion on inter-subject variability of sEMG patterns

The previous chapter estimated the mean and median frequency in resting muscle and isometrically contracting muscle (see table 7.3). It was observed that for certain subjects and certain muscles the MF and MNF increased whereas for others it decreased. A possible explanation for the lack of consistency in frequency change includes individual patterns of motor unit recruitment and differences in volume conductor properties (see subsection 7.3.3). Given that the direction in which the mean frequency varies as the force of muscle contraction increases, one would not anticipate similar patterns in mean frequency during stance. Figure 8.15 illustrates the variable patterns in mean frequency across the seven datasets for a representative muscle, biceps femoris. Referring to table 7.3, datasets A1 and A3rep demonstrate a decrease in mean frequency during an isometric contraction of BF. Figure 8.16 shows the mean frequency for the seven datasets, with the patterns for datasets A1 and A3rep inverted. Datasets A1, A2, A3, A3rep and A4rep display broadly similar patterns now. A more considered analysis is beyond the scope of this study.
8.3.3 Repeatability of STFT parameters during stance for group A

The CMC was then calculated for each subject for each muscle. The CMC values are listed in table 8.6.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
<th>Dataset A3</th>
<th>Dataset A3 rep</th>
<th>Dataset A4</th>
<th>Dataset A4 rep</th>
<th>Dataset A5</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>0.49</td>
<td>N/A</td>
<td>0.71</td>
<td>0.72</td>
<td>0.45</td>
<td>0.54</td>
<td>0.23</td>
<td>0.52</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.64</td>
<td>0.77</td>
<td>0.20</td>
<td>0.50</td>
<td>0.31</td>
<td>0.60</td>
<td>0.68</td>
<td>0.53</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.26</td>
<td>0.69</td>
<td>0.55</td>
<td>0.54</td>
<td>0.34</td>
<td>0.31</td>
<td>0.11</td>
<td>0.40</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>0.14</td>
<td>0.44</td>
<td>0.47</td>
<td>0.46</td>
<td>0.41</td>
<td>0.49</td>
<td>0.33</td>
<td>0.39</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.52</td>
<td>0.84</td>
<td>0.70</td>
<td>0.70</td>
<td>0.46</td>
<td>0.52</td>
<td>0.26</td>
<td>0.57</td>
</tr>
<tr>
<td>Mean</td>
<td>0.41</td>
<td>0.69</td>
<td>0.53</td>
<td>0.58</td>
<td>0.39</td>
<td>0.49</td>
<td>0.32</td>
<td>0.49</td>
</tr>
</tbody>
</table>

There was low overall repeatability of the STFT mean frequency across subjects and muscles. Dataset A2 had the least variability with GMED and BF having the greatest CMCs. Dataset A5 had the poorest repeatability with GMED having the highest CMC of only 0.68.

8.4 Adaptive Choi-Williams transform

8.4.1 ACWD parameters

The signals from Datasets A1, A3, A4 and A5 were then further analysed using an adaptive Choi-Williams transform [Gomes 1999]. The vector of sample sigmas ranged from 1 to 100, the length of performance window was 250 and the number of frequency points was 256. Figures 8.17a-e illustrates the contour trace for subject A1 for two stances and one swing for walk 33 for the five muscles.
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**Figure 8.17a.** Power spectral density applying ACWD with 250ms window and 256 frequency points for gluteus maximus for Dataset A1 during walk 33. – Point of heel-strike

**Figure 8.17b.** Power spectral density applying ACWD with 250ms window and 256 frequency points for gluteus medius for Dataset A1 during walk 33. – Point of heel-strike

**Figure 8.17c.** Power spectral density applying ACWD with 250ms window and 256 frequency points for rectus femoris for Dataset A1 during walk 33. – Point of heel-strike
Figure 8.17d. Power spectral density applying ACWD with 250ms window and 256 frequency points for adductor magnus for Dataset A1 during walk 33. ♦ – Point of heel-strike

Figure 8.17e. Power spectral density applying ACWD with 250ms window and 256 frequency points for biceps femoris for Dataset A1 during walk 33. ♦ – Point of heel-strike

The mean frequency was then estimated for each stance and the ensemble mean frequency was estimated having time normalised each stance to 30 points (see subsection 6.8.4.2). Figures 8.18a to 8.22d display the results.

Figures 8.18a – 8.18d. The mean frequency for gluteus maximus for group A datasets with error bars of +/- one standard deviation shown. ACWD applied with 250ms window, 256 frequency points.
**Figures 8.19a – 8.19d.** The mean frequency for gluteus medius for group A datasets with error bars of +/- one standard deviation shown. ACWD applied with 250ms window, 256 frequency points.

**Figures 8.20a – 8.20d** The mean frequency for rectus femoris for group A datasets with error bars of +/- one standard deviation shown. ACWD applied with 250ms window, 256 frequency points.
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Figure 8.21d
Figures 8.21a – 8.21d. The mean frequency for adductor magnus for group A datasets with error bars of +/− one standard deviation shown. ACWD applied with 250ms window, 256 frequency points.

Figure 8.22d
Figures 8.22a-8.22d. The mean frequency for biceps femoris for group A datasets with error bars of +/− one standard deviation shown. ACWD applied with 250ms window, 256 frequency points.

The four datasets showed varying patterns in their mean frequencies for the five muscles. However, some similarities can be observed. Dataset A3 exhibited a peak in mean frequency during midstance for all muscles except AM. Dataset A5 had a similar pattern of activity for GMED as A3, with a peak at about 60% of the stance phase. The mean frequency estimated for RF for A4 was comparable with that of dataset’s A3, although with a less pronounced peak. Likewise, the patterns for adductor magnus for A4 and A4 were similar.

8.4.2 Repeatability of ACWD parameters for stance for group A
The CMCs were then calculated for each of the datasets for each muscle. Table 8.7 lists the values of the CMCs.
Table 8.7. CMCs for four group A subjects for stance using ACWD parameters

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset A1</th>
<th>Dataset A3</th>
<th>Dataset A4</th>
<th>Dataset A5</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>0.52</td>
<td>0.47</td>
<td>0.52</td>
<td>0.27</td>
<td>0.47 (0.12)</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.57</td>
<td>0.46</td>
<td>0.52</td>
<td>0.65</td>
<td>0.55 (0.08)</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.40</td>
<td>0.56</td>
<td>0.46</td>
<td>0.29</td>
<td>0.43 (0.11)</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>0.45</td>
<td>0.41</td>
<td>0.50</td>
<td>0.30</td>
<td>0.42 (0.09)</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.58</td>
<td>0.67</td>
<td>0.63</td>
<td>0.14</td>
<td>0.51 (0.25)</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>0.50</td>
<td>0.51</td>
<td>0.53</td>
<td>0.33</td>
<td>0.47 (0.07)</td>
</tr>
</tbody>
</table>

The intra-individual repeatability for stance using ACWD mean frequency was low with dataset A5 having a mean CMC of 0.33. The highest CMC for any muscle was only 0.67, calculated for dataset A3 for BF.

8.5 Wavelet transform

8.5.1 WT parameters
The final parameters extracted from the sEMG were wavelet parameters. The `scalog.m` function in the Wavelet Toolbox Version 3.0 (1-Jun-96) developed by the Universidad de Vigo was used to calculate the wavelet parameters. This algorithm uses a Morlet wavelet. The scales were calculated from 30 to 2 which is approximately equivalent to 28 Hz - 425 Hz and is therefore within the anticipated frequency range of the EMG signal (see subsection 5.3.3). Figures 8.23a – 8.23e illustrate the scalograms for subject A1 for walk 33.

![Figure 8.23a. Scalogram for gluteus maximus for Dataset A1, walk 33. Morlet wavelet. Scales 2-30. Point of heel-strike](image-url)
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Figure 8.23b. Scalogram for gluteus medius for Dataset A1, walk 33. Morlet wavelet. Scales 2-30. ▲ Point of heel-strike

Figure 8.23c. Scalogram for rectus femoris for Dataset A1, walk 33. Morlet wavelet. Scales 2-30. ▲ Point of heel-strike

Figure 8.23d. Scalogram for adductor magnus for Dataset A1, walk 33. Morlet wavelet. Scales 2-30. ▲ Point of heel-strike

Figure 8.23e. Scalogram for biceps femoris for Dataset A1, walk 33. Morlet wavelet. Scales 2-30. ▲ Point of heel-strike

The mean scale was then estimated for all muscles for each dataset during stance (see subsection 6.8.4.2). Each stance was time normalised to 30 points and the ensemble
mean scale calculated. The mean scales and SDs for all five muscles are shown in figures 8.24 to 8.28.

Figures 8.24a – 8.24f. Mean scale during stance for gluteus maximus for group A datasets.

Figures 8.25a – 8.25g. Mean scale during stance for gluteus medius for group A datasets.
Figures 8.26a - 8.26g. Mean scale during stance for rectus femoris for group A datasets.

Figures 8.27a - 8.27g. Mean scale during stance for adductor magnus for group A datasets.
Figures 8.28a – 8.28g. Mean scale during stance for biceps femoris for group A datasets. A variety of patterns of ensemble mean scale was displayed amongst the datasets for a particular muscle. Some trends in the mean scale during stance could be discerned. Datasets A1, A3, A3rep and A5 displayed a trough in scale for GMAX at 50% of the stance phase. All the datasets showed a decrease in scale at between 50% to 75% for RF. The patterns of scale changes for A3, A3rep, A4, A4rep and A5 displayed similarities with a trough at 40% to 50% followed by a peak at 80% to 90%.

8.5.2 Repeatability of WT parameters for stance

Table 8.8. CMCs for seven group A datasets for stance using WT parameters

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
<th>Dataset A3</th>
<th>Dataset A3rep</th>
<th>Dataset A4</th>
<th>Dataset A4rep</th>
<th>Dataset A5</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gluteus maximus</td>
<td>0.51</td>
<td>0.32</td>
<td>0.54</td>
<td>0.58</td>
<td>0.31</td>
<td>0.41</td>
<td>0.54</td>
<td>0.46</td>
</tr>
<tr>
<td>Gluteus medius</td>
<td>0.39</td>
<td>0.66</td>
<td>0.48</td>
<td>0.29</td>
<td>0.19</td>
<td>0.46</td>
<td>0.50</td>
<td>0.42</td>
</tr>
<tr>
<td>Rectus femoris</td>
<td>0.12</td>
<td>0.58</td>
<td>0.29</td>
<td>0.37</td>
<td>0.35</td>
<td>0.35</td>
<td>0.22</td>
<td>0.33</td>
</tr>
<tr>
<td>Adductor magnus</td>
<td>0.20</td>
<td>0.31</td>
<td>0.33</td>
<td>0.33</td>
<td>0.46</td>
<td>0.54</td>
<td>0.34</td>
<td>0.36</td>
</tr>
<tr>
<td>Biceps femoris</td>
<td>0.22</td>
<td>0.53</td>
<td>0.66</td>
<td>0.58</td>
<td>0.55</td>
<td>0.46</td>
<td>0.66</td>
<td>0.52</td>
</tr>
<tr>
<td>Mean</td>
<td>0.29</td>
<td>0.48</td>
<td>0.46</td>
<td>0.43</td>
<td>0.37</td>
<td>0.44</td>
<td>0.45</td>
<td>0.42</td>
</tr>
</tbody>
</table>

(0.16) (0.16) (0.15) (0.14) (0.14) (0.07) (0.17) (0.08)
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The CMCs were calculated for the WT mean frequency between stances for each dataset and each muscle. Table 8.8 lists the CMC values calculated for the group A datasets. Overall, the repeatability for stance using the WT mean frequency was very low with mean dataset CMC values ranging from 0.29 to 0.48. The maximum CMC calculated was 0.66 for BF for datasets A3 and A5.

8.6 Comparison of the four sEMG parameter stance patterns

The four types of features extracted from the sEMG recorded from the group A subjects are shown in figures 8.29 – 8.33. The WT trace has been inverted since the scale is inversely related to the frequency. The MAV has been inverted in cases where the mean frequency was observed to decrease during an isometric contraction (see table 7.3).

Figures 8.29a – 8.29d. Mean parameter values during stance for gluteus maximus for group A datasets.

Figures 8.30a – 8.30c. Mean parameter values during stance for gluteus medius for group A datasets.
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Figures 8.30a – 8.30e. Mean parameter values during stance for gluteus medius for group A datasets

Figures 8.31a – 8.31e. Mean parameter values during stance for rectus femoris for group A datasets

Figures 8.32a – 8.32d. Mean parameter values during stance for adductor magnus for group A
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Figures 8.33a – 8.33e. Mean parameter values during stance for biceps femoris for group A datasets.

Although a likeness in pattern could be observed between all four features for certain datasets and muscles (see figures 8.30e, 8.31b, 8.32c and 8.33b), in some cases the MAV in particular did not resemble the other feature patterns (see figures 8.29a, 8.30c, 8.31e and 8.32b. This difference emphasises the different information that the features reflect. The main difference between the four feature traces was that the outline for the MAV was far smoother than the STFT, ACWD and WT outlines. This was principally due to the longer smoothing window of 100ms being applied to the sEMG to calculate the MAV compared to the windows selected to calculate the time frequency and scalar parameters.

In many cases where distinct peaks or troughs were present, phase of the maxima or minimal differed according to the feature observed. Although in the certain instances the WT peak / trough preceded those of the other features (see figures 8.29b, 8.30c and 8.30e) this was not universally the case. von Tscharner and Goepfert (2003) reported that changes in sEMG activity could be discerned first by changes in WT patterns. They considered that the differences in timings were a result of motor unit recruitment patterns being selected prior to an increase in muscle contraction and sEMG amplitude.
8.7 Conclusion

This chapter has presented information regarding sEMG parameters from dynamically contracting muscle, and the reproducibility of these parameters during stance for both the group A and group B subjects. The mean ensemble MAV patterns calculated for the five muscles for the group B subjects were in agreement with the findings published in previous studies. The inter-stance and inter-day variability for this group was however, greater than that reported by Kadaba et al. (1989). This disparity is arguably due mainly to the latter’s study investigating variability between entire gait cycles whereas the author’s study only analysed variability between stances. The value of the CMC derived from analysis of stance is therefore likely to be lower than the CMC derived from the entire gait cycle. The group A subjects’ MAV showed some differences in MAV patterns compared to that found in conventional TF amputees. This may be associated with altered kinematics of gait in osseointegrated TF amputees, for example the increase in hip-hiking. The author has not found any published reports of variability of sEMG during gait in TF amputees therefore comparison could not be made with previous findings. The mean ensemble MAV stance patterns for group A were similar to group B with however, an observable differences being an earlier minima of sEMG activity occurring for group A subjects compared to group B subjects (50% and 70% of stance phase respectively). This is possibly a consequence of the earlier onset of knee flexion that was observed to have occurred in group A (70% of stance phase) compared to that reported in an intact subject (81% of stance phase).

The time-frequency and time-scalar sEMG patterns were move variable than the MAV patterns both between stances and between subjects. The ACWD and WT parameters are more appropriate for analysis of a non-stationary stochastic signal (see subsection 3.3.2) therefore one might have expected better reproducibility for these parameters. However, only the mean frequency was assessed for these two types of parameters rather than specific frequency bands. Application of the STFT to the dynamic sEMG of group A subjects revealed the presence of a mains harmonic at 250Hz in certain signals. The presence of mains interference may therefore have distorted the time-frequency and time-scalar parameters.
As discussed in the previous chapter, the amputees were able to reproduce both their hip joint movements in the sagittal plane and the vertical component of the GRF for the stance phase to a high level. The sEMG of the muscles however did not show a highly reproducible pattern during stance with the exception of subject A3 for the MAV parameter. The amputees’ locomotor control mechanism would therefore appear to control joint movement rather than individual contraction of muscles.

The next chapter will cover the application of principal component to the four types of parameters described in this chapter and the subsequent investigation of patterns using cluster analysis.
Chapter 9
Results and Discussion Part III

9.1 Introduction

The previous two chapters described and discussed the subjects' characteristics, gait parameters, quality of the sEMG recordings, different types of sEMG parameters and repeatability of these parameters during stance for the group A and B datasets. This chapter is concerned with collating the sEMG variables described in the previous section, reducing them by applying PCA and identifying patterns through cluster analysis. The findings from PCA are outlined in section 9.2. Dataset A1 has been selected, as in the previous chapter, as a representative dataset for group A and graphs of this subject have been included to illustrate aspects of the analysis. The ensuing discussion of the results of PCA is made in section 9.3. The patterns identified from cluster analysis are presented in section 9.4. Section 9.5 discusses the results obtained from cluster analysis. Each of the four types of sEMG parameters (MAV, STFT mean frequency, ACWD mean frequency and WT mean scale) is presented consecutively for both methods of analysis.

9.2 Principal Component Analysis - Results

PCA is a feature reduction method that allows a large number of variables to be analysed simultaneously and reduced to a smaller number of components (principal components) providing that there is some correlation between the variables. The variables that were assessed by PCA were the four types of sEMG parameters (MAV, STFT mean frequency, ACWD mean frequency and WT mean scale) for the five hip muscles. A 30 x 5N DATA matrix was constructed for each dataset for each type of sEMG parameter (see figure 6.1) where N is the number of stances available for analysis (see table 7.7). The DATA matrix was then subjected to PCA using the Matlab statistics toolbox princomp function. The first output generated was a 5N x 5N square matrix where the columns represent the principal components (PCs). The second output was a 30 x 5N matrix representing the component scores. This consists of the original data projected onto a new co-ordinate system determined by the PCs. The 30 individual stance time-points can therefore be characterised by a combination of PCs. Each PC contains information regarding both
Chapter 9. Results Part III

individual stances and the five separate hip muscles’ activity. The third output consists of a vector containing the variances explained by each of the PCs. This allows the minimum number, $N_{\text{min}}$, of PCs necessary to account for at least 80% of the variance to be calculated. This number of PCs is generally sufficient to reflect accurately the underlying variables (see subsection 5.5.2). The greater the correlations between the variables the fewer PCs are needed.

