EMG Control of Prosthetic Ankle Plantar Flexion

by

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Abstract

Similar to biological human ankle, today’s commercially available powered ankle-foot prostheses can vary impedance and deliver net positive ankle work. These commercially available prostheses are intrinsically controlled. Users cannot intuitively change ankle controller’s behavior to perform movements that are not part of the repetitive walking gait cycle. For example, when transition from level ground walking to descending stairs, user cannot intuitively initiate or control the amount of ankle angle deflexion for a more normative stair descent gait pattern.

This paper presents a hybrid controller that adds myoelectric control functionality to an existing intrinsic controller. The system employs input from both mechanical sensors on the ankle as well as myoelectric signals from gastrocnemius muscle of the user. This control scheme lets the user to modulate the gain of command ankle torque upon push off during level ground walking and stair ascent. It also allows the user to interrupt level ground walking control cycle and initiate ankle plantar flexion during stair descent.

As a preliminary study, ankle characteristics such as ankle angle and torque were measured and compared to biological ankle characteristics. Results show that the proposed hybrid controller can maintain existing controller’s biomimetic characteristics. In addition, it can also recognize to a qualitative extent the intended command torque for ankle push off and user’s desire to switch between control modalities for different terrains. The study shows that it is possible and desirable to use neural signals as control signals for prosthetic leg controllers.

Keyword: Myoelectric control, powered prosthesis, proportional torque control

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Chapter 1

Introduction

Today’s commercially available bionic lower-leg system, such as PowerFoot BiOM, iWalk®, can simulate normative gait movement using solely intrinsic sensors such as accelerometers, ankle angle encoders and force sensors. The intrinsic control scheme is completely autonomous. Users currently have limited control over ankle behavior. It would be ideal if the user can interrupt the autonomous control scheme and exert neural control of ankle behavior to achieve a more biomimetic and natural interaction between amputees and their bionic limbs.

Neural control using myoelectric signals have achieved much success with upper limb prosthesis over the past decade. Kuiken et al. showed that using targeted muscle reinnervation, they could obtain strong myoelectric signals for real-time control of multifunction artificial arms [13]. Myoelectric control has not achieved as much success with lower limb prostheses for a couple of reasons: a) powered, self contained ankle-foot prostheses have only became commercially available within the past year; b) myoelectric signals measured from lower limb muscles are non-stationary and more prone to motion artifact interference due to weight-bearing than upper limb muscle signals. Thus existing myoelectric control scheme for upper limb prostheses cannot be directly used for lower limb prostheses control.

This thesis is set out to explore how to integrate surface EMG control into existing intrinsic control system for lower limb prostheses such that users can have more control over ankle behavior while the system maintains its biomimetic characteristics.
1.1 Literature Survey

Though not as extensively explored as upper limb prostheses, some investigation had been done to explore the feasibility of myoelectric control for lower limb prostheses. Notably, Au et al. used myoelectric signal to switch between two different control modalities of an ankle-foot prosthesis [1, 3]. Specifically, their myoelectric controller enables an amputee to switch between level ground and stair descent mode by flexing residual limb muscles during swing phase. Hargrove et al. implemented a phase-dependent classifier that identifies different modalities based on myoelectric signals from residual limb muscles of two transfemoral amputees [7]. Both studies show that myoelectric signals could be used as command signal to switch between different modalities of an intrinsic controller for lower limb prostheses.

In addition to switch between control modalities, recent studies also investigated the feasibility of using lower limb muscle myoelectric signals to classify varying degrees of motion freedom using pattern recognition[8]. Hargrove et al. conducted a study with four transfemoral amputees who were instructed to attempt to control a virtual lower limb prosthesis by flexing their residual limb muscles. For each subject, surface EMG of 9 lower limb muscles were measured. Preliminary test results showed promising feasibility of using EMG to identify in real-time of 2 degrees of freedom movement and with less robust classification performance, of 4 degrees of freedom. They came to the conclusion that targeted muscle reinnervation may not be required to achieve non-weight-bearing control of sagittal plane knee and ankle movements.

To the best of author’s knowledge, there is no investigation done thus far that uses myoelectric signals to proportionally modulate the gain of command ankle torque during powered plantar flexion phase of a gait cycle. Though this concept had not been applied to a powered ankle-foot prosthesis, similar studies had been conducted with lower limb orthosis. Ferris et al. had built pneumatically-powered lower limb exoskeletons for studying human physiology and re-training motor deficiencies [5]. With proportional myoelectric control, they showed that it can reduce overall energy expenditure of healthy human subjects and modify muscle recruitment patterns of
patients with incomplete spinal cord injury. Their study suggests that proportional myoelectric control may have distinct advantage over other types of control for robotic exoskeletons in basic science and rehabilitation.

Note that prosthesis and orthosis are fundamentally different devices. The obvious difference being prosthesis serves to replace the missing limb while orthosis is meant for assisting dysfunctional but nonetheless physically intact limb. Thus findings done on orthosis using proportional EMG-torque control might not hold for prosthesis.