<table>
<thead>
<tr>
<th>STANCE</th>
<th>TIME-POINT</th>
<th>GMAX</th>
<th>GMED</th>
<th>RF</th>
<th>AM</th>
<th>BF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stance 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>D_{1,1}</td>
<td>D_{1,2}</td>
<td>D_{1,3}</td>
<td>D_{1,4}</td>
<td>D_{1,5}</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>D_{2,1}</td>
<td>D_{2,2}</td>
<td>D_{2,3}</td>
<td>D_{2,4}</td>
<td>D_{2,5}</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>D_{3,1}</td>
<td>D_{3,2}</td>
<td>D_{3,3}</td>
<td>D_{3,4}</td>
<td>D_{3,5}</td>
<td></td>
</tr>
</tbody>
</table>

| Stance n |
| 1      | D_{1,(5N-4)} | D_{1,(5N-3)} | D_{1,(5N-2)} | D_{1,(5N-1)} | D_{1,5N} |
| 2      | D_{2,(5N-4)} | D_{2,(5N-3)} | D_{2,(5N-2)} | D_{2,(5N-1)} | D_{2,5N} |
| 3      | D_{3,(5N-4)} | D_{3,(5N-3)} | D_{3,(5N-2)} | D_{3,(5N-1)} | D_{3,5N} |

Figure 9.1. Representation of construction of the DATA matrix

In addition to PCA of the DATA matrix, two additional matrices derived from the DATA matrix were subjected to PCA. These matrices were as follows:

i) STANCE matrix – A $30 \times 5$ matrix for each stance where the rows are the time-points and the columns are the 5 muscles

ii) MUSCLE matrix – A $30 \times N$ matrix for each muscle where the rows are the time-points and the columns are the $N$ stances.

The following subsections describe the PCs calculated for the three types of matrices for each of the four different sEMG parameters. All the group A datasets were analysed for the MAV, STFT and WT parameters and four group A datasets (A1, A3, A4 and A5) for the ACWD parameters.
9.2.1 PCA of MAV parameters

Table 9.1 lists $N_{\text{min}}$ (the minimum number of PCs needed to explain 80% of the variance) for each stance and each dataset for the STANCE matrix containing the sEMG MAV parameters. The variance explained by $N_{\text{min}}$ is included in the table.

Table 9.1. Number of principal components, $N_{\text{min}}$, necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$. PCA applied to sEMG MAV parameters, STANCE matrix.

<table>
<thead>
<tr>
<th>STANCE</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
<th>Dataset A3</th>
<th>Dataset A3rep</th>
<th>Dataset A4</th>
<th>Dataset A4rep</th>
<th>Dataset A5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance ($%$)</td>
<td>$N_{\text{min}}$</td>
<td>Variance ($%$)</td>
<td>$N_{\text{min}}$</td>
<td>Variance ($%$)</td>
<td>$N_{\text{min}}$</td>
<td>Variance ($%$)</td>
</tr>
<tr>
<td>1</td>
<td>89.4  3</td>
<td>84.6  2</td>
<td>93.5  2</td>
<td>83.6  2</td>
<td>92  2</td>
<td>93.0  2</td>
<td>98.9  3</td>
</tr>
<tr>
<td>2</td>
<td>92.4  2</td>
<td>95.7  3</td>
<td>88.5  2</td>
<td>98.4  3</td>
<td>93.7  2</td>
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</table>

The minimum number of PCs necessary to explain the five variables for each stance was 3 with the mode being 2. Dataset A4rep had the lowest value of $N_{\text{min}}$ with 11 of the 27 stances requiring only 1 PC to adequately account for the variance. This suggests that there is significant co-activation of muscles for this dataset. Dataset A5 required the
highest number of PCs with 11 of the 18 stances needing a minimum of 3 PCs to account for a variance of 80%.

Results of PCA applied to the MUSCLE matrix is contained in table 9.2. Datasets A3 and A3rep required the smallest number of PCs to represent the variables whereas dataset A1 needed the greatest number of PCs.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
<th>Dataset A3</th>
<th>Dataset A3rep</th>
<th>Dataset A4</th>
<th>Dataset A4rep</th>
<th>Dataset A5</th>
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<tbody>
<tr>
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<td>84.3</td>
<td>89.0</td>
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<td>80.4</td>
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<td>80.2</td>
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<td>90.8</td>
<td>83.2</td>
<td>86.5</td>
</tr>
</tbody>
</table>

The minimum numbers of PCs required to represent the DATA matrix containing all the sEMG MAV parameters for one subject are listed in table 9.3. Between 2 and 3 PCs were sufficient for datasets A3 and A3rep respectively to reproduce the information whereas dataset A1 needed 4 PCs to account for a minimum variance of 80%.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Variance (%)</th>
<th>N_{min}</th>
</tr>
</thead>
<tbody>
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<tr>
<td>Dataset A2</td>
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</tr>
<tr>
<td>Dataset A3rep</td>
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<tr>
<td>Dataset A5</td>
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</tbody>
</table>

Each stance time-point can be plotted in principal component space. Figures 9.2a and 9.2b illustrate the stance time-points relative to the first and second PCs and the third and fourth PCs respectively for representative dataset A1. The PCs have been derived from the DATA matrix. The diagrams demonstrate how the stance time-points followed a meandering but numerically sequential path in principal component space. The points
are represented by different coloured spots, the colour of which denotes a cluster (see section 9.3). The scatterplots of the four PCs for the remaining six datasets are contained in Appendix 9.

Figure 9.2a. Scatter plot for Dataset A1 MAV DATA matrix. PCs 1 and 2.

Figure 9.2b. Scatter plot for Dataset A1 MAV DATA matrix. PCs 3 and 4.

9.2.2 PCA of STFT parameters

Table 9.4 records $N_{\text{min}}$ when PCA is applied to the STFT STANCE matrix for each stance and the variance that this number explains. For all datasets and all stances the number of PCs necessary to account for 80% of the variance could be reduced from a maximum of 5. The overall reduction in PCs was however less than that observed in table 9.1 for the MAV PCs. Two stances in dataset A3 required a minimum of 4 PCs to account for 80% of the variance. Dataset A2 required overall the smallest number of PCs with 6 stances needing 1 PC, 16 stances needing 2 PCs and 1 stance needing PCs. Table 9.5 lists the number of PCs derived from STFT MUSCLE matrix necessary to account for 80% of the variance and the amount of variance described. $N_{\text{min}}$ was higher overall than $N_{\text{min}}$ calculated for the MAV MUSCLE matrix, with the minimum number of PCs being 2 and the maximum being 9.
Chapter 9. Results Part III

Table 9.4. Number of principal components, $N_{\text{min}}$, necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$. PCA applied to STFT STANCE matrix.

<table>
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<th>Dataset A2</th>
<th>Dataset A3</th>
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<td>Variance (%)</td>
<td>$N_{\text{min}}$</td>
<td>Variance (%)</td>
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Table 9.5. Number of principal components necessary to explain 80% of variance and amount of variance explained by this number. PCA applied to STFT MUSCLE matrix.

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<th>Dataset</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
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<td>Var (%)</td>
<td>$N_{\text{min}}$</td>
<td>Var (%)</td>
<td>$N_{\text{min}}$</td>
<td>Var (%)</td>
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<td>n/a</td>
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The results of PCA analysis of the STFT DATA matrix are provided in table 9.6. It can be observed that for all datasets a greater numbers of PCs were needed to account for 80% of the variance compared to PCA of the MAV DATA matrix (see table 9.3).
Table 9.6. Number of principal components necessary to explain 80% of variance and amount of variance explained by $N_{min}$PCA applied to STFT DATA matrix.

<table>
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<th>DATASET</th>
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</tbody>
</table>

The representation of the sEMG STFT stance time-points for dataset A1 in principal component space for the first 4 PCs is given in figures 9.4a and 9.4b. The projections had different characteristics for both figures compared to the MAV projections. The paths taken by the STFT time-points were numerically less sequentially arranged and considerable clustering occurred for time-points 20 to 30 in both figures.

Figure 9.3a. Scatter plot for Dataset A1 STFT DATA matrix. PCs 1 and 2

Figure 9.3b. Scatter plot for Dataset A1 STFT DATA matrix. PCs 3 and 4
9.2.3 PCA of ACWD parameters

The third sEMG parameter investigated by PCA was the ACWD mean frequency. Only 4 sEMG datasets were analysed with the ACWD. The minimum number of PCs for each stance and their total variance accounted for is listed in table 9.7. The minimum number of PCs to explain 80% of the variance ranged from 2 to 4 for each stance.

Table 9.7. Number of principal components, $N_{\text{min}}$, necessary to explain 80% of variance and amount of variance explained $N^{\text{min}}$. PCA applied to ACWD STANCE matrix.

<table>
<thead>
<tr>
<th>STANCE</th>
<th>Dataset A1</th>
<th>Dataset A3</th>
<th>Dataset A4</th>
<th>Dataset A5</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Variance (%)</td>
<td>$N_{\text{min}}$</td>
<td>Variance (%)</td>
<td>$N_{\text{min}}$</td>
</tr>
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<td>80.6</td>
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<tr>
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<td>21</td>
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</tr>
</tbody>
</table>

A minimum of 7 or 8 PCs were required for all datasets and muscles to account for a variance of 80% apart from for GMED, RF and BF for dataset A3. Table 9.8 lists the number of PCs required to account for 80% of the variance for each muscle and the percentage of variance accounted for by this number. GMED required on average the lowest number and AM the highest number.
Chapter 9. Results Part III

Table 9.8. Number of principal components necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$ PCA applied to ACWD MUSCLE matrix

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset A1</th>
<th>Dataset A3</th>
<th>Dataset A4</th>
<th>Dataset A5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance (%)</td>
<td>$N_{\text{min}}$</td>
<td>Variance (%)</td>
<td>$N_{\text{min}}$</td>
</tr>
<tr>
<td>GMAX</td>
<td>81.1 7</td>
<td>80.0 7</td>
<td>82.0 8</td>
<td>81.8 8</td>
</tr>
<tr>
<td>GMED</td>
<td>80.1 7</td>
<td>81.4 3</td>
<td>82.8 8</td>
<td>81.5 7</td>
</tr>
<tr>
<td>RF</td>
<td>83.1 7</td>
<td>80.5 8</td>
<td>81.6 7</td>
<td>83.5 9</td>
</tr>
<tr>
<td>AM</td>
<td>83.1 7</td>
<td>83.4 8</td>
<td>80.7 7</td>
<td>80.4 7</td>
</tr>
<tr>
<td>BF</td>
<td>81.8 7</td>
<td>80.5 5</td>
<td>80.7 7</td>
<td>80.4 7</td>
</tr>
</tbody>
</table>

Table 9.9 contains the minimum number of PC necessary to account for 80% of the variance and the amount of variance accounted for.

Table 9.9. Number of principal components necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$. PCA applied to ACWD DATA matrix.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Variance (%)</th>
<th>$N_{\text{min}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset A1</td>
<td>82.9</td>
<td>14</td>
</tr>
<tr>
<td>Dataset A3</td>
<td>80.6</td>
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</tr>
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<td>Dataset A4</td>
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<tr>
<td>Dataset A5</td>
<td>83.2</td>
<td>12</td>
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</tbody>
</table>

Figures 9.4a and 9.4b illustrate the stance time-points for dataset A1 in principal component space for the first 4 PCs.

Figure 9.4a. Scatter plot for Dataset A1 ACWD DATA matrix. PCs 1 and 2

Figure 9.4b. Scatter plot for Dataset A1 ACWD DATA matrix. PCs 3 and 4
9.2.4 PCA of WT parameters

The final parameter subjected to PCA was the WT mean scale. Tables 9.10, 9.11 and 9.12 contain the results of PCA when the MUSCLE, STANCE and the WT DATA matrix were analysed respectively. Overall, the number of PCs necessary to explain 80% of the variance was greater than for the corresponding MAV and STFT matrices but less than the ACWD matrices.

Table 9.10. Number of principal components, $N_{\text{min}}$, necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$. PCA applied to WT SCALE matrix.

<table>
<thead>
<tr>
<th>STANCE</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
<th>Dataset A3</th>
<th>Dataset A3rep</th>
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<th>Dataset A4rep</th>
<th>Dataset A5</th>
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</thead>
<tbody>
<tr>
<td>Var (%)</td>
<td>$N_{\text{min}}$</td>
<td>Var (%)</td>
<td>$N_{\text{min}}$</td>
<td>Var (%)</td>
<td>$N_{\text{min}}$</td>
<td>Var (%)</td>
<td>$N_{\text{min}}$</td>
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Table 9.11. Number of principal components, $N_{\text{min}}$, necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$. PCA applied to \textit{WT MUSCLE} matrix.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>Dataset A1</th>
<th>Dataset A2</th>
<th>Dataset A3</th>
<th>Dataset A3rep</th>
<th>Dataset A4</th>
<th>Dataset A4rep</th>
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<td>$N_{\text{min}}$ Var (%)</td>
<td>$N_{\text{min}}$ Var (%)</td>
<td>$N_{\text{min}}$ Var (%)</td>
<td>$N_{\text{min}}$ Var (%)</td>
<td>$N_{\text{min}}$ Var (%)</td>
<td></td>
</tr>
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<td>6</td>
<td>80.8</td>
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</tbody>
</table>

Table 9.12. Number of principal components, $N_{\text{min}}$, necessary to explain 80% of variance and amount of variance explained by $N_{\text{min}}$. PCA applied to \textit{WT DATA} matrix.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Variance (%)</th>
<th>$N_{\text{min}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset A1</td>
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</tr>
<tr>
<td>Dataset A2</td>
<td>82.6</td>
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</tr>
<tr>
<td>Dataset A2rep</td>
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</tr>
<tr>
<td>Dataset A3</td>
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<td>8</td>
</tr>
<tr>
<td>Dataset A3rep</td>
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</tr>
<tr>
<td>Dataset A4</td>
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</tr>
<tr>
<td>Dataset A5</td>
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<td>10</td>
</tr>
</tbody>
</table>

The representations of the time-points in principal component space derived from the \textit{WT DATA} matrix for subject A1 are shown in figures 9.5a and 9.5b.

Figure 9.5a. Scatter plot for Dataset A1 \textit{WT DATA} matrix. PCs 1 and 2

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9.2.5 Summary of $N_{\text{min}}$ for the hip muscles

Table 9.13 shows the mean $N_{\text{min}}$ for the five different hip muscles for the four types of sEMG parameters. Overall, across the muscles, PCA of the sEMG MAV parameters produced the smallest $N_{\text{min}}$ with analysis of the WT parameters leading to the highest values. The muscle having the smallest value of $N_{\text{min}}$ varied with BF showing the lowest value for the MAV and STFT parameters. AM had the highest mean value.

Table 9.13. Mean minimum number of PCs necessary to account for 80% of the variance for the five hip muscles and PC matrices derived from the four sEMG parameters for the seven datasets. Standard deviation in parentheses.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>MAV</th>
<th>STFT</th>
<th>ACWD</th>
<th>WT</th>
<th>$\text{mean}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMAX</td>
<td>2.67 (1.51)</td>
<td>5.50 (2.07)</td>
<td>7.50 (0.58)</td>
<td>6.67 (0.89)</td>
<td>5.59 (2.11)</td>
</tr>
<tr>
<td>GMED</td>
<td>3.00 (1.15)</td>
<td>5.00 (1.63)</td>
<td>6.25 (2.22)</td>
<td>6.86 (0.90)</td>
<td>5.28 (1.70)</td>
</tr>
<tr>
<td>RF</td>
<td>3.14 (0.90)</td>
<td>5.96 (1.35)</td>
<td>6.75 (2.50)</td>
<td>7.00 (1.00)</td>
<td>5.69 (1.77)</td>
</tr>
<tr>
<td>AM</td>
<td>2.57 (0.98)</td>
<td>6.42 (0.53)</td>
<td>7.75 (0.96)</td>
<td>7.14 (0.69)</td>
<td>5.97 (2.33)</td>
</tr>
<tr>
<td>BF</td>
<td>2.71 (1.11)</td>
<td>4.86 (1.96)</td>
<td>6.50 (1.00)</td>
<td>7.00 (0.58)</td>
<td>5.27 (1.93)</td>
</tr>
<tr>
<td>$\text{mean}$</td>
<td>2.82 (0.24)</td>
<td>5.53 (0.64)</td>
<td>6.95 (0.65)</td>
<td>6.93 (0.18)</td>
<td></td>
</tr>
</tbody>
</table>

Table 9.14. Mean minimum number, $N_{\text{min}}$, of PCs necessary to account for 80% of the variance for the 5 hip muscles and 7 datasets. Standard deviation in parentheses.

<table>
<thead>
<tr>
<th>MUSCLE</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A3rep</th>
<th>A4</th>
<th>A4rep</th>
<th>A5</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMAX</td>
<td>5.50 (1.73)</td>
<td>n/a</td>
<td>4.75 (2.63)</td>
<td>4.33 (3.21)</td>
<td>6.25 (3.59)</td>
<td>5.33 (1.15)</td>
<td>6.00 (1.63)</td>
</tr>
<tr>
<td>GMED</td>
<td>5.50 (1.73)</td>
<td>3.33 (1.53)</td>
<td>4.50 (2.63)</td>
<td>5.33 (3.21)</td>
<td>6.25 (3.59)</td>
<td>5.33 (1.15)</td>
<td>5.50 (1.63)</td>
</tr>
<tr>
<td>RF</td>
<td>6.25 (1.73)</td>
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<td>4.50 (2.63)</td>
<td>5.33 (3.21)</td>
<td>6.00 (3.59)</td>
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</tr>
<tr>
<td>AM</td>
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<td>5.33 (1.53)</td>
<td>5.50 (2.63)</td>
<td>6.00 (3.21)</td>
<td>6.00 (3.59)</td>
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<tr>
<td>BF</td>
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<td>3.75 (2.63)</td>
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<td>5.50 (3.59)</td>
<td>5.67 (1.15)</td>
<td>6.25 (1.63)</td>
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<tr>
<td>$\text{mean}$</td>
<td>5.85 (0.34)</td>
<td>4.17 (0.88)</td>
<td>4.60 (0.63)</td>
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<td>6.00 (0.31)</td>
<td>5.47 (0.38)</td>
<td>6.00 (0.31)</td>
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</table>

Figure 9.5b. Scatter plot for Dataset A1 WT DATA matrix. PCs 3 and 4
Chapter 9. Results Part III

The mean $N_{\text{min}}$s for the five hip muscles for the five datasets are shown in table 9.14. Dataset A2 had the smallest $N_{\text{min}}$ and A4 and A5 had the highest $N_{\text{min}}$. There was no consistent $N_{\text{min}}$ ranking for the muscles.

9.3 Principal Component Analysis - Discussion

9.3.1 PCA from STANCE matrix

PCA reduced the number of factors for all matrices to $N_{\text{min}}$, the number of factors necessary to account for 80% of the variance (see tables 9.1, 9.4, 9.7, 9.10). The value of $N_{\text{min}}$ varied according to the subject, the stance number and parameter selected. The maximal decrease was when PCA was applied to the MAV STANCE matrix (see table 9.1). This resulted in a reduction from 5 variables (muscles) to between 1 and 3 factors. Application of PCA to the STFT, ACWD and WT STANCE matrices for each dataset produced a smaller reduction in factors. The better performance in reduction produced by the MAV parameter can be explained by the same arguments presented in section 8.7. The implication of this reduction is that there was significant co-activation of muscles occurring. This has been reported in previous studies of intact subjects [Ivanenko et al. 2002] but not as far as the author is aware of in amputees. The presence of co-activation implies simplification of the neural control mechanism with fewer signals being generated from the CNS necessary to activate the muscles. Co-activation is therefore suggestive of the existence of an underlying CPG mechanism.

An alternative explanation for the apparent co-activation is that cross-talk was recorded in the signal. The only two muscles in close proximity to each other where cross-talk might have been present were GMED and GMAX. The definitive way to eliminate the possibility of cross-talk would be to obtain scans for each subject [Jaegers et al. 1996] or additionally insert wire electrodes [Ivanenko et al. 2004].

9.3.2 PCA from MUSCLE matrix

A reduction in the number of factors necessary to account for 80% of the variance resulted when PCA was applied to the MUSCLE matrices (see tables 9.3, 9.6, 9.9 and 9.12) indicating repeatability of muscle activity during stance. PCA applied to the MAV
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*MUSCLE* matrix resulted in the greatest reduction of factors and the smallest was when applied to the *ACWD* and *WT MUSCLE* matrices. This reflects the reproducibility of the sEMG parameters and approximately corresponds to the ranking of the CMCs calculated for these parameters (see tables 8.1, 8.7 and 8.8). Both the cleaved and intact muscles displayed a significant decrease in factors necessary to account for the variance. No one muscle displayed a consistent decrease in the number of components necessary to explain the variance. Reproducibility of the sEMG was therefore independent of the structure of the muscle. Subject A3 had a high reduction in features for the MAV parameter (see table 9.2) which is expected given the high CMC values (see table 8.1).

9.3.3 PCA from *DATA* matrix
Combining all the data for each dataset into one matrix and applying PCA yielded a decrease in the number of factors. The factors contain information concerning both individual stances in addition to data from the five muscles. Previous studies have used ensemble averages which loses the inherent variability present in the sEMG data [Davis & Vaughan 1993; Patla 1985; Wootten *et al.* 1990]. There are therefore no results with which to compare this study's PC findings.

The greatest decrease in features necessary to account for 80% of the variance was for the *MAV DATA* matrix (see table 9.3) with the least reduction being for the *ACWD DATA* matrix (see table 9.9). Dataset A3rep needed only two PCs to account for the variance when PCA was applied to its *MAV DATA* matrix compared to the ten needed when applied to its *ACWD DATA* matrix.

9.3.4 Representation in PC space of dataset A1
The first and second PCs derived from the *MAV DATA* and *STFT DATA* matrices followed a numerically ordered pathway. However, the arrangement of points differed with clustering of points occurring for the STFT derived PCs from 11 to 16 and from 20 to 30. The difference in arrangements of the time-points is explained by the different information that MAV parameters convey compared to the STFT parameters.

The two dimensional mapping of the first two PCs derived from *ACWD DATA* and *WT DATA* matrices did not display a sequentially ordered arrangement of time-points. This irregularity in the order of time-points for the ACWD and WT PCs was due to the higher
values of $N_{\text{min}}$, being 14 and 13 respectively. The values of $N_{\text{min}}$ from PCA of MAV and STFT parameters were 4 and 7 respectively. It may be the case that in 13 or 14 dimensional space the time-points for the ACWD or WT PCs would follow a numerically ordered pathway.

### 9.4 Cluster Analysis - Results

#### 9.4.1 Introduction to cluster analysis results

The previous section presented the results from applying a feature reduction method to the four different types of sEMG derived parameters. In the case of PCs derived from the MAV DATA matrices, organised patterns were visible for the 30 time-points. Another analytical technique must be applied to determine patterns for high level multi-variate data and to provide a value of statistical significance. Cluster analysis is a method that identifies groupings within data with no \textit{a priori} knowledge of the data and provides an index of fit, the cophenetic correlation coefficient (CCC). The MATLAB function \textit{cluster} was applied to the datasets' PCs derived from the four different DATA matrices. The number of PCs selected for cluster analysis was $N_{\text{min}}$, the minimum number necessary to account for 80% of the variance. The hierarchical patterns were represented graphically in the form of dendrograms generated by the MATLAB function \textit{dendrogram}. The MATLAB function \textit{cophenet} was determined from the MATLAB \textit{cophenet} routine. The following section lists the CCCs calculated for the 4 different sEMG parameters for each subject and illustrates the dendrograms for the cluster analyses undertaken on the group A subjects.

#### 9.4.2 Cophenetic correlation coefficient

The values of the CCCs are shown in table 9.15. Only four of the datasets had a CCC of less than 0.800 (see subsection 5.5.3). The sEMG of dataset A5 could not be accurately represented for three of the four parameters investigated. Dataset A1 had a CCC of only 0.606 for cluster analysis of PCs derived from the ACWD mean frequency.
Table 9.15. Cophenetic correlation coefficient (CCC) for cluster analysis of \textit{DATA PC} matrices

<table>
<thead>
<tr>
<th>DATASET</th>
<th>CCC MAV</th>
<th>CCC STFT</th>
<th>CCC ACWD</th>
<th>CCC WT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset A1</td>
<td>0.807</td>
<td>0.887</td>
<td>0.606</td>
<td>0.850</td>
</tr>
<tr>
<td>Dataset A2</td>
<td>0.832</td>
<td>0.933</td>
<td>n/a</td>
<td>0.947</td>
</tr>
<tr>
<td>Dataset A3</td>
<td>0.831</td>
<td>0.872</td>
<td>0.800</td>
<td>0.825</td>
</tr>
<tr>
<td>Dataset A3 rep</td>
<td>0.843</td>
<td>0.882</td>
<td>n/a</td>
<td>0.880</td>
</tr>
<tr>
<td>Dataset A4</td>
<td>0.825</td>
<td>0.870</td>
<td>n/a</td>
<td>0.800</td>
</tr>
<tr>
<td>Dataset A4 rep</td>
<td>0.834</td>
<td>0.836</td>
<td>0.803</td>
<td>0.892</td>
</tr>
<tr>
<td>Dataset A5</td>
<td>0.756</td>
<td>0.754</td>
<td>0.736</td>
<td>0.909</td>
</tr>
</tbody>
</table>

9.4.3 Dendrograms

The following four subsections illustrate the clustering patterns obtained for the four types of sEMG parameters.

9.4.3.1 Cluster Analysis of \textit{MAV DATA PC matrix}

Figures 9.6a to 9.6g show the dendrograms derived from cluster analysis applied to \textit{MAV DATA PC} matrices for datasets A1 to A5. The clusters are colour coded according to the default threshold (see subsection 6.8.8).

Figure 9.6a. Dataset A1 Dendrogram of cluster analysis applied to \textit{MAV DATA PC} matrix.

Figure 9.6b. Dataset A2 Dendrogram of cluster analysis applied to \textit{MAV DATA PC} matrix.
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Figure 9.6c. Dataset A3 Dendrogram of cluster analysis applied to MAV DATA PC matrix

Figure 9.6d. Dataset A3rep Dendrogram of cluster analysis applied to MAV DATA PC matrix

Figure 9.6e. Dataset A4 Dendrogram of cluster analysis applied to MAV DATA PC matrix

Figure 9.6f. Dataset A4rep Dendrogram of cluster analysis applied to MAV DATA PC matrix

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The number of PCs investigated with cluster analysis varied from 2 to 4 (see table 9.3). The data points from six of the seven datasets could be divided into three (datasets A3 and A3rep) or four (datasets A1, A2, A4 and A4rep) groups containing adjacent time-points. Cluster analysis of dataset A5's data points yielded 4 separate groups although one group contained two separate sequences of points which were from 6 to 15 and from 27 to 30. However, as listed in table 9.13 the CCC for this dataset was only 0.756 indicating that the clusters formed were not a strong representation of the data. The time-point at which the clusters started and finished varied although patterns could be identified. Six of the seven datasets had a separate cluster for the last 7 to 9 stance time-points. The exception was dataset A5. Three of the datasets with CCCs above 0.8 had a cluster consisting of the first 5 to 6 time-points whereas the remaining three datasets had a cluster comprised of the first 9 to 11 points. Datasets A3 and A3rep cluster patterns were similar with the groups formed at approximately one third intervals along the timescale. Likewise subject A4’s groupings for the two datasets were comparable with divisions in clusters occurring at approximate 25% intervals, with the first cluster being shorter. Dataset A1 and A2 had similar cluster patterns to dataset A3 and A3rep.

9.4.3.2 Cluster Analysis of STFT DATA PC matrix

The dendrograms for datasets A1 to A5 are presented in figures 9.7a to 9.7g. Three of the datasets are split into 2 clusters, one into 3 clusters, one into 4 clusters and two into 5 clusters. Datasets A1 and A2 which divided into 2 clusters had one cluster comprised of the first 11 or 12 points and the second cluster made up of the remaining data points. Four of the seven cluster patterns had clusters composed of numerically contiguous data.
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points. Dataset A5 which had a CCC of 0.754 possessed 3 clusters with 2 clusters containing non adjacent time-points. There were no obvious similarities between the cluster patterns between datasets A3 and A3rep and between A4 and A4rep. There did not appear to be clear correlations between the cluster patterns obtained for the MAV PC matrices and the STFT PC matrices.

1.5

\[
\begin{align*}
&\text{Figure 9.7a. Dataset A1 Dendrogram of cluster analysis applied to } \text{STFT DATA PC matrix} \\
&\text{Figure 9.7b. Dataset Dendrogram of cluster analysis applied to } \text{STFT DATA PC matrix} \\
&\text{Figure 9.7c. Dataset A3 Dendrogram of cluster analysis applied to } \text{STFT DATA PC matrix}
\end{align*}
\]
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Figure 9.7d. Dataset A3rep Dendrogram of cluster analysis applied to STFT DATA PC matrix

Figure 9.7e. Dataset A4 Dendrogram of cluster analysis applied to STFT DATA PC matrix

Figure 9.7f. Dataset A4rep Dendrogram of cluster analysis applied to STFT DATA PC matrix

Figure 9.7g. Dataset A5. Dendrogram of cluster analysis applied to STFT DATA PC matrix
9.4.3.3 Cluster Analysis of ACWD DATA PC matrix

Cluster analysis was applied to the datasets A1, A3, A4 and A5 which had the ACWD applied to their sEMG data. The four dendrograms are shown in figures 9.8a to 9.8d. In comparison to the cluster patterns obtained for the MAV and STFT DATA PC matrices, the number of clusters was greater and were comprised of time-points less well sequentially organised. Two groups had CCCs below 0.8 and both displayed clusters containing a non-numerically arranged assortment of data points. Only one dataset, A4, possessed clusters containing numerically adjacent time-points.

**Figure 9.8a.** Dataset A1. Dendrogram of cluster analysis applied to ACWD DATA PC matrix

**Figure 9.8b.** Dataset A3. Dendrogram of cluster analysis applied to ACWD DATA PC matrix

**Figure 9.8c.** Dataset A4. Dendrogram of cluster analysis applied to ACWD DATA PC matrix
Figure 9.8d. Dataset A5. Dendrogram of cluster analysis applied to ACWD DATA PC matrix

9.4.3.4 Cluster Analysis of WT DATA PC matrix

The final cluster analysis was performed on PCs derived from the WT DATA matrix for each of the seven datasets. The dendrograms are shown in figures 9.9a to 9.9g. The CCCs for all the datasets was above 0.8. The number of clusters varied from 4 for dataset A4 to 6 for dataset A1. Three of the seven patterns had groups containing numerically contiguous data points. For dataset A1, 4 of the 6 clusters were made up of non-adjacent data points. The cluster patterns for A3 and A3rep were similar, with each pattern comprised of 5 clusters and the partitioning of clusters occurring within 2 time-points for each group. The resemblance between the cluster patterns for A4 and A4rep was not obvious.

Figure 9.9a. Dataset A1 Dendrogram of cluster analysis applied to WT DATA PC matrix
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Figure 9.9b. Dataset A2 Dendrogram of cluster analysis applied to WT DATA PC matrix

Figure 9.9c. Dataset A3 Dendrogram of cluster analysis applied to WT DATA PC matrix

Figure 9.9d. Dataset A3rep Dendrogram of cluster analysis applied to WT DATA PC matrix

Figure 9.9e. Dataset A4 Dendrogram of cluster analysis applied to WT DATA PC matrix
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9.5 Cluster analysis - Discussion

9.5.1 Cophenetic correlation coefficient

Cluster analysis could be applied to the PC matrices with a CCC of greater than 0.8 in twenty one out of the twenty five cases analysed (see table 9.15). However, as discussed in chapter 3, a CCC with a value above 0.8 is not necessarily sufficient to reject the null hypothesis. Observation of the cluster patterns must additionally be made. The majority of the cluster patterns with a CCC above 0.8 consisted of clusters containing sequential time-points (see table 9.16). All four cluster patterns with a CCC below 0.8 had clusters containing non consecutive time-points. The minimum CCC value of 0.8 would therefore appear to be an acceptable threshold.
Table 9.16. Results of cluster analysis applied to the amputee PC matrices derived from the MAV, STFT, ACWD and WT parameters. Members of the cluster group in terms of stance time-point.

<table>
<thead>
<tr>
<th>DATASET</th>
<th>Cluster Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAV</td>
<td>1 2 3 4 5 6 7 8 9 10 11</td>
</tr>
<tr>
<td>A1</td>
<td>1-6 7-16 17-23 24-30</td>
</tr>
<tr>
<td>A2</td>
<td>1-11 12-17 18-22 23-30</td>
</tr>
<tr>
<td>A3</td>
<td>1-10 11-21 22-30</td>
</tr>
<tr>
<td>A3rep</td>
<td>1-9 10-22 23-30</td>
</tr>
<tr>
<td>A4</td>
<td>1-5 6-15 17-22 23-30</td>
</tr>
<tr>
<td>A4rep</td>
<td>1-5 7-12 13-23 24-30</td>
</tr>
<tr>
<td>A5</td>
<td>1-6 6-15,27-30 16-19 20-26</td>
</tr>
<tr>
<td>STFT</td>
<td>1-11 12-30</td>
</tr>
<tr>
<td>A2</td>
<td>1-12 13-30</td>
</tr>
<tr>
<td>A3</td>
<td>1-7 2-25-30 8-20 21-24</td>
</tr>
<tr>
<td>A3rep</td>
<td>1-10,23-30 11-22</td>
</tr>
<tr>
<td>A4</td>
<td>1-4 5-10 11-16 17-18 19-30</td>
</tr>
<tr>
<td>A4rep</td>
<td>1-7 8-9 10-16 17-21 22-30</td>
</tr>
<tr>
<td>A5</td>
<td>1-14,15-20 5-8,9,12-14 8-7,10-11 23-30</td>
</tr>
<tr>
<td>ACWD</td>
<td>1-9,11 2-3,5,6,8 4,7,13,20 10,14,30 12,19,23-24,27-29 15,18,16 17 21-22,25-26</td>
</tr>
<tr>
<td>A3</td>
<td>1-4,23-29 5-7 8-19 20-22 30</td>
</tr>
<tr>
<td>A4</td>
<td>1-4 5-10 11-15 16-17 18-28 29-30</td>
</tr>
<tr>
<td>A5</td>
<td>1-2,18-20 3-5 6-9 10-13 14-17 21-28 29-30</td>
</tr>
<tr>
<td>A2</td>
<td>1-7 8-11 12-17,23-27 18-22 28-30</td>
</tr>
<tr>
<td>A3</td>
<td>1-8 9-12 13-19 20-22 23-30</td>
</tr>
<tr>
<td>A3rep</td>
<td>1-9 10-13 14-21 22-24 25-30</td>
</tr>
<tr>
<td>A4</td>
<td>1-4 5-9 10-15 16-22,30 23-29</td>
</tr>
<tr>
<td>A4rep</td>
<td>1-3,30 4-7,24-29 8-13 14-19 20-23</td>
</tr>
<tr>
<td>A5</td>
<td>1-8 9-12 13-21 22-23 24-30</td>
</tr>
</tbody>
</table>

9.5.2 Similarities of cluster patterns between datasets

Similarities existed between datasets belonging to different subjects. For example, the MAV cluster pattern dataset A1 was almost identical to the MAV cluster pattern of A4. The STFT cluster pattern of A1 was similar to the STFT cluster pattern of A2. This would suggest that there are a number of common locomotor control patterns but with individual variations. A comparison between the cluster patterns derived from the MAV DATA PC matrix and the WT DATA PC matrix suggests a resemblance between datasets.
A2, A3, A3rep, A4 and A4rep. The major difference is that with the exception of dataset A4, there were subdivisions of certain of the MAV clusters in the WT pattern.