1.2 Thesis Objective

This thesis is a preliminary study on how to use myoelectric signals to proportionally modulate command torque gain on a powered ankle-foot prosthesis. The overall goal is to implement a hybrid controller that is a modification of an existing intrinsic controller, such that myoelectric signals from the gastrocnemius muscle of the powered prosthesis user can modulate the gain of ankle command torque. In addition, the proposed hybrid controller uses myoelectric signal to switch between level ground walking, stair ascent and stair descent modes in the intrinsic controller.

In order to test if this hybrid controller can maintain similar biomimetic characteristics as the original intrinsic controller, a set of parameters were measured on the prosthetic ankle using the two controllers and were then compared to an existing dataset measured on biological ankles. The parameters used for comparison are ankle angle, ankle torque, ankle peak power per percent gait cycle, ankle net work per percent gait cycle and percent time of gait cycle at which peak power occurs.

1.3 Chapter Summary

Chapter Two summarizes background concepts and facts that are pertinent to this thesis work. Topics covered are human walking gait patterns, physiological origin of myoelectric signals, and how they are related to muscle force generated.

Chapter Three explains design considerations of the hybrid controller, describes
its statemachine and the method used to process the myoelectric control signal, the
hardware used and the experiments conducted to obtain the parameters used for com-
paring powered ankle performance using intrinsic and hybrid controllers to biological
ankles.

Chapter Four presents results conducted for level ground walking across three
speeds, and stair ascent/descent at a single speed.

Chapter Six is discussion on the experimental results and suggestions for future
work to improvement and expand the project.
Chapter 2

Background

This chapter summarizes background concepts and facts pertaining this thesis. Specifically, it covers walking gait patterns, physiological origin of myoelectric signals, relation between myoelectric signals and muscle force generated, myoelectric signal profile of relevant muscles from non-amputees during level ground walking and how they change across speed.

2.1 Biomechanics of Human Walking

2.1.1 Level Ground Walking

Human walking is a periodic motion. A typical gait cycle for level ground walking is defined as heel strike of one foot till the next heel strike of the same foot. Conventional gait analysis normalizes time period per gait cycle to range from 0-100%, 0% being heel strike. A complete gait cycle consists of two phases: stance and swing. Stance phase begins at heel strike and terminates upon toe off. Swing phase is the remainder of the gait cycle. Each phase can be further divided for better characterization. This paper adapts the same convention as done by Au et al. [3].

Stance phase consists of three subphases: Controlled Plantar Flexion (CP), Controlled Dorsiflexion (CD), and Powered Plantar Flexion (PP). Swing phase is divided into early swing (ESW) state and terminal swing (TSW). Figure 2-1 depicts the afore-
mentioned breakdown of the gait cycle as well as suggested functions of each phase. Definition and detailed analysis on each stage of the gait is described in Au et al [3]. What is particularly pertinent to this thesis is that during PP, the ankle does not net positive work that is equal to or greater than the work absorbed during CP and CD.

![Figure 2-1: Level ground walking gait pattern](image)

2.1.2 Stair Ascent and Descent

Stair ascent and descent gait is typically defined as from toe strike of one foot till the next toe-strike of the same foot. Gates et al. [6] had studied and modeled biological ankle characteristics on walking up and down the stairs. Fig. 2-2, taken from Gates’ thesis, depicts detailed gait breakdown and suggested ankle function for stair ascent. Adapting similar convention as for level ground walking, stair ascent stance can be subdivided into Controlled Dorsiflexion 1 (CD1), Powered Plantarflexion 1 (PP1), Controlled Dorsiflexion 2 (CD2) and Powered Plantarflexion 2 (PP2). Gates’ breakdown for stair descent gait is depicted in Fig. 2-3. For stair descent stance phase, the sub-phases are Controlled Dorsiflexion 1 (CD1), Controlled Dorsiflexion 2 (CD
2) and Powered Plantar Flexion (PP).

Figure 2-2: Stair ascent gait pattern[6].

Figure 2-3: Stair descent gait pattern[6].
2.2 Electromyography

Electromyography (EMG) is a technique for recording and analyzing myoelectric signals generated by skeletal muscles. The following sections will explain in more detail of the physiological origin of EMG and why it can be used to estimate muscle force and in turn, joint torque.

2.2.1 Physiological Origin of Myoelectric Signal

When a person wants to flex his muscle, his motor nervous system is responsible for sending this command signal to the corresponding muscle and trigger that muscle to contract. In other words, the motor nervous system is responsible for controlling muscles to produce desired movement.

In the spinal cord of brain stem, there is distinct clusters of motor neurons called motor nucleus. While the cell bodies of these motor neurons lie in the spinal cord, their axons extend much further. The axons traverse down the spinal cord, branch to smaller peripheral nerves and finally end at the corresponding muscle fibers they are responsible for innervating. When a person thinks about flexing his/her muscle, an electric signal, called action potential is sent from the motor neurons, through the route described above, down to the corresponding muscle fiber[11].

The functional junction between the axon of motor neurons and muscle fibers are called end-plates. At these neuromuscular synapses, neurotransmitter acetylcholine would be released from motor neuron axon end and diffuse to postsynaptic end of neuromuscular junction. When the membrane potential of the postsynaptic end of the neuromuscular junction is depolarized to its threshold, an action potential is sent down the muscle fiber. As the action potential travels down the muscle fiber, potential gradients can be measured in the extracellular fluid near the muscle fiber.

Note that a single action potential from the motor neuron can activate hundreds of muscle fibers. Thus the measured potential gradient in the extracellular membrane is the sum of transmembrane currents generated by the hundreds of muscle fibers being activated in synchrony[11]. This potential can also be measured on the surface of the
overlying skin. The signal is typically on the order of milivolts. The measured signal is also known as myoelectric signal or electromyogram.

2.2.2 EMG and Muscle Force Estimation Models

When skeletal muscles contract, in addition to producing measurable myoelectric signals, they also generate force. Since both factors are result of motor neuron activating the muscle to contract, one could attempt to study motor control and muscle behaviors by studying the relative timing and amplitude of EMG patterns and how it relates to muscle force generated.

Skeletal muscle contraction is a result of microscale mechanisms working in concert. Skeletal muscles are composed of bundles of stringlike fascicles lying in parallel. Each bundle of fascicles are composed of stringlike multinucleated cells, also known as muscle fibers. A muscle unit is an ensemble of muscle fiber cells that are innervated by the same motor neuron. A motor unit is defined as the muscle unit and its corresponding motor neuron[11].

Each muscle fiber contains many stringlike myofibrils lying in parallel. Each myofibril contains longitudinally repeating units called sarcomeres. Each sarcomere contains interdigitated thick and thin filaments, otherwise known as thin filament (F-actin) and thick filament (myosin). Myosin heads can attach themselves onto the binding sites on the actin filament and "pull" themselves towards the direction of progression[11]. When millions of myosin heads work in concert, it results in what observed in the macroscale as muscle contraction.

As shown above, both EMG and muscle force can be modeled as a weighted sum of a large number of individual events. Thus, there is direct proportionality between two factors[10]. High EMG amplitude in comparison to its resting potential in general implies large force being generated by the muscle. However, the exact mapping between the two parameters is not as straightforward. Many investigations have been done in attempt to relate the two factors.

One method of estimating force using EMG is through empirically based mathematical models. Recently, Krishnaswami et al. proposed a human leg model that
can predict ankle muscle-tendon morphology, state, roles and energetics in walking. Their method involves feeding empirically measured calf muscles’ EMG profiles and other muscle parameters into a neuromuscular model to estimate torque generated by the ankle during level ground walking[12]. More specifically, they used EMG to estimate muscle activation by using two mathematical models in series. First they used EMG to estimate muscle activation using Sanger’s Bayesian model [14] and then they estimated neural activation using a bilinear form of the Zajac model[16]. The neural activation parameter is then passed onto Hill model along with muscle length and contraction velocity parameters to estimate muscle force [9]. Once the muscle force is estimated, they can calculate ankle torque through ankle joint kinematic relations.

Two assumptions made by using the neuromuscular model to estimate joint torque is that a) the empirical model for muscle activation and force generation relation holds for all population b) the muscle has load on both end, thus it is possible to calculate joint kinematics. All the work done by Krishnaswami et al. is with healthy, able bodied subjects. In the case of estimating ankle joint torque from residual limb muscles of transtibial amputees, the above assumptions do not hold. Thus, a simpler approach is used for this thesis, which is explained in the method section.

2.2.3 Myoelectric Signal Profile From Non-Amputees

For level ground walking, myoelectric signals from non-amputees have been measured and well documented in literature. An example taken from Krishnaswami et al. is shown in Figure 2-4. The figure shows that gastrocnemius and soleus muscles are activated during controlled dorsi flexion phase of the gait cycle and are deactivated right before toe off occurs. The tibialis anterior muscle is activated during swing phase of the gait cycle and become deactivated right before heel strikes. This suggest that amputees who still have the above three or combinations of muscle sets could potentially produce similar EMG profiles as non-amputees during level ground walking. In this case, the myoelectric signal measured from residual limb muscle, specifically gastrocnemius or soleus muscle could be used to control plantar flexion torque before toe off.
In terms of proportionality between ankle torque and EMG signal amplitude, Winter observed that as level ground walking speed increases, the myoelectric signal amplitude and peak power exerted by the ankle before toeoff increases[15]. Winter also noted that the overall patterns of ankle angle, torque, power and myoelectric signal profiles of related muscles are invariant of speed. Thus he hypothesized that biological ankles adapt to speed variations through gain control rather than modulating the timing. Based off Winter’s findings in biological ankles, one way of making the prosthetic ankle more biomimetic is to use myoelectric signal of either gastrocnemius or soleus muscle to proportionally modulate the gain of ankle torque exerted.

Figure 2-4: Level ground walking EMG patterns measured from non-amputees [12].
Chapter 3

Methods

3.1 Control Statemachine

As proposed, the myoelectric controller should work in concert with the intrinsic controller to control the powered ankle. The intrinsic controller used for this thesis is similar to what Au et al. had done in 2009 [2]. The intrinsic controller is provided by iWalk ©. The intrinsic controller controls ankle behavior for all times unless it is interrupted by the myoelectric controller. The purpose for the myoelectric controller, as set for this investigation, is the following:

1) for level ground walking and stair ascent, it modulates the gain parameter of torque commanded on the powered ankle;

2) for stair descent, it initiates plantar flexion of the ankle.