9.5.3 Variations in clusters according to the parameter
The cluster patterns varied for the same dataset depending on the parameter matrix being analysed. A number of explanations for the different groupings can be presented. Firstly, the information that the MAV parameter conveys relates to the summated amplitude of the motor units whereas the frequency and scalar parameters provide information regarding the number, frequency and types of motor units firing. A second consideration is that a phase difference between time-frequency/scalar and time-dependent parameters have been reported [Von Tscharner & Goepfert 2003]. Differences in the three clustering patterns for individual datasets for the time frequency and scalar patterns however are also present. The number of clusters from STFT for all datasets is less or equal to the number of clusters from ACWD or WT parameters (see table 9.16). For example, the dataset A4 ACWD cluster pattern was similar to the cluster pattern derived from the STFT DATA PC matrix for approximately the first half of the data points. The remaining data points formed only one group in the STFT cluster pattern whereas in the ACWD cluster pattern they were split into three groups. A likely explanation for this is that the STFT does not give good time resolution for a rapidly changing non-stationary stochastic signal unlike the ACWD and WT (see subsection 5.3.3). Small changes in frequency are therefore not likely to be picked up by STFT analysis. Consequently, cluster analysis of the ACWD and WT parameters is likely to reveal changes in neuromuscular activity of very brief duration.

9.5.4 Intra-subject reproducibility of cluster patterns
The two subjects A3 and A4 had repeat recordings made of their sEMG with a time gap of approximately 11 months between recordings. The reproducibility of the clustering pattern for subjects A3 and A4 using the MAV parameters was very similar. Dataset A3 and A3rep were split into three groups with only a difference of one time-point between the group divisions. The presence of mains noise in dataset A3 did not appear to affect adversely the cluster pattern. Datasets A4 and A4rep were divided into 4 groups with the main difference in patterns being the time-point between clusters 2 and 3. The WT
cluster patterns for datasets A3 and A3rep were alike, with each set being divided into 5 groups and a maximum difference in divisions of the groups of only 2 time-points. Datasets A4 and A4rep were likewise split into 4 groups and although a resemblance could be discerned, it was not as marked as for the A3 and A3rep WT cluster patterns. The STFT cluster patterns for A4 were similar with maximum difference of 3 time-points between corresponding clusters. The inference one can make from the constancy of cluster patterns, is that the neuronal locomotor patterns remain relatively unchanged during the eleven-month period between measurements. This is despite muscle atrophy, alterations in innervation and fatty infiltration that may have occurred during this period. The constancy of patterns provides support for the existence of a CPG (see section 3.3). No repeat kinematic recordings were made for subjects A3 and A4 therefore no comparison could be made between kinematic and sEMG data.

9.5.5 Relationship of cluster patterns to stance parameters
Cluster analysis revealed divisions in the stance phase as determined from the sEMG data. However, what is the significance of these groupings and how do they relate to the recognised stance phases and parameters? Table 9.17 indicates the stance tasks as described by Perry (1992) for intact subjects in terms of stance time-points.

<table>
<thead>
<tr>
<th>Task during stance</th>
<th>Stance time-points (1/30)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight acceptance</td>
<td>1-5</td>
</tr>
<tr>
<td>Single limb support</td>
<td>Mid-stance</td>
</tr>
<tr>
<td></td>
<td>Terminal stance</td>
</tr>
<tr>
<td>Preswing</td>
<td>16-25</td>
</tr>
<tr>
<td></td>
<td>26-30</td>
</tr>
</tbody>
</table>

Table 9.17. Phases of stance for intact subjects in terms of time-point (1/30 of stance)

Table 9.18 lists stance events calculated from the five subjects’ first set of measurements. Dataset A1 had a cluster pattern for the MAV parameter comprised of 4 clusters which approximate the four tasks during stance and are associated with 3 gait events listed in table 9.18 (1\textsuperscript{st} GRF peak, knee flexion and 2\textsuperscript{nd} GRF peak). Datasets A2, A4, A4rep and A5 MAV were similarly divided into 4 clusters although the cluster divisions did not match as well with the events recorded in table 9.18. Datasets A3 and A3rep had a different cluster pattern for the MAV parameter consisting of only three clusters.
However, subject A3 had a gait that differed from the other subjects (see subsection 7.2.3.3). This suggests that A3 had a different system of neuromuscular control consisting of only 3 phases namely initial double support phase, the single support phase and the second double support phase. Subject A3 in addition to having a triphase cluster pattern also exhibits high reproducibility for his sEMG MAV parameters (see table 8.1).

Table 9.18. Average time-point (1/30 of stance) when key events occur for the amputee datasets

<table>
<thead>
<tr>
<th>DATASET</th>
<th>GRF 1st Peak (stance time-point)</th>
<th>Knee flexion (stance time-point)</th>
<th>GRF 2nd Peak (stance time-point)</th>
<th>Hip flexion (stance time-point)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>5</td>
<td>18</td>
<td>21</td>
<td>29</td>
</tr>
<tr>
<td>A2</td>
<td>7</td>
<td>20</td>
<td>19</td>
<td>28</td>
</tr>
<tr>
<td>A3</td>
<td>8</td>
<td>27</td>
<td>22</td>
<td>28</td>
</tr>
<tr>
<td>A4</td>
<td>8</td>
<td>20</td>
<td>21</td>
<td>27</td>
</tr>
<tr>
<td>A5</td>
<td>8</td>
<td>19</td>
<td>20</td>
<td>28</td>
</tr>
</tbody>
</table>

9.6 Conclusion

This chapter has presented and discussed the results of PCA and cluster analysis applied to the variables described in the previous chapter. For the three types of matrices analysed - DATA matrix, STANCE matrix and MUSCLE matrix – PCA was able to reduce the number of variables considerably. Overall, the PCs derived from the MAV matrices produced a smaller $N_{\text{min}}$ than those derived from the remaining sEMG parameter matrices with ACWD matrices generally resulting in the smallest reduction of PCs necessary to account for 80% of the variance. The seven different datasets additionally yielded varying $N_{\text{min}}$s. Dataset A5 produced the highest $N_{\text{min}}$ for the PCs derived from the MAV and STFT DATA matrices. The lowest $N_{\text{min}}$ was obtained for datasets A3rep, A2, A3 and A4 from the MAV, STFT, ACWD and WT DATA matrices respectively. Analysis of the MUSCLE DATA matrices produced different values of $N_{\text{min}}$ for the five hip muscles depending on the sEMG parameter and the dataset being analysed. PCA of the MUSCLE matrices indicated that there was significant co-activation of the five hip muscles measured. This suggests that the CNS activates a number of muscles collectively as opposed to individually.
Cluster analysis was applied to three types of PC matrices. The DATA PC matrix contained all the muscle and stance sEMG for an individual subject. The majority of previous studies have utilised ensemble measurements, which remove the inherent variability of sEMG. Statistically significant clustering could be identified from cluster analysis of the DATA PC matrix for twenty one of the twenty five datasets analysed. Subject A5 had only one statistically significant cluster pattern. This subject as reported in subsection 7.3.2 had sustained considerable soft tissue injury.

The 4 clusters derived from the MAV DATA PC matrices for subjects A1, A2, A4 and A5 approximate the loading phase, mid-stance, terminal stance and pre-swing phases of gait. Cluster analysis of subject A3’s MAV PC matrix yielded only 3 cluster groups. This subject however had a different kinematic pattern compared to the other subjects and had a high repeatability for the sEMG data. The clusters were based on sEMG data that included all the different stances and the different muscles. Despite the high sEMG intra-subject variability between stances, clusters could still be determined. The implications of this are that definite patterns of neuromuscular activity are present during the stance phase. Two amputee subjects had two sets of sEMG recorded with 11 months between measurements. The clustering patterns for both measurements for the two subjects remained relatively unchanged despite the recordings being taken almost a year apart. There does therefore appear to be individual patterns of locomotor control, which remain unchanged over time.

In conclusion, information extracted from sEMG can identify different phases of stance in the absence of extensive soft tissue damage. The number and duration of phases differ depending on the parameter being analysed and varies between subjects. The finding that statistically significant clustering exists and that it is time invariant suggests that utilisation of the sEMG as a potential natural sensor is possible. However, identification of the phases must involve simultaneous analysis of a number of muscles since there is too great variability during stance for determination of phase from individual muscles. In this study, the MAV parameter yielded the highest between stance reproducibility for the sEMG and the clearest cluster patterns. Cluster analysis applied to the WT PCs however resulted in more detailed cluster groups.
Chapter 10

Conclusion

10.1 Introduction

This study examined patterns of sEMG activity in five residual limb muscles during the stance phase of level walking in five transfemoral amputees who had been fitted with an osseo-integrated prosthesis. This type of prosthesis has only recently been developed and therefore only a limited number of investigations of gait in subjects with this prosthesis have been undertaken. No published research is available assessing the activity patterns of the muscles of the residual limb in this subject group during locomotion.

The types of variables assessed in this study and the methods of pattern analysis selected represent a unique approach to the investigation of motor control during locomotion. An additional feature of this investigation was that the stance phase of the gait cycle was focussed on. In addition to the amputee group, a second group consisting of ten healthy males with intact limbs were also involved in the study. Only limited analysis of sEMG was performed on this group since the purpose of this second group was to allow comparison of basic gait parameters, examine similarities and differences in individual muscles' MAV patterns and assess variations in repeatability of stance MAV.

The small number of subjects limited the application of statistical tests. However, the results obtained from this study are valuable since they provide an indication of levels of electrical activity in the muscles of the residual limb with subsequent implications for surgery, rehabilitation, prosthetic control design and locomotor control theory.

The following two sections will review the hypotheses and the aims and objectives presented in the first chapter and how well the study accomplished them. Recommendations for future developments and limitations of the study are contained in the final chapter.
10.2 Hypotheses

In chapter 1, five different hypotheses were presented. These hypotheses will now be examined and conclusions drawn as to whether from the experimental evidence these hypotheses should be accepted or rejected.

Hypothesis 1 - *The three cleaved muscles, rectus femoris, adductor magnus and biceps femoris have increased sEMG activity during resisted movement.*

► Yes

All the muscles in the TF amputees showed an increase in their mean rectified value during isometric contraction although the increase was negligible for RF in one subject who had sustained a shotgun injury to his lower limb. The increase ranged from an average 185% for dataset A5 to 1475% for dataset A4 (see table 7.3). This increase in activity in the case of the cleaved muscles occurred despite gross disturbance to the muscle fibres, disruption of attachments of the muscles, and severance of nerves and motor endplates.

Hypothesis 2 - *Gluteus maximus, gluteus medius, rectus femoris, adductor magnus and biceps femoris will each display patterns of sEMG activity during stance.*

► Yes

General trends in mean ensemble sEMG patterns could be discerned during the stance phase for the different muscles. All five muscles showed maximum amplitude at the onset of stance. The amplitude decreased to a minimum at about 50% of the stance cycle then increased to a peak prior to toe-off. The timing of this peak was dependent on the muscle with the earliest peak occurring for gluteus medius at 70% and adductor magnus having the latest peak at 87% (see figures 8.7a - 8.7e).

Hypothesis 3. *Co-contraction of the five residual limb muscles, gluteus maximus, gluteus medius, rectus femoris, adductor magnus and biceps femoris occurs during the stance phase of locomotion.*

► Possibly

Through the application of PCA, the feature set could be reduced for all 3 types of matrices analysed (*STANCE, MUSCLE, DATA*). In the case of the *MAV STANCE* matrices the 5 muscles could be reduced to between 1 and 3 factors which accounted for at least 80% of
the variance (see table 9.1). PCA of the MAV DATA matrix containing the sEMG for all the muscles and stances could be reduced to between 2 and 4 factors (see table 9.3). This reduction indicates that there is repetition of muscle activity during stance and co-activation of the five hip muscles. The reduction of the feature set was smaller when PCA was applied to matrices containing STFT, ACWD or WT sEMG variables. However, the reduction in features may be a result of cross-talk in addition to co-contraction of the muscles (see subsection 11.3.6).

Hypothesis 4 - The sEMG can be used to divide the stance phase into clusters

► Yes

Clear cluster groups with a cophenetic correlation coefficient of above 0.8 could be generated for 21 of the 25 groups analysed (see table 9.15). Individual datasets revealed different cluster grouping dependent on the type of variable the principal component matrix was derived from (see table 9.16). Cluster analysis of the MAV PC matrix for the seven datasets produced clusters numbering three or four in total. Two basic types of division patterns could be discerned for these cluster groupings. The individual cluster groups could be linked to the different kinematic events occurring.

Hypothesis 5 - Cluster patterns will not change over time.

► Limited evidence

The cluster patterns for MAV for the two amputees, A3 and A4, who had repeat measurements taken approximately 11 months later, were very similar. There was a less obvious similarity when cluster patterns derived from STFT and WT variables were compared. The reproduction of the MAV cluster patterns suggests the existence of a predetermined pattern of activity arising from possible fixed circuitry within the spinal cord. Indirectly these results support the theory of a CPG partially regulating locomotion.

10.3 Aims and objectives of the study

The overall objective of this study was to acquire information about the sEMG activity of muscles in TF amputees and thereby offer a better understanding of muscle activation patterns during locomotion in this subject group. Clinically the results of the study are likely to be of benefit to surgeons, prosthetists, physiotherapists and bioengineers involved with prosthetic design. The aims of the study as stated in the introductory
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Chapter were to answer three basic questions, the answers to which have different clinical implications. The following three sections will cover these three different questions.

**Question 1 - Do the cleaved muscles display activity during the stance phase of gait?**

The muscles in all instances displayed increased sEMG activity during gait. The presence of MUAPs indicates that the muscle has the potential to contract and to exert a force on a structure. The amount of force generated depends on a number of factors. These include the ability of crossbridges to develop between the actin and myosin, the ability of fascial sheaths of muscle to glide smoothly, the length of the muscle and adequate fixation of the cleaved muscle to a fixed structure. Surgical techniques should preserve as much of the muscle as possible, cause minimal adhesions between muscles, and firmly fix cleaved muscles to immoveable tissue. Rehabilitation methods should aim at restoring the function of the cleaved muscles to their maximal potential.

**Question 2 - Can sEMG be used as a natural sensor during locomotion?**

Results from this study indicate that sEMG has the potential to be employed as a natural sensor. However the reproducibility of individual muscles as assessed in this investigation is too low to permit isolated muscles to be used. In future sEMG recordings it may be possible to improve the reproducibility by fixing trailing wires, careful skin preparation, grounding of the examiner and applying more extensive filtering. However, it is unlikely that a sufficiently high level of reproducibility can be attained for individual muscles since the variability appears to be part of the neuromuscular control system. The objective of the locomotor control system is arguably to attain highly reproducible joint kinematics rather than reproduce individual muscle activity. There are, as described in previous chapters, an indeterminate number of ways that muscles can contract in order to achieve a desired joint angle. Hence each successive stance will involve slightly different patterns of sEMG activity. The solution to using sEMG as a natural sensor lies in combining information from a variety of muscles. This study opted for PCA and cluster analysis as appropriate methods to merge sEMG data from all five muscles. Significant cluster groups were obtained and cluster groups showed a consistency in pattern over an eleven month period. The latter point satisfies the condition that there must be constancy in sEMG patterns during locomotion if sEMG is to be considered as a natural sensor.
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A question that should be considered is what is the minimum reproducibility of the sEMG signal necessary to enable the sEMG to be used as a natural sensor? A sEMG sensor working in isolation with no other sensor involved must be 100% reliable. This is unlikely to ever be the case even for multi-muscle sEMG. Therefore the likely role of sEMG as a sensor is to operate in conjunction with other sensors.

Given the high variability that sEMG shows, the immediate response may well be to reject the option of using sEMG as a natural sensor. However the potential advantages of sEMG are that firstly that the muscle activity will precede movement of the joint by an average 100ms (see subsection 2.10.2). A second benefit of sEMG is that information about intended movement can be recorded even when there is no recordable movement occurring at a joint. For example, during the action of sitting to standing the initial events that occur will be contraction of the hip extensors, knee extensors and ankle dorsiflexors. This will be followed by movement of the hip, knee and ankle joints and forward and upward propulsion of the trunk. This predictive feature of movement is potentially valuable to a TF amputee. A TF amputee may not have the necessary muscle power to initiate movement of the prosthetic knee and ankle joints. However, a sensor linking the activity of, for example, the rectus femoris to the prosthetic knee could cause the knee to be resistant to knee flexion, thereby aiding the action of trunk elevation.

**Question 3 - What is the neural control mechanism following an amputation?**

Section 3.3 discussed the neural control of locomotion and the concept of CPG. The CPG is considered to be modulated by neuronal impulses arising from higher centres in the brain in addition to impulses being transmitted from the periphery through the peripheral afferent fibres. A number of investigators have investigated locomotor patterns in spinal cord injury subjects and concluded that there is evidence of CPG in humans. Spinal cord injury subjects will have no or very few neuronal impulses reaching the spinal cord segments caudal to the level of the injury. However no research has been undertaken that the author is aware of to assess the effect that reduced peripheral afferent input as a result of amputation might have on the CPG. High level TF amputees will have a substantial reduction in afferent input to the spinal cord. One might therefore anticipate that the CPG patterns would be significantly affected resulting in a major change of the individual muscle activity during gait.
Chapter 10. Conclusion

Results from the study indicate that the sEMG MAV patterns are very similar for the amputee group compared to the intact group. The absence of sensory information from the muscles, tendons, fascia, ligaments and joints distal to the amputation level does not therefore appear to have a significant effect on the hypothesised CPG activity. The CPG theory postulates that functionally related groups of muscles are simultaneously activated. Results from the PCA of the sEMG MAV data reveal that co-contraction of the muscles occurs in TF amputees indicating an underlying CPG.

10.4 Conclusion

This study represents a preliminary investigation into patterns of sEMG activity during the stance phase of walking in subjects fitted with osseo-integrated prostheses. There have been no published studies on the muscles of this subject group undertaken previously and very little research done on the activity of muscles in TF amputees fitted with conventional prostheses. To an extent this investigation represented a voyage of discovery since it was uncertain what results would ensue and what were the most appropriate methods of analysis to apply. The final results reveal that there is a regular pattern of sEMG activity (depending on the parameters selected) in groups of muscles of the residual limb despite the devastation to that limb. Functionally, this is indicative of an underlying CPG. This finding has not previously been reported in published studies. This observation has implications for rehabilitation and development of control systems for micro-computer controlled prosthetic joints. In summary, cluster analysis of the sEMG provides a novel clinical tool to categorise different neuromotor control mechanisms and assess changes resulting from varying types of prostheses and rehabilitation methods.

The challenge of the future is to develop a prosthetic limb which has an interface with the subject’s own locomotor control system thereby permitting smooth locomotion. The two key difficulties that must be overcome are firstly that the signal processing must be fast enough to allow the signal to be used in real-time. Secondly, the intrinsic stance to stance variability in individual muscles activity must be reduced through selection of appropriate sEMG variable and signal analysis methods. An improved way of proceeding may be to implant nerve cuff electrode around the nerves in the residual limb. However it must be
remembered that the greatest demand for prostheses in young previously active people is in economically poor countries. A further challenge therefore is to develop a prosthesis incorporating natural sensors but also to make it financially viable for these subjects. This study has been eclectic in approach, involving many disciplines including amputation surgery, gait biomechanics, prostheses, locomotor control mechanisms and signal analysis. Certain areas such as motor control have been scantily covered. Scope for future development is therefore to integrate the sEMG results with motor control theories. It is highly probable that medical advances will reduce the number of amputations due to diabetes, cardiovascular disease, carcinoma and infection. Traumatic amputations however are likely to continue unabated. There is therefore likely to be a continuing need for research into biomechanics of the amputee and prosthetic design to improve functioning of the amputee for some time. The trauma may be a road traffic accident such as was the case for study subjects A1, A2, A3 and A4. It may be a careless accident like in the case of subject A5 who shot himself in the leg. In countries with an ongoing or recent history of war the trauma responsible for amputation may be the consequent of landmines. A few unlucky individuals will sustain an injury requiring amputation through sport such as the hurdler John Register in 1994. Whatever the nature of the trauma, a common feature of traumatic amputees is that they are younger than those subjects whose cause of amputation is through pathology. If these individuals are unable to pursue a full and active life there is a high cost to society an addition to the severe limitation of the individual’s quality of life. The mission statement set out by the World Health Organisation best summarises the role of society to the inflicted individual:

*The enjoyment of the highest attainable standard of health is one of the fundamental rights of every human being without distinction of race, religion, political belief, economic or social condition.*

World Health Organization (1946), Constitution, Geneva
Chapter 11
Limitations and future developments

11.1 Introduction
This study was a preliminary investigation into the sEMG activity of five hip joint muscles during level walking in two groups of subjects. The signal analysis techniques chosen in this study were based on resources available, previously published research, time considerations and expertise of the author. In addition there was a heuristic element in instances where information from published studies was not available. Having completed the study, it is apparent that there are a number of procedures which could be modified or further developed in any future progression of the research. The following sections highlight those aspects where alterations or additions could be made. Section 11.2 discusses methodological aspects, section 11.3 considers signal analysis and section 11.4 investigates the challenge of relating sEMG activity to spinal cord activity.

11.2 Methodology
The following subsections consider the methodology employed in this study. This includes the numbers of subjects, type of control group, activity selected and equipment used.

11.2.1 Subject numbers
The study group A was comprised of only five osseo-integrated amputees and the control group B was made up of ten intact subjects. These numbers limit the application of statistical tests. Group A was low since it reflected the small number of amputees with osseo-integrated prostheses who attend the Gait Laboratory at Queen Mary’s Hospital, Roehampton. The entire worldwide population group of subjects who have been fitted with an osseo-integrated prosthesis comprises only about eighty individuals [Lee et al. 2006]. The subjects are located in Australia, Canada, Germany, England, Portugal and Sweden [Grundei 2006; Lee et al. 2006]. Ideally, a future study would be
international and involve assessing the entire population group of TF amputees fitted with an osseo-integrated prosthesis.

Two groups were selected for this study, the osseo-integrated group A and the intact group B. The purpose of the intact group was firstly to help validate the initial part of the procedure. This was necessary since there is a dearth of data regarding patterns of sEMG activity during locomotion for TF amputees and none that the author is of aware of for osseo-integrated amputees. However, there have been a number of studies undertaken on patterns of sEMG data during locomotion in intact subjects. In addition, comparisons were made between the control and amputee group for certain gait parameters, the MAV sEMG variability and the repeatability. Kinematic data was not collected for the intact group due to temporal and technical staffing limitations in the Gait Laboratory. Kinematic information for the intact group would have been valuable since it would allow one to determine how closely the amputee’s lower limb kinematics approximated the intact subject’s kinematics.

Clinically, it would be valuable to compare the sEMG of the osseo-integrated group with that of conventional TF amputees to determine what effect the radical muscle surgery involved in osseo-integrated surgery has had on muscle activity. Additionally, an evaluation of sEMG activity in amputees who have undergone osseo-integrated prosthesis as developed in Sweden [Brânemark et al. 2001] compared to the that developed in Germany [Staubach & Grundei 2001] would be desirable. Although both osseo-integrated methods share the common element of having the prosthesis attached directly into the femur via a titanium pin they differ in their surgical approach to the muscles and the construction of the components. The German method emphasises the importance of creating a strong fixture point for the cleaved muscles. The osseo-integrated component therefore incorporates a titanium mesh oriented at right angles to the metal pin to encourage fixation of the soft tissue. This thereby creates a firm anchorage for the muscles to pull against when they contract. In contrast, the muscle surgery advocated in the Swedish method involves the muscle and surrounding fascia being attached to surrounding tissue with no additional synthetic structures being
Chapter 11. Limitations

involved with fixation. There is to date no published research examining the differences in the clinical efficacy between the two different approaches.

11.2.2 Skin preparation

Skin preparation was limited to cleaning the subject's skin with an alcohol wipe. The minimal skin preparation was performed according to the advice stated in the Biometrics manual. This stated that 'little or no skin preparation should be required' [Biometrics Ltd. 2004]. There were however, problems in some subjects with adhesion of the electrodes on the skin possibly due to glandular secretions on the skin surface or the application of cosmetic creams or oils. This was a particularly the case for subject A2, although partially remedied by fixing the electrodes with surgical tape. A number of participants, mostly in group B, had large amounts of hair on their lower limbs. This resulted in a noisy signal due firstly to hairs moving between the electrodes and the skin and secondly to movement of the electrode relative to underlying skin as a consequence of the poorer adherence. In future, more skin preparation including shaving should be undertaken prior to recording.

11.2.3 Placement, number and type of electrodes and muscles selected

Only five surface electrodes were placed on muscles of the residual limb. The number was determined by the maximum capacity of the Biometrics Datalink system which was limited to 8000 Hz. Financial restrictions precluded the acquisition of a system with a larger capacity. However, this number of muscles recorded represents only a small sample of the actual number of muscles acting on the hip during locomotion, which may range up to twenty muscles (see table 6.1). In a future study more muscles should be assessed thereby providing as much information about the effectors acting on the hip joint as possible. The use of wire electrodes would permit the deeper muscles to be monitored, in particular iliopsoas, which is the strongest flexor of the hip joint. Wire electrodes were not used in this study due to the invasive nature of applying the electrodes.

Valuable information regarding muscle co-ordination and neural control could be acquired by measuring muscles of the intact limb in addition to the trunk muscles and
upper extremities. Merkle et al. (1998) reported significant co-ordinated activity between the neck and trunk muscles and the lower extremity muscles during treadmill walking in intact subjects. There is likely to be a stronger relationship between these two groups of muscles in TF amputees who use their upper bodies to a greater extent than intact subjects to propel themselves forwards during locomotion.

This investigation used only one single bipolar electrode per muscle. Therefore only a small section of the muscle was sampled. Multi-electrodes have been reported to provide improved information regarding the spatial properties of the motor unit [Stegeman et al. 2006; Zwarts & Stegeman 2003]. These motor unit characteristics include position, spatial extent, endplate zone’s position, propagation of action potential and direction and length of the muscle fibres [Zwarts & Stegeman 2003]. The reader is referred to Farina’s, Merletti’s and Disselhorst-Klug’s account of multichannel techniques for more information [Farina et al. 2004].

Determining accurate placement of electrodes on the cleaved muscles (BF, AM and RF) is problematic without MRI, computerised tomography (CT) or ultrasound scanning. Unlike the intact muscles, there are no recommended placements for electrodes on cleaved muscles. Even with MRI scans available, determination of the location of the individual muscles may be difficult due to the distortional effect that the metal contained in and protruding out of the femur will have on the scan. The type of metal contained in the implant is titanium. Titanium is non-ferromagnetic so will only create a small artefact compared to a pin composed of stainless steel. Ramos-Cabrera et al. (2004) have reported on an improved method of removing artefacts created by metal implants. The disadvantages of both MRI and CT scanning are that they are expensive and may not be readily available. By contrast, ultrasound scanning is more accessible and cheaper. Studies have been undertaken measuring muscle belly length, pennation angles and muscle thickness in the lower limb [Benard et al., 2008; Blazevich et al., 2006; Fry et al., 2003; Loram et al., 2004; Manal et al., 2008]. The maximum errors in measurement of muscle thickness, border of the muscle transverse to the probe and pennation angle were reported to be 0.97mm, 2.6mm and 1.22°. Localisation of muscle by ultrasound scanning is therefore sufficiently accurate for the larger limb muscles.
Ideally any future study recording sEMG of cleaved muscles would ensure that the subjects underwent MRI, CT or ultrasound scanning to assist in the correct positioning of the electrodes and subsequent reduction of cross-talk.

11.2.4 Sampling
The sampling frequency was 1000 Hz. The SENIAM recommendations published in 2001 recommended sampling frequencies of 1-2 kHz [Freriks & Hermens 2000] although guidelines that are more recent recommend a sampling frequency of 2 kHz [Hermens 2006]. However, as discussed in subsection 2.6.4, little additional information is gained by oversampling.

11.2.5 Isometric contraction
The isometric contractions were performed with each participant resisting a force applied by the author. The force applied was the maximum that the author could generate or the maximum that the participant could comfortably resist against. The magnitude and direction of the applied force was not measured and there is likely to have been some variation in the force during the period in which it was applied. In subsection 7.2.2, it was observed that muscles from an intact limb produce a more consistent amplitude of the sEMG than muscles from an amputated limb. However, without quantitative information regarding the resisted force one cannot exclude the possibility that variation shown by the amputees in their sEMG amplitude was not due to variations in applied force. In any future study the force should be measured using a dynamometer in order to be able to quantify the force.

11.2.6 Dynamic sEMG measurements
The sEMG was monitored whilst the subject traversed a 10m long walkway. This type of walking is not representative of everyday functional activity. Future studies should consider using a data logger and foot contact switches to monitor the sEMG and gait events whilst the subject for example is walking along different inclines, varying speeds, turning corners, or ascending and descending stairs. Further types of movement that would be clinically valuable to investigate are transitional events such as getting into and out of a chair, and initiating and stopping walking. Stability of the prosthesis is
essential during these transitional events since there are rapid changes in forces acting on
the joints.

The sEMG variables were determined from a total of on average 20 stances for each
subject. This number of cycles has been reported as being the minimum level necessary
to reduce the variability of the sEMG amplitude to an acceptable level (see subsection
7.3.3). However, as discussed in subsection 3.2.1, not only are there variations in the
sEMG between successive gait cycle patterns, there are additionally non-random
changes in patterns over time. These changes have a temporal structure to them.
Ideally in a future study, successive gait cycles would be monitored at intervals over a
period of time. This would allow an assessment to be made of the natural fluctuations
present in the ensemble average. There would however be a limit as to how long TF
amputees would be able to walk before the onset of muscle fatigue.

The morphology of the tissues in the residual limb in TF amputees changes over time,
which will necessarily alter the sEMG patterns. Repeat measurements at regular
intervals would provide an indication of the constancy of the sEMG patterns. In terms
of using sEMG as a natural sensor to control a prosthetic knee accurately, constancy of
the signal pattern is an essential prerequisite.

11.2.7 Hip muscle strength measurements
This study only investigated the sEMG activity of hip muscles during locomotion. One
of the aims as outlined in section 1.2 was to identify the functional contribution of the
cleaved muscles during gait following an above-knee amputation. Although evidence of
increased sEMG activity during locomotion indicates evidence of increased electrical
activity of the muscle fibre, it does not necessarily imply an increase in contractile force
of that fibre. Measurement of the muscle force through the use of a dynamometer would
provide information regarding the strength of the muscle.

11.2.8 Arrangement of cables and electrical equipment
Loeb emphasises in ‘Electromyography for experimenters’ [Loeb 1986] that care must
be taken with the physical arrangement of the electrical devices and cables within the
laboratory in order to minimise mains noise. In any future sEMG recording, more
attention should be paid to the large number of cables and where possible these should be fixed. There was evidence of mains interference and harmonics thereof present in the sEMG recorded from both the isometric and dynamic muscle contractions. Although the presence of this type of artefact is not likely to be a major issue since changes in activity rather than absolute magnitude were being investigated, the ideal is to reduce noise and interference as much as possible.

11.3 Methods of analysis

Chapter 3 described the types of analysis that investigators have applied to sEMG. This study has selected certain types of signal analysis to determine pattern analysis. Selection has been based on a number of different factors. Firstly consideration has been given to the type of signal being analysed and the most appropriate processing method for this type of signal. Further factors included time considerations for analysis and the limited expertise of the author in the area of signal analysis. The following subsections provide a critique of the methods selected and recommendations for future developments of this study.

11.3.1 Noise and filtering.

The Biometrics pre-amplifier incorporated a low-pass eighth order filter and a high-pass third order filter. These filters restricted the frequency range being recorded to between 15 Hz and 450 Hz. No further filters were applied prior to extraction of the sEMG variables.

There was obvious power line interference in the signals of one subject at 50 Hz, 150 Hz and 250 Hz during isometric contraction. This will distort the amplitude of the signal and the mean frequency. Noise reduction in this study is not as essential as in the case of image and acoustic processing where it is essential that noise is reduced as much as possible to create as sharp and well defined a reproduction of the original image or signal as possible. However it is still desirable that as much noise as possible is eliminated to clarify the changing patterns of the sEMG variables. Ideally an adaptive filter would have been applied to the signal prior to processing, as described in subsection 5.2.1, to minimise the 50 Hz interference.
Whitening, a procedure that increases the statistical bandwidth was discussed in subsection 5.2.1. This technique was not applied for reasons given in section 6.9. Future analysis of the sEMG should consider applying a Wiener adaptive whitening filter.

**11.3.2 Synchronisation and division of sEMG signal**

Synchronisation between the sEMG signal and the kinetic and kinematic signals was achieved by the subject pressing a contact switch which triggered a 100 Hz signal (see section 6.5). The contact switch signal was transmitted to one computer which received the 1 kHz signal from the sEMG electrodes and to another computer which received the signals from the force walkway (2 kHz) (see figure 6.8). As a result of the different pathways within the base unit, different length cables to the computers and different sampling frequencies there was a small error in synchronisation.

The determination of the gait events was obtained from force walkway data. Since the sampling frequency of the walkway was 2000 Hz determination of initial contact and toe-off was accurate to +/- 0.5 ms. Only the stance part of the gait was selected for analysis. The rationale for this choice was that the most critical part of the gait cycle during which control of the prosthetic knee is essential is the stance phase. Time considerations did not allow for the swing phase in addition to the stance phase to be analysed. However, in a future study, in order to obtain a full picture of the activity of the muscles and locomotor control modes during walking the entire gait cycle should be analysed.