Since the myoelectric controller is only used to interrupt the intrinsic controller and take over control of the ankle controller when it is appropriate, its statemachine is built to monitor and shadow the six important states on the intrinsic controller. Fig. 3-1 is the statemachine used on the myoelectric controller. Note that the intrinsic controller has more than six states, but only the six depicted in Fig. 3-1 is being monitored.

For level ground walking, only the bottom four states (CP, CD, PP, and (E)SW) are used. The diagram can be understood starting with controlled plantar flexion (CP), which is defined as from heel strike till foot flat. The myoelectric controller
is idle during CP. Upon arriving CD, the myoelectric controller starts to measure EMG (myoelectric signal) from the residual limb muscle (Lateral Gastrocnemius) of a transtibial amputee. Processed EMG is then linearly mapped to the gain parameter on the intrinsic controller. This gain parameter scales the amount of torque to command from the powered ankle motor. The intrinsic controller uses a feedforward control scheme to control the ankle torque. The command torque equals to measured ankle torque cubed. This positive feedback control scheme simulates the afferent reflex in the sense that as more torque is sensed, more torque will be commanded. Thus the commanded torque is calculated as follows:

\[
T_{\text{command}} = \text{gain(EMG)} \times T_{\text{measured}}^3
\]

After PP, the ankle enters swing state (E)SW, which includes both ESW and TSW for level ground walking loop, shown as the bottom four states of the statemachine in Figure. 3-1. The cycle repeats as ankle enters CP.

Stair ascent uses the same four states. The myoelectric controller remains idle during toe strike (CD1). As ankle plantar flexes (PP1), the myoelectric controller enters CP. As the ankle dorsiflexes again (CD2), the myoelectric controller enters CD. Same as in level ground walking, myoelectric signal is measured and used to modulate the gain of the command torque on the ankle. As powered ankle plantar flexes again (PP2), the myoelectric controller enters PP and provides calculated torque. The myoelectric controller remains idle during swing state same as for level ground walking.
Stair descent uses a different loop as shown in Fig. 3-1. This is because for stair descent, it is more important for the user to have control over ankle angle than modulating the amount of power at push off. Starting at (E)SW, the myoelectric controller starts to measure myoelectric signal from the gastrocnemius muscle as used for level ground walking. A threshold detection algorithm is used to identify user intended motion for the next step. That is, if measured EMG is greater than a set threshold, then the myoelectric controller enters the loop for stair descent and takes over control from the intrinsic controller. Otherwise, the myoelectric controller assumes it is level ground or stair ascent, ie the bottom loop, the intrinsic controller remains in main control over the ankle.

During TSW of stair descent loop, the ankle plantar flexes at a fixed rate. Depending on the amount of time the ankle is in the air, it determines the amount of plantar flexion angle before toe strike. Upon toe strike of the ankle, the myoelectric controller shorts the leads of the ankle motor, causing it to behave as a nonlinear damper during stair descent stance stage. The cycle repeats as the ankle pushes off and enter (E)SW.
3.2 Myoelectric Signal Processing

This section summarizes EMG signal characteristics and describes the signal processing method used for this thesis.

3.2.1 Signal Characteristics

As explained in the background section, EMG signal contains valuable information about muscle activation. With proper processing, EMG signal can be used to robustly indicate if the muscle is activated or resting, and to some extent the level of muscle activation based on the normalized amplitude. The reason EMG signal cannot be used in real time to indicate level of muscle activation robustly is because like many other physiological signals, EMG is known to be non-stationary and prone to interference.

Clancy et al. had summarized potential sources of EMG signal interference [4], which is listed below:

1) Skin conductance and tissue characteristics are subject to change daily. This is mostly due to physiological changes and body temperature variations.

2) Cross talk between neighboring muscles’ EMG superpose on EMG generated by muscle of interest, but this is more of an issue for clinical studies.

3) Changes in relative position between muscle belly and electrode site on the skin surface. This is likely to occur due to movement or external pressure, which likely results in baseline shift or spikes of very short duration and large amplitude in the measured signal.

4) Power hum and other electrical signals in the environment could interfere with EMG measurement due to improper grounding.

5) Noisy signals from electronics that are used to measure EMG. Electronic devices have internal noise. In addition, improper board design could result in poor signal readings. Hence the quality of electrodes, pre-amplifiers and the rest of EMG measurement unit is very important.
3.2.2 EMG Signal Processing

This thesis used a standard method to process the EMG signal. The EMG signal was high pass filtered, clipped, rectified, and then smoothed by calculating its moving average with a 200ms time window.

The above method is determined for the following reasons. For the given EMG measurement system, motion artifacts as well as the electronics used were causing baseline drift in the measured signal. Motion artifact is known to concentrate most of its signal power in frequencies lower than 10Hz. Electronics caused DC offset concentrates most of its signal power around 0Hz. Thus it is decided that the EMG signal should be high-pass filtered by a 2nd order Butterworth digital filter to get rid of DC drift and motion artifacts. The cutoff frequency is set at 15 Hz due to slow roll off of the second order filter.

Motion artifact generated signals are also observed to be of large amplitude, typically 2 or 3 times greater than the amplitude of the signal generated due to maximum muscle contraction. Thus after high pass filtering, the signal is clipped to zero if it is 3 times greater than the MVC signal.

Following clipping, EMG signal is rectified by taking the absolute value of the input signal. Another common method of rectifying the signal is to square the input. Hogan et al. had investigated the differences between the two methods and decided that the difference is trivial [10]. This thesis uses the absolute value approach because it is easy to implement and faster to calculate.

After calculating the moving average, the maximum within the specified time window of controlled dorsiflexion phase of the gait cycle is selected. The maximum is then compared to a set threshold to further eliminate background electrical noise. If it is above the threshold, then the signal is used to scale the gain of command torque, otherwise the gain is set to a small number such that little torque is generated at toe off. This control scheme is similar to what Ferris et al. implemented in the orthosis [5]. Processed EMG signal across three speeds is shown in Figure 3-2.

Even though EMG signal is non-stationary across gait cycle, a qualitative trend is
observed across three speed within the time window of interest. Though it is not very ideal, the signal can be used to proportionally modulate the gain parameter of command torque. The mapping between EMG signal amplitude and the command torque gain parameter is linear with medium speed gain set at the gain subject preferred to walk at. The ensemble average of EMG profile across speeds is plotted in Figure 3-2. The standard deviation is the colored area, the mean is the solid line. Shaded region is the window of interest for proportional command torque gain control.

Figure 3-2: EMG profile measured from an amputee's gastrocnemius muscle across three speeds.
3.3 Hardware Setup

3.3.1 Ankle

This investigation used a powered ankle-foot prosthesis that was first designed at Biomechatronics Group, Media Lab, MIT and now commercialized by iWalk earlier this year. The basic architecture of the electromechanical design is depicted in Fig. 3-3. It consists of a unidirectional spring in parallel to an actuator with a series spring similar to the design done by Au et. al. [3]. The prosthesis can generate positive net work at the prosthetic ankle joint during the stance phase of walking. Ankle stiffness and power delivery is set by the built-in micro-controller inside the bionic ankle. The magnitude and timing of power delivery is measured directly from sensors within the prosthesis and then adjusted to match the performance of a biological ankle.

The sensors include motor shaft and ankle joint output encoders, and a six degree of freedom inertial measurement unit comprised of three accelerometers and three rate gyroscopes. Similar to biological muscle reflex responses that utilize afferent feedback to modulate muscle force, the bionic prosthesis uses positive force feedback; an increase in the sensed prosthetic ankle joint torque triggers an increase in the torque generated by the actuator, resulting in an increase in net positive ankle work production as walking velocity increases.

3.3.2 EMG module

An EMG measurement module was designed and implemented by the lab technician at Biomechatronics Group, Media Lab, MIT to work with the commercialized powered ankle. At the input stage, the module uses a commercially available pre-amplifier designed by Motion Lab Systems with a gain of 20 to pick up EMG. Due to lack of physical space between the residual limb and the socket, the pre-amplifier cannot be directly connected to the gastrocnemius muscle. Instead, fabric electrodes were used. This method was developed at Northwestern University. They used fabric electrodes in the liner to pick up myoelectric signals and redirected the signal to upper thigh
where there is room for the pre-amplifier to be attached.

Output of pre-amplifier is connected to another amplifier with fixed gain of 10. The amplified signal is low pass filtered by a $2^{nd}$ order low pass filter with cut off at 800 Hz to avoid aliasing. The signal is then passed to a 32 bit ADC and processed digitally by a microcontroller. The EMG signal was sampled at 1.5kHz and then downsampled to 500Hz.

The overall hardware setup is shown in Figure 3-4. The EMG measurement module is mounted externally onto the ankle. Data is transmitted from an onboard IEEE 802.11g wireless radio to a nearby computer via local wifi network.
Figure 3-4: Hardware setup
3.4 Data Collection Procedures

Experiments were conducted to evaluate the performance of proposed myoelectric-driven, finite state controller in comparison to existing intrinsic controller and data measured from biological ankles. For an initial pilot investigation, the device was tested on a healthy male, bilateral transtibial amputee. The subject wore the powered prosthesis on his right leg and a conventional passive prosthesis on his left leg. Initial walking experiments were conducted in the Biomechatronics Group within the MIT Media Lab. The experiments were approved by MITs Committee on the Use of Humans as Experimental Subjects (COUHES). The participant volunteered for the study and was permitted to withdraw from the study at any time and for any reason. Before taking part in the study, the participant read and signed a statement acknowledging informed consent.

Mechanical factors including ankle angle, torque and myoelectric signal were measured for all trials. Three gait patterns were observed: level ground walking, stair ascent and stair descent walking. This chapter describes experimental procedures in detail.

3.4.1 Preparation

Preparation involves two main steps: 1) helping subject don the system and 2) calibrate the system by measuring MVC signal and threshold determination.