**11.3.3 Electro-mechanical delay (EMD)**

There is not an immediate alteration in the force acting on a joint or changes in joint angle corresponding to changes in the sEMG. This lag between the variations in the sEMG signal and kinetic and kinematic fluctuations is known as the EMD (see subsection 2.10.2). In this study, EMD was not accounted for. In reality, changes in sEMG will occur prior to the kinetic and kinematic onset of stance. Originally, the investigation intended to include the EMD in its calculations. The division of sEMG into stance segments was to contain a section of the signal preceding the time of initial
contact as recorded by the force walkway. However, the value of the EMD is not well defined and may indeed vary during a dynamic action such as occurs in locomotion. It was therefore decided to maintain equal temporal relationships between the sEMG signal and the kinetic and kinematic signals. Future analysis should however investigate the effect of sEMG stance signal which commence prior to the onset of initial contact. Cross-correlations could be performed between sEMG and kinetic data to determine the value of the EMD.

11.3.4 sEMG analysis of intact group
The only sEMG variable calculated for subjects in group B was the MAV. Future analysis should include estimations of the STFT values, the ACWD values and the WT values for this group. This information may provide an insight into how muscle function changes in amputated muscle. In particular, individual differences in mean frequency and mean scale of an intact muscle with a cleaved muscle may provide neurophysiologically important information. A statistically significant change in frequency may indicate either a change in muscle fibre type or neuronal firing rate. PCA and cluster analysis were not performed on the intact group, again due to time limitations. These pattern recognition methods should be performed on the intact data in future analysis. A comparison of cluster patterns between the two groups may reveal different locomotor control modes.

11.3.5 Parameter selected for each category
There is no one single parameter that best reflects the underlying pattern of activity of the motor unit action potential. Instead, a wide range of parameters have been employed by different investigators to determine muscle activity. These range from the simple amplitude based ‘on / off’ parameter to the parameters derived from complex non-linear wavelet analysis [von Tscharner 2000]. The former is appropriate for clinical applications where rapid acquisition of information is imperative in order to determine whether and when a muscle is being activated. The wavelet based parameters may be used for deeper interpretation of muscle activity including analysis of fatigue, types of fibres firing and neural control patterns.
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The study applied four different types of filters and transforms, which had been routinely employed in previous sEMG studies (see figure 6.13). Two of the algorithms, `filtfilt` and `specgram` were taken from the MATLAB Signal Analysis Toolbox, the ACWD algorithm `tfracwd` was developed at the Universidad de Vigo and the WT was written by W.J.Gomes for the ECE674 Time-Frequency Methods for Signal Processing [Gomes 1999].

Decisions had to be undertaken as to size and types of parameters to include in the algorithms. In certain instances, such as selection of the window length for determination of the MAV and STFT values, assessment of repeatability using different lengths of windows was made (see figure 6.12, table 6.4 and table 6.5). Selection of the window length was based on a compromise between reasonable repeatability, ability to detect gait events and minimising the time delay. The decision to employ other parameters, such as the Hamming window in the STFT or the Morlet wavelet in the WT was determined by parameter selection in previous studies and theoretical considerations (see subsection 6.8.3). The final processing involved normalisation of the MAV variable to the maximum value recorded during the stance and calculation of the mean frequencies and scales. Temporal normalisation consisted of applying a piecewise cubic Hermite interpolating polynomial (MATLAB `pchip` function) to the variables thus resulting in 30 data points per stance (see subsection 6.8.4.3). This type of polynomial was applied rather than the regular cubic spline interpolation (MATLAB `spline` function) since it results in a smoother spline, no overshoots and fewer oscillations [Mathworks 2004]. The reason for selecting thirty as the number of data points to be determined was based on the number selected in several previous studies. In determining the variables, an attempt has been made to be objective at each stage of the analysis. However there is invariably a subjective and heuristic element in the processing. Ideally, at every stage of the processing, the results from using different parameters would be statistically tested and objective criteria would be attained for selection of the parameters.

Considerations for developments in any future study include using an adaptive window for the MAV, investigating different bands of frequencies or scales rather than the mean frequency, and using different types of mother wavelets in the WT.
11.3.6 Feature reduction methods

Feature reduction was achieved by applying PCA to three types of matrices. The MATLAB function `princomp` centres the columns of the matrix by subtracting the mean from each column, but does not standardise the data. The sEMG data was however normalised prior to PCA. Each muscle was assumed to contribute equally to the matrix. This however is not likely to be the case. Future analysis of the data should investigate selecting different weighting to the individual muscle data when applying PCA. Only one category of variable (MAV, STFT, ACWD or WT) was used at a time when determining the PCs. Since the variables offer different information about the MUAPs, it may be productive to combine different categories of variables when applying PCA. Additionally other gait parameters could be incorporated into the matrix being subjected to analysis such as kinematic and force together with sEMG data.

There was no discussion of the contribution of each muscle to each principal component or the role a principal component played during different parts of stance. Investigation of the importance of individual muscles is clinically important since it highlights the role the muscle plays during different parts of the cycle. The information is important since it firstly emphasises which muscles may be useful to act as natural sensors and may indicate whether the subject is overusing certain muscles and under using others. This could then be addressed through appropriate physiotherapy and rehabilitation.

A reduction in the number of features needed to describe the data may be the result of cross-talk in addition to co-activation of muscles (see section 9.3.1). Cross-talk can be minimised by ensuring correct placement of electrodes (see section 11.2.3) and by applying double differential electrodes (see section 2.7).

11.3.7 Pattern recognition methods

Cluster analysis was the method selected to determine the presence of groupings within the data. This technique has been applied to sEMG recorded during gait by previous researchers [Shiavi and Griffin 1981; White and McNair 2002; Zhang et al. 1991]. Another pattern recognition method that has been applied frequently to sEMG data particularly with regard to prosthetic control of the upper limb is the artificial neural
network (see subsection 3.5.3). There has however been only limited application of ANNs to dynamic sEMG data recorded during locomotion [Cheron et al. 2003; Sepuldeva et al. 1993]. A future study could use ANN with sEMG as the input and the kinematic as the output to determine stance phase.

The MATLAB function *cluster* was chosen to examine clustering patterns within the data. This hierarchical method was picked because it is similar in structure to the manner in which gait is descriptively divided (see figure 3.2). However there is no experimental evidence that the locomotor control mechanism is hierarchical in nature rather than switching between distinct modes. Different methods of cluster analysis, such as K-Means clustering, should therefore be investigated in future analysis.

Decisions had to be made regarding appropriate parameters to be selected for use in the *cluster* algorithm. There is no 'best' parameter that has been determined by previous investigators. A small amount of testing was therefore conducted by varying the parameters. Based on the results it was decided to use 'cosine' as the distance and 'average' as the method of linkage (see subsection 6.8.8). As was the case with previous analyses more rigorous testing of techniques should be undertaken.

The number of components selected for cluster analysis was the number that accounted for 80% of the variance. However, there are different methods available to select a subset of principal components that accurately reflect the data (see section 5.5.2). Selecting a larger number of components that accounted for 90% of the variance would include eigenvectors with lower eigenvalues. Davis and Vaughan (1993) have stated that components with an eigenvalue of less than 1 described noise. However, Ivanenko et al. (2004) reported that eigenvectors with a eigenvalue of less than 1 contained important features with regard to early swing. Limiting the future set to components that accounted for only 80% of the variance may therefore have limited the information and affected the cluster patterns. Peres-Neto et al. (2005) discuss methods for determining the number principal components including the Bartlett's test and Kaiser measure which have been applied in several studies [Ivanenko et al. 2004; Merkle et al.1998].
Chapter 11. Limitations

11.4 Spinal cord segmental activation

The method of assessing locomotor control modes in the study was to identify groupings generated by cluster analysis. An alternative method is to construct a spatiotemporal map of motorneurone activity [Grasso et al. 2004; Yakovenko et al. 2002]. Grasso et al. applied this technique on eleven spinal cord injury (SCI) patients and eleven healthy control subjects. The signals were recorded from upper and lower extremity muscles in addition to trunk muscles. The sEMG data was then mapped onto a spatiotemporal representation of the spinal cord extending spatially from C3 rostrally to S2 caudally and temporally distributed over a normalised gait cycle (see figure 11.1). The location of the mapping of a muscle onto a spinal cord segment was determined by previously published charts. A future study could assess spinal cord segmental activation patterns in amputees in a similar way that SCI subjects have been analysed as outlined above. This would necessitate recording a functionally varied selection of muscles as recommended in subsection 11.2.3. Clinically, this representation would be beneficial since it would emphasise the balance between how much the amputee was using the upper body to perform locomotion compared to the lower extremity. The efficacy of rehabilitation methods and types of prostheses could thereby be assessed.

Figure 11.1. Spatiotemporal mapping of motorneurone activity along the spinal cord for a normalised gait cycle. SCI = spinal cord injury. [Grasso et al. 2004]
11.5 Conclusion

Many different decisions were made regarding both the methodology and the signal analysis. The main areas in the methodology that could be modified or extended are:

- A larger number of osseointegrated TF amputees should be assessed
- Skin preparation should be more thorough and include hair removal
- Activities being recorded could be extended to included altered walking velocities, varying inclines, stair climbing and stopping / starting.
- MRI, CT or ultrasound scans would improve the positioning of the electrodes.
- A greater number of muscles should be sampled to include trunk muscles and muscles of the contra-lateral lower limb.

In the case of the signal processing, in many instances there was no ‘best choice’ of processing method or selection of parameters based on previous experimental evidence or theoretical foundations. Ideally every decision would be justified by solid statistical support or theoretical knowledge. Future recommendations are:

- Account for EMD by including a portion of the sEMG signal prior to the onset of initial contact.
- Apply cross-correlation to the sEMG and kinematic data to determine EMD.
- Apply a whitening filter and Wiener adaptive filter to the raw sEMG signal.
- Use an adaptive window for the MAV calculation
- Investigate different bands of frequencies and scales instead of solely the mean frequency
- Apply PCA to matrices containing different sEMG variables in addition to kinetic and kinematic data.
- Apply statistical tests to the principal components to determine the number needed to represent the data best.
- Investigate using an ANN to the principal components.
- Determine spinal cord activation patterns.
In any future study, the data collected for the control group should be the same as for the study group. The depth of signal analysis should additionally be equal thus allowing a full comparison between the groups.

This chapter highlights the great variability in results that can be obtained depending on the method of analysis selected and the parameters within the algorithms chosen. This leads to difficulties in comparing results from one study with another since there is no 'like for like'. There is thus much more rigorous analysis that must be undertaken before information from the sEMG signal during locomotion can be realistically applied in a clinical setting. The natural question is, whether there is any purpose in analysing a signal which presents so many complications. However, as Cheron et al. (2003) state:

'EMG is the only non-invasively accessible signal related to the final command of movement ... is a reasonable reflection of the firing rate of a motoneuronal pool'.
Appendix 1. Project Information Sheet

Pattern recognition of electromyographic signals during walking in transfemoral amputees

I am currently undertaking an investigation into the (electromyographic) activity of selected hip muscles in subjects who have undergone a transfemoral amputation and been fitted with an osseointegrated prosthesis. This study is part of a larger clinical investigation being undertaken by a team from the Bioengineering Department at Surrey University and Queen Mary’s Hospital evaluating this new method of prosthetic attachment. The aim of my study is to investigate whether there is a repeatable pattern of muscle activity during walking which could be used as a sensor for control of a prosthetic limb. In addition useful information will be gained as to how muscle functioning is affected following surgery.

Procedure

The measuring procedure will be linked to existing clinical reviews in the gait laboratory. Measurement of muscle activity is a routine technique used in the assessment of gait. You will be asked to wear shorts and lie on a couch. Five electrodes will be placed on the skin of the residual limb. The electrodes measure the electrical activity of the muscles and do not transmit electric current through the skin. They will be attached to the skin by means of self adhesive tape. A wristband containing a reference electrode will be worn and a small box into which the electrodes insert will be fixed by a belt around your waist. You will then be asked to stand. Eleven markers (reflective balls) will be placed on your legs, which you will be familiar with from previous gait analysis sessions. You will then be asked to push
with your residual limb against resistance in four different directions to establish that the electrodes are correctly positioned.

The next part of the procedure will involve walking along the 3.3m walkway at your normal walking speed. This process will be repeated 10 times. If you feel fatigued or in pain whilst walking you can stop. The total time taken for measurement of muscle activity will be approximately one hour.

Participation in the study is purely voluntary and you are able to withdraw from the study at any time. You are welcome to contact me for further information by email or telephone (details at top of sheet).

Annette Pantall

Site of placement of 2 electrodes on outside and back of thigh

Site of placement of 3 electrodes on inside and front of thigh

Surface electrode
Appendix 2. Consent form

University of Surrey
Annette Pantall, Centre for Biomedical Engineering
School of Engineering
Tel 01732 522317 Mob. 07734 981571 a.pantall@surrey.ac.uk

Pattern recognition of electromyographic signals during walking in transfemoral amputees

Project Consent Form

• I, the undersigned voluntary agree to take part in the study measuring muscle activity of the stump muscles using surface electrodes whilst walking.

• I have read and understood the Information Sheet provided. I have been given a full explanation by the investigators of the nature, purpose, location and likely duration of the study, and of what I will be expected to do. I have been given the opportunity to ask questions on all aspects of the study and have understood the advice and information given as a result.

• I agree to comply with any instruction given to me during the study and to co-operate fully with the investigators.

• I understand that all personal data relating to volunteers is held and processed in the strictest confidence and in accordance with the Data Protection Act (1998). I agree that I will not seek to restrict the use of the results of the study on the understanding that my anonymity is preserved.
Appendix 2, Consent Form

• I do / do not (delete as appropriate) give permission for videos or photographs of tests in which I feature to be used in seminars, publications or publicity.

• I understand that I am free to withdraw from the study at any time without needing to justify my decision and without prejudice.

• I confirm that I have read and understood the above and freely consent to participating in this study. I have been given adequate time to consider my participation and agree to comply with the instructions and restrictions of the study.

Name of volunteer.................................
(BLOCK CAPITALS)

Signed ......................................................

Date .....................................................

Name of Witness .................................
(BLOCK CAPITALS)

Signed.......................................................

Date .....................................................

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Appendix 4. Matlab zeroforceemg algorithm

% This program loads a number of consecutive EMG(1000Hz) and force walkway
% data(1000Hz) MAT files and concatenates them into a single synchronised
% matrix. The force data for the platform 1 is in the first column.
% Columns 2-6 contains emg data (gmax,gmed,rectfem,addmag,bic fem)
for i=2:2:22
    emg=[
    forcesync=[
        fforcename =sprintf('mc%dforcesync.mat',i);
        femgname =sprintf('mc%d.mat',i);
        load (fforcename); load (femgname)
    %find frame when contact on emg data.
    n=length(emg)
    for ct=2:n;
        if emg(ct,6)==emg(ct-1,6);
            continue;
        else cont=ct
            break
        end
    end
    mcemgcon=emg(cont*10:n, 1:5);
    timstartemg=cont*10;
    % zero emg data
    b=length(mcemgcon)
    z=sum(mcemgcon(:,1:5))/b;
    ZG=repmat(z,b,1);
    ZEMG=mcemgcon(:,1:5)-ZG;
    % ZEMG=zeroed raw emg. Use for TF calculations
    TEST3=sum(ZEMG)
    %equalise frequency of force data with EMG - reduce by half
    n=length(ZEMG)
    l=length(forcesync)
    v=min([n 1])
    %concatenate emg and force data into single forceemg matrix
    forceemg=[forcesync(1:v)' ZEMG(1:v,:)] ;
    zname=sprintf('mc%drawzeroforceemg',i)
    save (zname,'forceemg' ,'timstartemg' )
    %plot force and 5 raw zeroed emg graphs. xaxis-msecs
    figure(i/2)
    subplot (6,1,1);plot(forceemg(:,2))
    xlabel('time (msecs)');ylabel('mV');
    title([EMG of mc',int2str(i),' glut max']);
    subplot (6,1,2);plot(forceemg(:,3))
    xlabel('time (msecs)');ylabel('mV');
    title([EMG of mc',int2str(i),' glut med']);
    subplot (6,1,3);plot(forceemg(:,4))
    xlabel('time (msecs)');ylabel('mV');
    title([EMG of mc',int2str(i),' rect fem']);
    subplot (6,1,4);plot(forceemg(:,5))
    xlabel('time (msecs)');ylabel('mV');
    title([EMG of mc',int2str(i),' add mag']);
    subplot (6,1,5);plot(forceemg(:,6))
    xlabel('time (msecs)');ylabel('mV');
    title([EMG of mc',int2str(i),' bic fem']);
    subplot (6,1,6);plot(forceemg(:,1))
    xlabel('time from switch (msecs)');ylabel('force(N)');
    title([Force walkway of mc',int2str(i)]);
end
Appendix 5. Matlab linear envelope and normalisation algorithm

% This program loads a number of consecutive dmrawzeroemg files and files
% containing heel strike/toe off times (ms).
% The data is then divided into heel strike and toe off. Maximum 3 stance
% and 2 swings (prosthetic side)
% The MAV data for stance and swing is spined
% windows 25,50,100,200,300 msec
% Individual MAV plotted

ns=input('enter first walk number to be analysed - ')
ne=input('enter last walk number to be analysed - ')
s=ne-ns+1
load dm30_40st_sw
z=find(isnan(Sheet1));
Sheet1(z)=zeros(size(z));

% Create cell to store data for stance and swing stft for different walk
% cycles for gmx. Cell(walk, st/swing, 25/50/100/200/300/unfiltered window)
dmmav=cell(s,5,6);

% load raw zeroed force & emg files for dm
for i=ns:ne;
a=i-ns
a=a+1
ffemgname=sprintf('dm%drawzeroforceemg',i);
load (ffemgname)

len1=length(forceemg);

% Get full wave rectified value.
absforceemg=abs(forceemg);

% normalise data according to Davis and Vaughan
% Apply different length moving average filters
dmMAV25=filtfilt(ones(1,25),25,absforceemg(:,3:7));
dmMAV50=filtfilt(ones(1,50),50,absforceemg(:,3:7));
dmMAV100=filtfilt(ones(1,100),100,absforceemg(:,3:7));
dmMAV200=filtfilt(ones(1,200),200,absforceemg(:,3:7));
dmMAV300=filtfilt(ones(1,300),300,absforceemg(:,3:7));

% Get stance hs and toeoff
phsl=round(Sheet1((i-30+1),1));
ptol=round(Sheet1((i-30+1),4));
phs2=round(Sheet1((i-30+1),5));
ptol=round(Sheet1((i-30+1),8));
phs3=round(Sheet1((i-30+1),9));
ptol=round(Sheet1((i-30+1),12));

if phs1+pto1==abs(phs1-pto1);
st1=0;
else st1=pto1-phs1+1;
end

if pto1+phs2==abs(pto1-phs2);
s2=0;
else sw1=phs2-pto1+1;
end

if pto2+phs3==abs(pto2-phs3);
st2=0;
else sw2=phs3-pto2+1;
end
if phs3+pto3==abs(phs3-pto3);
st3=0;
else st3=pto3-phs3+1;
end

% Algorithm to calculate splines for MAV stance and swing data. Use
% piecewise cubic hermite polynomial.
if stl==0;
  pchMAV25=0;pchMAV50=0;pchMAV100=0;pchMAV200=0;pchMAV300=0;pchabs=0;
else
  Perc=((1:stl)/stl)*30)
  for tt=1:5
    if tt==1
      name =‘glut max’
    elseif tt==2
      name =‘glut med’
    elseif tt==3
      name =‘rect fem’
    elseif tt==4
      name =‘add mag’
    elseif tt==5
      name =‘bic fem’
    end
    for n=1:30
      pchMAV25(tt,n)=pchip((Perc),dmMAV25(phsl:pto1,tt),n);
      pchMAV50(tt,n)=pchip((Perc),dmMAV50(phs1:pto1,tt),n);
      pchMAV100(tt,n)=pchip((Perc),dmMAV100(phs1:pto1,tt),n);
      pchMAV200(tt,n)=pchip((Perc),dmMAV200(phs1:pto1,tt),n);
      pchMAV300(tt,n)=pchip((Perc),dmMAV300(phs1:pto1,tt),n);
      pchabs(tt,n)=pchip((Perc),absforceemg(phs1:pto1,tt+2),n)
    end
    MAX25(tt)=max(pchMAV25(tt,:));
    MIN25(tt)=min(pchMAV25(tt,:));
    A25(tt)=MAX25(tt)-MIN25(tt);
    MAX50(tt)=max(pchMAV50(tt,:));
    MIN50(tt)=min(pchMAV50(tt,:));
    A50(tt)=MAX50(tt)-MIN50(tt);
    MAX100(tt)=max(pchMAV100(tt,:));
    MIN100(tt)=min(pchMAV100(tt,:));
    A100(tt)=MAX100(tt)-MIN100(tt);
    MAX200(tt)=max(pchMAV200(tt,:));
    MIN200(tt)=min(pchMAV200(tt,:));
    A200(tt)=MAX200(tt)-MIN200(tt);
    MAX300(tt)=max(pchMAV300(tt,:));
    MIN300(tt)=min(pchMAV300(tt,:));
    A300(tt)=MAX300(tt)-MIN300(tt);
    MAXabs(tt)=max(pchabs(tt,:));
    MINabs(tt)=min(pchabs(tt,:));
    Aabs(tt)=MAXabs(tt)-MINabs(tt);
  end
  for n=1:30
    pchMAV25(tt,n)=100*((pchMAV25(tt,n)-MIN25(tt))/A25(tt));
    pchMAV50(tt,n)=100*((pchMAV50(tt,n)-MIN50(tt))/A50(tt));
    pchMAV100(tt,n)=100*((pchMAV100(tt,n)-MIN100(tt))/A100(tt));
    pchMAV200(tt,n)=100*((pchMAV200(tt,n)-MIN200(tt))/A200(tt));
    pchMAV300(tt,n)=100*((pchMAV300(tt,n)-MIN300(tt))/A300(tt));
    pchabs(tt,n)=100*((pchabs(tt,n)-MINabs(tt))/Aabs(tt));
  end
  figure(tt+a*25)
end
Appendix 5. Matlab linear envelope and normalisation algorithm

n=(1:30);plot(n,pchabs(tt,:),n,pchMAV25(tt,:),n,pchMAV50(tt,:),n,pchMAV100(tt,:),n,pchMAV200(tt,:),n,pchMAV300(tt,:));
legend('unfiltered','25ms','50ms','100ms','200ms','300ms')
xlabel('% of stance cycle')
ylabel('Volts')
title(['Stance 1-dm.Walk',num2str(i),'Moving average filter of different lengths for ',name])
dmMAV {ss, 1,1 }=pchMAV25 ;dmMAV {ss, 1,2 }=pchMAV50;dmMAV {ss, 1,3 }=pchMAV100;dmMAV {ss, 1,4 }=pchMAV200;dmMAV {ss, 1,5 }=pchMAV300;dmMAV {ss, 1,6 }=pchabs;
end
end
if swl==0
pchMAV25=0;pchMAV50=0;pchMAV100=0;pchMAV200=0;pchMAV300=0;pchabs=0;
else swl=phs2-pto1+1;
pchMAV25=0;pchMAV50=0;pchMAV100=0;pchMAV200=0;pchMAV300=0;pchabs=0;

Perc=((l:swl)/swl)'*20;
for tt=l:5
if tt==l
name = 'glut max'
end
if tt==2
name = 'glut med'
end
if tt==3
name = 'rect fem'
end
if tt==4
name = 'add mag'
end
if tt==5
name = 'bic fem'
end
for n=1:20
pchMAV25(tt,n)=pchip((Perc),dmMAV25(pto1:phs2,tt),n);
pchMAV50(tt,n)=pchip((Perc),dmMAV50(pto1:phs2,tt),n);
pchMAV100(tt,n)=pchip((Perc),dmMAV100(pto1:phs2,tt),n);
pchMAV200(tt,n)=pchip((Perc),dmMAV200(pto1:phs2,tt),n);
pchMAV300(tt,n)=pchip((Perc),dmMAV300(pto1:phs2,tt),n);
pchabs(tt,n)=pchip((Perc),absforceemg(pto1:phs2,tt+2),n)
end
MAX25(tt)=max(pchMAV25(tt,:));
MIN25(tt)=min(pchMAV25(tt,:));
A25(tt)=MAX25(tt)-MIN25(tt);
MAX50(tt)=max(pchMAV50(tt,:));
MIN50(tt)=min(pchMAV50(tt,:));
A50(tt)=MAX50(tt)-MIN50(tt);
MAX100(tt)=max(pchMAV100(tt,:));
MIN100(tt)=min(pchMAV100(tt,:));
A100(tt)=MAX100(tt)-MIN100(tt);
MAX200(tt)=max(pchMAV200(tt,:));
MIN200(tt)=min(pchMAV200(tt,:));
A200(tt)=MAX200(tt)-MIN200(tt);
MAX300(tt)=max(pchMAV300(tt,:));
MIN300(tt)=min(pchMAV300(tt,:));
MAXabs(tt)=max(pchabs(tt,:));
MINabs(tt)=min(pchabs(tt,:));
Aabs(tt)=MAXabs(tt)-MINabs(tt);
for n=1:20
    pchMAV25(tt,n)=100*((pchMAV25(tt,n)-MIN25(tt))/A25(tt));
    pchMAV50(tt,n)=100*((pchMAV50(tt,n)-MIN50(tt))/A50(tt));
    pchMAV100(tt,n)=100*((pchMAV100(tt,n)-MIN100(tt))/A100(tt));
    pchMAV200(tt,n)=100*((pchMAV200(tt,n)-MIN200(tt))/A200(tt));
    pchMAV300(tt,n)=100*((pchMAV300(tt,n)-MIN300(tt))/A300(tt));
    pchabs(tt,n)=100*((pchabs(tt,n)-MINabs(tt))/Aabs(tt));
end
figure(tt+a*25+5)
n=(1:20);plot(n,pchabs(tt,:),n,pchMAV25(tt,:),n,pchMAV50(tt,:),n,pchMAV100(tt,:),n,pchMAV200(tt,:),n,pchMAV300(tt,:));
    legend('unfiltered','25ms','50ms','100ms','200ms','300ms')
    xlabel('% of stance cycle')
    ylabel('Volts')
    title(['Swing 1-dm.Walk ',num2str(i),Moving average filter of different lengths for ,name])
end
for n=1:30
    pchMAV25(tt,n)=pchip((Perc),dmMAV25(phs2:pto2,tt),n);
    pchMAV50(tt,n)=pchip((Perc),dmMAV50(phs2:pto2,tt),n);
    pchMAV100(tt,n)=pchip((Perc),dmMAV100(phs2:pto2,tt),n);
    pchMAV200(tt,n)=pchip((Perc),dmMAV200(phs2:pto2,tt),n);
    pchMAV300(tt,n)=pchip((Perc),dmMAV300(phs2:pto2,tt),n);
    pchabs(tt,n)=pchip((Perc),absforceemg(phs2:pto2,tt+2),n)
end
MAX25(tt)=max(pchMAV25(tt,:));
MIN25(tt)=min(pchMAV25(tt,:));
A25(tt)=MAX25(tt)-MIN25(tt);
MAX50(tt)=max(pchMAV50(tt,:));
MIN50(tt)=min(pchMAV50(tt,:));
A50(tt)=MAX50(tt)-MIN50(tt);
MAX100(tt)=max(pchMAV100(tt,:));
MIN100(tt)=min(pchMAV100(tt,:));
A100(tt)=MAX100(tt)-MIN100(tt);
Appendix 5. Matlab linear envelope and normalisation algorithm

MAX200(tt)=max(pchMAV200(tt,:));
MIN200(tt)=min(pchMAV200(tt,:));
A200(tt)=MAX200(tt)-MIN200(tt);
MAX300(tt)=max(pchMAV300(tt,:));
MIN300(tt)=min(pchMAV300(tt,:));
A300(tt)=MAX300(tt)-MIN300(tt);
MAXabs(tt)=max(pchabs(tt,:));
MINabs(tt)=min(pchabs(tt,:));
Aabs(tt)=MAXabs(tt)-MINabs(tt);

for n=1:30
  pchMAV25(tt,n)=100*((pchMAV25(tt,n)-MIN25(tt))/A25(tt));
  pchMAV50(tt,n)=100*((pchMAV50(tt,n)-MIN50(tt))/A50(tt));
  pchMAV100(tt,n)=100*((pchMAV100(tt,n)-MIN100(tt))/A100(tt));
  pchMAV200(tt,n)=100*((pchMAV200(tt,n)-MIN200(tt))/A200(tt));
  pchMAV300(tt,n)=100*((pchMAV300(tt,n)-MIN300(tt))/A300(tt));
  pchabs(tt,n)=100*((pchabs(tt,n)-MINabs(tt))/Aabs(tt));
end

end

if sw2==0
  pchMAV25=0;pchMAV50=0;pchMAV100=0;pchMAV200=0;pchMAV300=0;pchabs=0;
else sw2=phs3-pto2+1;pchMAV25=0;pchMAV50=0;pchMAV100=0;pchMAV200=0;pchMAV300=0;pchabs=0;
  Perc=((1:sw2)/sw2)*20;
  for tt=1:5
    if tt==1
      name = 'glut max'
    end
    if tt==2
      name = 'glut med'
    end
    if tt==3
      name = 'rect fem'
    end
    if tt==4
      name = 'add mag'
    end
    if tt==5
      name = 'bic fem'
    end
    for n=1:20
      pchMAV25(tt,n)=pchip((Perc),dmMAV25(pto2:phs3,tt),n);
      pchMAV50(tt,n)=pchip((Perc),dmMAV50(pto2:phs3,tt),n);
      pchMAV100(tt,n)=pchip((Perc),dmMAV100(pto2:phs3,tt),n);
      pchMAV200(tt,n)=pchip((Perc),dmMAV200(pto2:phs3,tt),n);
      pchMAV300(tt,n)=pchip((Perc),dmMAV300(pto2:phs3,tt),n);
      pchabs(tt,n)=pchip((Perc),absforceemg(pto2:phs3,tt+2),n)
    end
end
**Appendix 5. Matlab linear envelope and normalisation algorithm**

\[
\begin{align*}
\text{MAX25}(tt) &= \max(pch\text{MAV}25(tt,:)) \\
\text{MIN25}(tt) &= \min(pch\text{MAV}25(tt,:)) \\
A25(tt) &= \text{MAX25}(tt) - \text{MIN25}(tt) \\
\text{MAX50}(tt) &= \max(pch\text{MAV}50(tt,:)) \\
\text{MIN50}(tt) &= \min(pch\text{MAV}50(tt,:)) \\
A50(tt) &= \text{MAX50}(tt) - \text{MIN50}(tt) \\
\text{MAX100}(tt) &= \max(pch\text{MAV}100(tt,:)) \\
\text{MIN100}(tt) &= \min(pch\text{MAV}100(tt,:)) \\
A100(tt) &= \text{MAX100}(tt) - \text{MIN100}(tt) \\
\text{MAX200}(tt) &= \max(pch\text{MAV}200(tt,:)) \\
\text{MIN200}(tt) &= \min(pch\text{MAV}200(tt,:)) \\
A200(tt) &= \text{MAX200}(tt) - \text{MIN200}(tt) \\
\text{MAX300}(tt) &= \max(pch\text{MAV}300(tt,:)) \\
\text{MIN300}(tt) &= \min(pch\text{MAV}300(tt,:)) \\
A300(tt) &= \text{MAX300}(tt) - \text{MIN300}(tt) \\
\text{MAXabs}(tt) &= \max(pch\text{abs}(tt,:)) \\
\text{MINabs}(tt) &= \min(pch\text{abs}(tt,:)) \\
Aabs(tt) &= \text{MAXabs}(tt) - \text{MINabs}(tt) \\
\end{align*}
\]

\[
\begin{align*}
\text{for } n=1:20 \\
pch\text{MAV}25(tt,n) &= 100 \times \frac{(pch\text{MAV}25(tt,n) - \text{MIN25}(tt))}{A25(tt)} \\
pch\text{MAV}50(tt,n) &= 100 \times \frac{(pch\text{MAV}50(tt,n) - \text{MIN50}(tt))}{A50(tt)} \\
pch\text{MAV}100(tt,n) &= 100 \times \frac{(pch\text{MAV}100(tt,n) - \text{MIN100}(tt))}{A100(tt)} \\
pch\text{MAV}200(tt,n) &= 100 \times \frac{(pch\text{MAV}200(tt,n) - \text{MIN200}(tt))}{A200(tt)} \\
pch\text{MAV}300(tt,n) &= 100 \times \frac{(pch\text{MAV}300(tt,n) - \text{MIN300}(tt))}{A300(tt)} \\
pch\text{abs}(tt,n) &= 100 \times \frac{(pch\text{abs}(tt,n) - \text{MINabs}(tt))}{Aabs(tt)} \\
\end{align*}
\]

\[
\begin{align*}
n &= (1:20); \text{plot}(n,pch\text{abs}(tt,:),n,pch\text{MAV}25(tt,:),n,pch\text{MAV}50(tt,:),n,pch\text{MAV}100(tt,:),n,pch\text{MAV}200(tt,:),n,pch\text{MAV}300(tt,:)) \\
\text{legend}('unfiltered','25ms','50ms','100ms','200ms','300ms') \\
\text{xlabel}('\% of stance cycle') \\
\text{ylabel('Volts')} \\
\text{title}(['Swing 2-dm. Walk', num2str(i), 'Moving average filter of different lengths for ', name]) \\
\end{align*}
\]

\[
\begin{align*}
\text{dmMAV}[ss,4,1] &= pch\text{MAV}25; \text{dmMAV}[ss,4,2] = pch\text{MAV}50; \text{dmMAV}[ss,4,3] = pch\text{MAV}100; \text{dmMAV}[ss,4,4] = pch\text{MAV}200; \text{dmMAV}[ss,4,5] = pch\text{MAV}300; \text{dmMAV}[ss,4,6] = pch\text{abs}; \\
\end{align*}
\]

\[
\begin{align*}
\text{end} \\
\text{end} \\
\text{if } st3==0 \\
\text{pchMAV25}=0; \text{pchMAV50}=0; \text{pchMAV100}=0; \text{pchMAV200}=0; \text{pchMAV300}=0; \text{pchabs}=0; \\
\text{else } st3=pto3- \\
\text{phts3+1}; \text{pchMAV25}=0; \text{pchMAV50}=0; \text{pchMAV100}=0; \text{pchMAV200}=0; \text{pchMAV300}=0; \text{pchabs}=0; \\
\text{Perc} =((1:st3)/st3) * 30; \\
\text{for } tt=1:5 \\
\text{if } tt==1 \\
\text{name} = 'glut max' \\
\text{end} \\
\text{if } tt==2 \\
\text{name} = 'glut med' \\
\text{end} \\
\text{if } tt==3 \\
\text{name} = 'rect fem' \\
\text{end} \\
\text{if } tt==4 \\
\text{name} = 'add mag' \\
\text{end} \\
\text{if } tt==5 \\
\text{name} = 'bic fem' \\
\text{end} \\
\end{align*}
\]
Appendix 5. Matlab linear envelope and normalisation algorithm

for n=1:30
    pchMAV25(tt,n)=pchip((Perc),dmMAV25(phs3:pto3,tt),n)
    pchMAV50(tt,n)=pchip((Perc),dmMAV50(phs3:pto3,tt),n)
    pchMAV100(tt,n)=pchip((Perc),dmMAV100(phs3:pto3,tt),n);
    pchMAV200(tt,n)=pchip((Perc),dmMAV200(phs3:pto3,tt),n);
    pchMAV300(tt,n)=pchip((Perc),dmMAV300(phs3:pto3,tt),n);
    pchabs(tt,n)=pchip((Perc),absforceemg(phs3:pto3,tt+2),n);
end