Don the system

As described in the hardware section, the system has two main parts: the ankle prosthesis and an EMG measurement unit. Proper caution need to be taken when putting on the EMG measurement unit to ensure good signal quality.

This includes proper skin preparation and careful positioning of the electrodes. Skin preparation for EMG measurement includes hair removal and proper cleaning at the measurement site to ensure maximal contact between the electrodes and skin. For best quality, conventional method recommends cleaning with special abrasive and
 conducitive cleaning paste or sand paper to remove dead skin cells, dirt and sweat. Since this thesis uses a novel fabric electrode approach, simple alcohol cleaning is sufficient for its purpose.

As noted in the signal processing section, myoelectric signal is nonstationary and prone to motion artifact interference. Signal quality and level is especially sensitive to changes in measurement site position and also varies from day to day because human skin conductance is also non-stationary. Thus it is essential that the subject, when putting on the liner, they position the electrodes directly over the muscle belly and that the electrodes maintain stable, position fixed contact with the skin. A reference electrode should be placed at an electrically unaffected but nearby area, such as joints or bony areas. In this case, the subject was instructed to place it over the knee cap.

**MVC Measurement**

Maximum voluntary contraction (MVC) is measured in order to normalize EMG. It should be performed against static resistance. Clinical studies require measurement of true maximum innervation, because this value is less subject to change from day to day. However, for the purpose of this thesis, such accuracy is not necessary. Acceptable MVC is defined as maximum effort of muscle contraction exerted by the subject.

Conventional method of measuring MVC from gastrocnemius muscle is done when subject is sitting with legs parallel to the floor. The subject would be asked to plantar flex at 90 degrees ankle position. However, difference of signal strength between sitting and standing is observed when the conventional method was at first used. Stronger signal is observed when the subject is standing. This is likely result of better electrode-skin contact due to weight-bearing. Thus for this thesis, MVC of gastrocnemius is measured when the subject is standing and the subject is asked to imagine to plantar flex the gastrocnemius muscle as hard as he can. The subject is instructed to maintain MVC contraction for 5 seconds. The average EMG of the whole 5 seconds is used.
Threshold Detection

The control scheme requires two threshold values. For proportional torque control, a threshold value is needed to distinguish EMG signal measured due to contraction and the baseline noise due to motion artifact. Intrinsic controller is used during the threshold determination process. The subject is first instructed to walk without flexing the muscle for 10 gait cycles. Then the subject is instructed to walk while flexing the muscle during dorsi flexion for 10 gait cycles. A threshold value is determined based on collected EMG profile. It is the lowest EMG amplitude that best separates the two scenarios.

The second threshold value is used to switch between level ground and stair descent modes. Similar method is used. The stair descent mode is used for the threshold detection process. The subject is asked to walk down the stairs without flexing the muscle during swing for 10 stair steps. Then the subject is instructed to walk down the stairs and flex the muscle during swing for 10 stair steps. A threshold value is determined to be the smallest EMG amplitude that best separates the two scenario.

3.4.2 Data Collection

Level ground walking

For level ground walking, the subject was instructed to walk at three different speeds using one of the two controllers. Measurements were taken on two separate days. First the hybrid controller was used. The subject was instructed to consciously flex his residual limb muscle during controlled dorsiflexion phase of the gait cycle to modulate the amount of torque obtained at push off. On a different day, the same experiments were performed using the intrinsic controller. The subject was not instructed to flex residual limb muscle during controlled dorsiflexion. For both conditions, the subject was instructed to walk at the following speeds: 1.0m/s, 1.25m/s and 1.5m/s. Only data with walking speed within 5% of error is accepted. For each speed, 7 walking trials with total of 35 gait cycles were collected.
Stair ascent

For stair ascent, two conditions were tested to show that threshold detection method works. The subject was asked to walk up the stairs without consciously flexing the muscle. Then the subject was asked to walk up the stairs and consciously flexes the muscle during dorsiflexion to obtain desired torque. No speed variation or amplitude variation was tested at this point. The purpose of the testing is just to show that threshold detection method works to distinguish motion artifact noise and actual torque control command signal. Due to time constraint, only 10 gait cycles of each condition were collected.

Stair descent

For stair descent, similar two conditions were tested to show that threshold detection method works to switch between level ground walking and stair descent mode. The subject was asked to walk down the stairs without consciously flexing the muscle. Then the subject was asked to walk down the stairs and consciously flexing the muscle during swing to switch to stair descent mode. Due to time constraint, only 6 gait cycles of stair descent with no muscle firing and 10 gait cycles with muscle firing were collected.

3.5 Data Processing

Ankle angle, torque and statemachine states were recorded on the powered ankle. Both parameters were sampled at 500Hz. All the data were parsed into gait cycles starting at heel strike. Heel strike is first roughly estimated using the built-in statemachine. All data within the gait cycle were interpolated and downsampling to 1000 data points per gait cycle. The plotted ankle torque showed negative ankle torque during terminal swing, which should not be the case if the gait is parsed properly. The ankle is programmed to be passive throughout the swing phase. This suggests that the statemachine threshold set for detecting heel strike is not accurate. Negative ankle torque is normally observed upon heel strike, thus it is believed that part of the next
step’s heel strike is mistakenly included in the previous step’s terminal swing. Since walking pattern is repetitive, adjustment is made to circularly shift ankle ankle and ankle torque of the same gait cycle by the same amount. The amount of shift is decided as the number of data points from the time ankle torque changes from zero to negative to the end of the gait cycle.