MAX25(tt)=max(pchMAV25(tt,:));
MIN25(tt)=min(pchMAV25(tt,:));
A25(tt)=MAX25(tt)-MIN25(tt);
MAX50(tt)=max(pchMAV50(tt,:));
MIN50(tt)=min(pchMAV50(tt,:));
A50(tt)=MAX50(tt)-MIN50(tt);
MAX100(tt)=max(pchMAV100(tt,:));
MIN100(tt)=min(pchMAV100(tt,:));
A100(tt)=MAX100(tt)-MIN100(tt);
MAX200(tt)=max(pchMAV200(tt,:));
MIN200(tt)=min(pchMAV200(tt,:));
A200(tt)=MAX200(tt)-MIN200(tt);
MAX300(tt)=max(pchMAV300(tt,:));
MIN300(tt)=min(pchMAV300(tt,:));
A300(tt)=MAX300(tt)-MIN300(tt);
MAXabs(tt)=max(pchabs(tt,:));
MINabs(tt)=min(pchabs(tt,:));
Aabs(tt)=MAXabs(tt)-MINabs(tt);

for n=1:30
    pchMAV25(tt,n)=100*((pchMAV25(tt,n)-MIN25(tt))/A25(tt)) ;
    pchMAV50(tt,n)=100*((pchMAV50(tt,n)-MIN50(tt))/A50(tt));
    pchMAV100(tt,n)=100*((pchMAV100(tt,n)-MIN100(tt))/A100(tt));
    pchMAV200(tt,n)=100*((pchMAV200(tt,n)-MIN200(tt))/A200(tt));
    pchMAV300(tt,n)=100*((pchMAV300(tt,n)-MIN300(tt))/A300(tt));
    pchabs(tt,n)=100*((pchabs(tt,n)-MINabs(tt))/Aabs(tt));
end

figure(tt+a*25+20)

n=(1:30);plot(n,pchabs(tt,:),n,pchMAV25(tt,:),n,pchMAV50(tt,:),n,pchMAV 100(tt,:),n,pchMAV200(tt,:),n,pchMAV300(tt,:));
legend('unfiltered','25ms','50ms','100ms','200ms','300ms')
xlabel('% of stance cycle')
ylabel('Volts')
title(['Stance 3-dm.Walk',num2str(i),Moving average filter of different lengths for muscle ' ,name])

end

save dmMAV dmMAV
Appendix 6. Matlab Correlation algorithm

load ('dmMAV')
%Create cell dmMAVstats(muscle,window,mean/std/var/cov/corr/p)
dmMAVstats=cell(5,6,6)
% c is the number of filters
for c=1:6
%Get 5x100 matrices for all stances for each filter
SIGTOT1a=cell2mat(dmMAV(1,1,c));SIGTOT1b=cell2mat(dmMAV(1,3,c));
SIGTOT2a=cell2mat(dmMAV(2,1,c));SIGTOT2b=cell2mat(dmMAV(2,3,c));
SIGTOT3a=cell2mat(dmMAV(3,1,c));SIGTOT3b=cell2mat(dmMAV(3,3,c));SIGTOT3c=cell2mat(dmMAV(3,5,c));
SIGTOT4b=cell2mat(dmMAV(4,3,c));SIGTOT4c=cell2mat(dmMAV(4,5,c));
SIGTOT5a=cell2mat(dmMAV(5,1,c));SIGTOT5b=cell2mat(dmMAV(5,3,c));
SIGTOT6a=cell2mat(dmMAV(6,1,c));SIGTOT6b=cell2mat(dmMAV(6,3,c));SIGTOT6c=cell2mat(dmMAV(6,5,c));
SIGTOT7a=cell2mat(dmMAV(7,1,c));SIGTOT7b=cell2mat(dmMAV(7,3,c));
SIGTOT8a=cell2mat(dmMAV(8,1,c));SIGTOT8b=cell2mat(dmMAV(8,3,c));SIGTOT8c=cell2mat(dmMAV(8,5,c));
SIGTOT9a=cell2mat(dmMAV(9,1,c));SIGTOT9b=cell2mat(dmMAV(9,3,c));
SIGTOT10a=cell2mat(dmMAV(10,1,c));
for d=1:5
 %for each muscle and each filter concatenate an 18x100 matrix
 SIG = [SIGTOT1a(d,:); SIGTOT1b(d,:);SIGTOT2a(d,:); SIGTOT2b(d,:);SIGTOT3a(d,:);
 SIGTOT3b(d,:);SIGTOT3c(d,:);SIGTOT4b(d,:);SIGTOT4c(d,:);SIGTOT5a(d,:);
 SIGTOT5b(d,:);SIGTOT6b(d,:);SIGTOT6c(d,:);SIGTOT7a(d,:);SIGTOT7b(d,:);
 SIGTOT8a(d,:);SIGTOT8b(d,:);SIGTOT9a(d,:);SIGTOT9b(d,:);SIGTOT10a(d,:)];
 dmMAV mean=mean(SIG)
 dmMAV stats{d,c,1}=mean(SIG)
 dmMAV stats{d,c,2}=std(SIG)
 dmMAV stats{d,c,3}=var(SIG)
 dmMAV stats{d,c,4}=cov(SIG')
 [r,p]=corrcoef(SIG)
 dmMAV stats{d,c,5}=r
 dmMAV stats{d,c,6}=p
end
end
for d=1:5
 figure(250+d)
 FIGDAT1=cell2mat(dmMAV stats(d,1,1));FIGDAT2=cell2mat(dmMAV stats(d,2,1));FIGDAT3=cell2mat(dmMAV stats(d,3,1));
 FIGDAT4=cell2mat(dmMAV stats(d,4,1));FIGDAT5=cell2mat(dmMAV stats(d,5,1));FIGDAT6=cell2mat(dmMAV stats(d,6,1));
 n=(1:100);plot(n,FIGDAT1,n,FIGDAT2,n,FIGDAT3,n,FIGDAT4,n,FIGDAT5,n,FIGDAT6)
 if d==1
 name='glut max'
 elseif d==2
 name='glut med'
 elseif d==3
 name='rect fem'
 elseif d==4
 name='add mag'
 elseif d==5
 name='bic fem'
 end
 legend('25ms','50ms','100ms','200ms','300ms','unfiltered')
 xlabel('% of stance cycle')
 ylabel('Volts')
 title(['Stance dm.Mean moving average filter of different lengths for ',name])
end
save dmMAVstats dmMAVstats
Appendix 7.
Raw sEMG for isometric contraction for datasets A1 and B2.

Figure A7a  sEMG of gluteus maximus during resisted hip extension for Dataset A1.

Figure A7b  sEMG of gluteus medius during resisted hip abduction for Dataset A1.

Figure A7c  sEMG of rectus femoris during resisted hip flexion for Dataset A1.

Figure A7d  sEMG of adductor magnus during resisted hip adduction for Dataset A1.

Figure A7e  sEMG of gluteus maximus during resisted hip extension for Dataset B2.

Figure A7f  sEMG of gluteus medius during resisted hip abduction for Dataset B2.

Figure A7g  sEMG of rectus femoris during resisted hip flexion for Dataset B2.

Figure A7h  sEMG of adductor magnus during resisted hip adduction for Dataset B2.
## Appendix 8. Visual3D Kinematic reports

### Dataset A1

**Dataset A1 18.11.04 EMG linked 10x normal walking**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value</th>
<th>StdDev</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>1.34 m/s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride</td>
<td>Wid(18) 0.222±0.015m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cycle Time</td>
<td>Computed: 1.12 s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed</td>
<td>0.79 Statures/s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride</td>
<td>Len(18) 1.500±0.027m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cycle Time</td>
<td>Actual (18) 1.12±0.02 s</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Left:
- **Step Length**: 0.793±0.024 m (14)
- **Step Time**: 0.55±0.03 s (14)
- **Stance Time**: 0.65±0.04 s (9)
- **Swing Time**: 0.47±0.04 s (9)

#### Right:
- **Step Length**: 0.705±0.030 m (15)
- **Step Time**: 0.57±0.02 s (15)
- **Stance Time**: 0.64±0.05 s (9)
- **Swing Time**: 0.47±0.04 s (9)

#### Double Limb Support Time (39)
- Initial: 0.18±0.07 s
- Terminal: 0.10±0.04 s

### Dataset A1 Sagittal plane

[Graphs showing joint angles over time for the right and left legs in the sagittal plane]
Appendix 8: Visual3D Kinematic reports

Dataset A1

Dataset A1 Coronal plane

Dataset A1 transverse plane
### Dataset A2

**Dataset A2 10.11.05 EMG linked 10x normal walking**

<table>
<thead>
<tr>
<th>Speed</th>
<th>1.20 m/s</th>
<th>0.66 Statures/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stride</td>
<td>Wid(13) 0.239±0.013m</td>
<td>Len(15) 1.38±0.032m</td>
</tr>
<tr>
<td>Cycle Time</td>
<td>Computed: 1.16 s</td>
<td>Actual (15) 1.16±0.02 s</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Measure±StdDev (Count)</th>
<th>Measure±StdDev (Count)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left: 0.72±0.024 m (8)</td>
<td>Step Length</td>
</tr>
<tr>
<td>Right: 0.66±0.022 m (11)</td>
<td></td>
</tr>
<tr>
<td>Left: 0.65±0.02 s (8)</td>
<td>Step Time</td>
</tr>
<tr>
<td>Right: 0.52±0.02 s (11)</td>
<td></td>
</tr>
<tr>
<td>Left: 0.62±0.02 s (9)</td>
<td>Stance Time</td>
</tr>
<tr>
<td>Right: 0.73±0.02 s (6)</td>
<td></td>
</tr>
<tr>
<td>Left: 0.53±0.01 s (9)</td>
<td>Swing Time</td>
</tr>
<tr>
<td>Right: 0.43±0.02 s (6)</td>
<td></td>
</tr>
</tbody>
</table>

Double Limb Support Time (24) 0.20±0.04 s
Right Initial Double Limb Support Time (12) 0.11±0.02 s
Right Terminal Double Limb Support Time (12) 0.08±0.02 s

### Dataset A2 Sagittal plane

![Graphs showing ankle, knee, and hip movements in the sagittal plane.](image-url)
Appendix 8. Visual3D Kinematic reports

Dataset A2

Dataset A2 Coronal plane

Dataset A2 transverse plane

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Appendix 8. Visual3D Kinematic reports

Dataset A3

Dataset A3 09.12.04 EMG linked 10x normal walking

- Speed: 1.21 m/s
- Stride Width (7): 0.291 ± 0.010 m
- Cycle Time: Computed: 1.21 s
- Measure ± StdDev (Count)
  - Left: 0.722 ± 0.060 m (5)
  - Step Length: Right: 0.699 ± 0.027 m (7)
  - Left: 0.54 ± 0.04 s (5)
  - Step Time: Right: 0.63 ± 0.04 s (11)
  - Left: 0.69 ± 0.03 s (3)
  - Stance Time: Right: 0.69 ± 0.02 s (4)
  - Left: 0.48 ± 0.02 s (3)
  - Swing Time: Right: 0.50 ± 0.04 s (4)
  - Double Limb Support Time (28): 0.23 ± 0.05 s
  - Right Initial Double Limb Support Time (14): 0.09 ± 0.02 s
  - Right Terminal Double Limb Support Time (12): 0.14 ± 0.03 s

Dataset A3 Sagittal plane

- Right Ankle (+ve df)
- Right Knee (+ve flex)
- Right Hip (+ve extension)
- Left Ankle (+ve df)
- Left Knee (+ve flex)
- Left Hip (+ve extension)
Appendix 8. Visual3D Kinematic reports

Dataset A3

Dataset A3 Coronal plane

Dataset A3 transverse plane
# Dataset A4

## Dataset A4 02.12.04 EMG linked 10x normal walking

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Value</th>
<th>Standard Deviation</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>1.25 m/s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride</td>
<td>Wid(22) 0.223±0.009m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cycle Time</td>
<td>Computed: 1.08 s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed</td>
<td>0.73 Statures/s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride</td>
<td>Len(23) 1.343±0.047m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cycle Time</td>
<td>Actual (23) 1.08±0.03 s</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Left:**
- Step Length: 0.678±0.040 m (14)
- Step Time: 0.53±0.03 s (14)
- Stance Time: 0.64±0.03 s (14)
- Swing Time: 0.43±0.03 s (14)
- Double Limb Support Time: 0.21±0.04 s (42)
- Right Initial Double Limb Support Time: 0.09±0.02 s (19)
- Right Terminal Double Limb Support Time: 0.12±0.02 s (23)

**Right:**
- Step Length: 0.666±0.024 m (18)
- Step Time: 0.56±0.02 s (18)
- Stance Time: 0.65±0.03 s (9)
- Swing Time: 0.44±0.01 s (9)

### Sagittal plane

- **R ANKLE (+ve df):**
  - Degrees: -67.1
  - Time (s): 0.0 to 100.0

- **R KNEE (+ve flex):**
  - Degrees: 59.8
  - Time (s): 0.0 to 100.0

- **R HIP (+ve extension):**
  - Degrees: 34.9
  - Time (s): 0.0 to 100.0

- **L ANKLE (+ve df):**
  - Degrees: -45.0
  - Time (s): 0.0 to 100.0

- **L KNEE (+ve flex):**
  - Degrees: 60.0
  - Time (s): 0.0 to 100.0

- **L HIP (+ve extension):**
  - Degrees: 20.0
  - Time (s): 0.0 to 100.0
Appendix 8. Visual3D Kinematic reports

Dataset A4

Dataset A4 Coronal plane

Dataset A4 transverse plane

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Appendix 8: Visual3D Kinematic reports

Dataset A5

Dataset A5 16.11.04 EMG linked 10x normal walking

<table>
<thead>
<tr>
<th>Measure</th>
<th>Standard Deviation</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>1.06 m/s</td>
<td>0.65 Statures/s</td>
</tr>
<tr>
<td>Stride</td>
<td>Wid(16) 0.213±0.016m</td>
<td>Len(16) 1.249±0.033m</td>
</tr>
<tr>
<td>Cycle Time</td>
<td>Computed: 1.16 s</td>
<td>Actual (16) 1.18±0.04 s</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Measure</th>
<th>Standard Deviation</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left: Step Length</td>
<td>0.595±0.042 m</td>
<td>(14)</td>
</tr>
<tr>
<td>Right: Step Length</td>
<td>0.649±0.035 m</td>
<td>(12)</td>
</tr>
<tr>
<td>Left: Step Time</td>
<td>0.60±0.03 s</td>
<td>(14)</td>
</tr>
<tr>
<td>Right: Step Time</td>
<td>0.57±0.03 s</td>
<td>(12)</td>
</tr>
<tr>
<td>Left: Stance Time</td>
<td>0.75±0.04 s</td>
<td>(6)</td>
</tr>
<tr>
<td>Right: Stance Time</td>
<td>0.72±0.02 s</td>
<td>(10)</td>
</tr>
<tr>
<td>Left: Swing Time</td>
<td>0.42±0.02 s</td>
<td>(6)</td>
</tr>
<tr>
<td>Right: Swing Time</td>
<td>0.45±0.03 s</td>
<td>(10)</td>
</tr>
</tbody>
</table>

Double Limb Support Time (34) | 0.29±0.04 s
Right Initial Double Limb Support Time (18) | 0.17±0.02 s
Right Terminal Double Limb Support Time (16) | 0.12±0.02 s

Dataset A5 Sagittal plane

<table>
<thead>
<tr>
<th>Measure</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right Ankle (+ve df)</td>
<td>-55.2</td>
</tr>
<tr>
<td>Left Ankle (+ve df)</td>
<td>-56.8</td>
</tr>
<tr>
<td>Right Knee (+ve flex)</td>
<td>59.8</td>
</tr>
<tr>
<td>Left Knee (+ve flex)</td>
<td>39.6</td>
</tr>
<tr>
<td>Right Hip (+ve flex)</td>
<td>34.9</td>
</tr>
<tr>
<td>Left Hip (+ve flex)</td>
<td>20.0</td>
</tr>
</tbody>
</table>
Dataset A5

Dataset A5 Coronal plane

Dataset A5 transverse plane

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Appendix 9. Scatterplots of PCs for group A subjects

Appendix 9 — Scatterplots of PCs for group A subjects
Appendix 9 - Scatterplots of PCs for group A subjects

Scatter plot for Dataset A4 TOTAL MAV data

Scatter plot for Dataset A4rep TOTAL MAV data

Scatter plot for Dataset A5 TOTAL MAV data

Scatter plot for Dataset A4 TOTAL MAV data

Scatter plot for Dataset A4rep TOTAL MAV data

Scatter plot for Dataset A5 TOTAL MAV data
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