Thus, per each gait cycle measured, the above method is used to ensure the gait cycle is aligned properly in terms of having the ankle torque being non-negative during swing and turn negative at heel strike. Per each parsed gait cycle, ankle net work is calculated by integrating ankle torque (in Nm) with respect to ankle angle (in radians). Ankle power is calculated by taking the time derivative of the calculated ankle work. Toeoff ankle angle, net ankle work, peak ankle power, and percent time at which peak power occurs are also recorded for each gait cycle. The ensemble average and standard deviation is then calculated for all gait cycles for each speed during level ground walking.

Data from the biological ankle is obtained from lab collaborators collected for a separate study. The dataset includes 7 subjects. For each subject, three gait cycles of ankle angle and torque data were recorded for five speeds, three of which is pertinent to this thesis, namely 1.0m/s, 1.25m/s and 1.50m/s. The dataset is already parsed into gait cycles with heel strike at 0 %. The ensemble average of the three sets of ankle angle and torque per each subject is first calculated. Then ensemble average and standard deviation across 7 subjects is calculated for ankle work, power, peak ankle power, toe off angle and percent time at which peak power occurs.
Chapter 4

Results and Discussion

This chapter presents results obtained from the three sets of experiments conducted to test how well the hybrid controller worked compare to the intrinsic controller. The three sets of experiments were: level ground walking across three speeds, stair ascent and stair descent. Biological ankle data were also included for level ground walking as reference.\(^1\)

4.1 Level ground walking

Ankle angle

Ankle angle measured from the biological ankle, the prosthetic ankle using the intrinsic controller and the hybrid controller is shown in Figure 4-1. The prosthetic ankle angle profile using both controllers are consistent with each other. The prosthetic ankle has a mechanical hard stop preventing the ankle to dorsiflex. Thus no dorsiflexion is observed between 20% to 60% and 80% to 100% of the gait cycle on prosthetic ankle measurements. Aside from lack of dorsiflexion, the prosthetic ankle angle profile resembles the biological ankle profile qualitatively. Particularly, at push off, plantar flexion angle observed on both prosthetic ankle measurements are between 10 and 20\(^\circ\).

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\(^1\)The biological dataset was taken from lab collaborators who collected them for a separate study. Provided data was already processed and parsed into gait cycles. Heel strike was not detected as accurately as desired, but the dataset is still sufficient to demonstrate qualitative profile of biological ankle characteristics.
degrees, which is within the normal biological ankle angle range.

It is worth noting that less plantar flexion angle is observed on the prosthetic ankle than the biological ankle during the first 20% of the gait cycle. This suggests that either the prosthetic ankle impedance is too high or that the prosthetic ankle quickly slaps the flex foot to foot-flat position to initiate controlled dorsiflexion, thus only small angle of plantar flexion took place.

The plot also shows that as speed increases, the overall ankle angle profile for both the biological and the prosthetic ankle stays the same. Winter noted in his paper that as speed increases, there is an increase in ankle angle at push off [15]. Although this trend is not observed in the biological data in Figure 4-1, it is observed in the prosthetic ankle using both controllers.

![Ankle Angle Comparison](image)

Figure 4-1: Ankle angle comparison for level ground walking across three speeds.

It is also noted that the biological ankle is non-zero at 0%, it suggests that the method used to identify heel strikes on biological ankle measurements is probably not
accurate. Data from Winter [15] shows that biological ankles have maximum plantar flexion angle centered at around 60% of the gait cycle. Thus it is believed that the biological ankle data should be shifted to earlier percentage of the gait cycle by about 5% to be consistent with similar studies done in the field. Nonetheless, the overall biological ankle angle profile is consistent with what is been published in literature. No data shifting is done in the presented result, because the cause for delayed plantar flexion in the biological data is unknown, thus it is difficult to decide how much shift should be done to compensate the mistake.

**Ankle torque**

Ankle torque measured from the biological ankle, the prosthetic ankle using the intrinsic controller and the hybrid controller is shown in Figure 4-2. There is qualitative resemblance between all three measurements. The prosthetic ankle torque peaks earlier in the gait cycle than the biological ankle. This is probably because the battery cannot provide enough power to drive the motor or that the motor simply cannot exert as much torque as the biological ankle. This suggests that a more powerful motor should be used in order for the prosthetic ankle to match up with the biological ankle performance.

There is no significant torque profile differences between the two prosthetic ankle controllers. This is because even though the myoelectric signal is modulating the gain parameter of the command torque, the dominant term in the command torque is still the positive feedback $T_{\text{measured}}^3$ term. The intrinsic controller uses measured pitch velocity to predict walking velocity and sets the gain parameter accordingly. The hybrid controller uses myoelectric signal amplitude to modulate the same gain parameter. Of the particular dataset collected, it shows that the hybrid controller commands larger torque at fast speed, but no difference between slow and medium speeds. This shows that using myoelectric signal to achieve fine tuned gain control is very difficult. Better myoelectric signal quality and more training is required for more precise gain modulation.
Figure 4-2: Ankle torque comparison for level ground walking across three speeds.

Ankle power

Ankle power is calculated by taking the time derivative of the integral of ankle torque with respect to ankle angle. Ankle power profile is calculated for each individual trials. Figure 4-3 shows the ensemble average of individual trial power across three speeds.

There is no negative power observed in the prosthetic ankle because it cannot dorsiflex. Otherwise, the qualitative profile of the prosthetic ankle power curve resembles what's observed in the biological ankle. The prosthetic ankle exerts larger peak power at higher speed than biological ankles. This is because the command torque gain is set higher than biological values. Peak power of the prosthetic ankle occurs earlier than what's observed in the biological data due to two reasons: 1) the biological data heel strike was not detected correctly, typical biological ankle peak
power occurs at around 50% of the gait cycle [15]; 2) prosthetic ankle cannot provide sufficient torque.

Figure 4-3: Ankle power comparison for level ground walking across three walking speeds.

Between the two controllers used in the prosthetic ankle, hybrid controller is able to match up with intrinsic controller’s command power for both slow and fast speed. For medium speed, it shows the hybrid controller controlled ankle provides less peak power than the intrinsic one. This is consistent with what is observed in the ankle torque profile. Also, referring back to Figure 3-2, the difference between slow and medium speed myoelectric signal during controlled dorsiflexion is small, thus less peak power differences is observed between slow and medium speed. This suggests that the mapping between EMG and command torque gain should be non-linear. The exact mapping between EMG and command torque gain parameter can be obtained empirically. The real problem is poor myoelectric signal quality. With standard
myoelectric signal processing method, the data shows large variances between trials and across speed. Signal quality can be improved by using a different method to obtain EMG and use other signal processing methods to improve signal quality.

**Ankle net work**

Average net work per gait cycle per speed is plotted in Figure 4-4. All three data sets show that the ankle does more work at faster speeds than slower ones. The biological data set shows near zero net work for all speeds because ankle angle and torque collected has been misaligned with respect to each other. Typical values for biological ankle net work should be between 0.1 and 0.3 Nm/kg. Comparing between the intrinsic and hybrid controller, plot shows that the hybrid controller and the intrinsic controller exerts similar amount of net work for the three speeds observed.

Significance testing using one-way ANOVA followed by Tukey HSD follow up procedure is performed to test if there is statistical significant differences between the datasets. The null hypothesis is that all three means are the same. Statistics result shows that with 95% confidence interval for the true difference of the mean value between the intrinsic and the hybrid controller is [-3.86 and 2.6]. Since the difference interval includes zero, it shows that there is no statistical difference between the intrinsic and the hybrid controller. Table 4.1 lists all the difference intervals calculated for 95% confidence interval.

<table>
<thead>
<tr>
<th>Speed</th>
<th>Bio VS Int</th>
<th>Bio VS EMG-Int</th>
<th>Int VS EMG-Int</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0 m/s</td>
<td>-14.8184, -8.3485</td>
<td>-15.4388, -8.9689</td>
<td>-3.8554, 2.6146</td>
</tr>
<tr>
<td>1.25 m/s</td>
<td>-24.0108, -17.8797</td>
<td>-21.0711, -14.9400</td>
<td>-0.1259, 6.0053</td>
</tr>
<tr>
<td>1.50 m/s</td>
<td>-30.0529, -22.6769</td>
<td>-24.8724, -17.4964</td>
<td>1.4925, 8.8685</td>
</tr>
</tbody>
</table>

Table 4.1: Tukey HSD testing result showing 95% confidence difference interval for net work for all three speeds.
Figure 4-4: Ensemble average of net work calculated for three speeds.

Peak ankle power

Average peak power per each speed is plotted in Figure 4-5. The plot shows the general trend that as speed increases, the peak power exerted by the ankle increases. It also shows that the hybrid controller and the intrinsic controller exerts similar amount of peak power per each speed. Normally less power is observed at higher speed in prosthetic ankles than biological ankles. This dataset does not reflect the same trend because the gain parameter was set too high. In order to achieve more biomimetic behavior, the prosthetic ankle gain should be tuned down for future experiments.

The peak power plotted here is the ensemble average of the peak power per each trial per speed. The power plot in Figure 4-3 is the average of power calculated per gait cycle per trial. Therefore the peak powers are not the same.

Statistical testing result is shown in Table 4.2. With 95% confidence interval,
there is no statistical difference for 1.0m/s between the three data sets. There is no statistically significant differences between the two prosthetic controllers for 1.25m/s and 1.5m/s either. The differences between the prosthetic ankle and the biological ankle is non-zero but small for those two speeds.

Figure 4-5: Ensemble average of peak power calculated for three speeds.

Table 4.2: Tukey HSD testing result showing 95% confidence difference interval for peak power for all three speeds.
Toeoff ankle angle

Toe off angle is defined as the ankle angle at which maximum plantar flexion occurs at push off. The prosthetic ankle using two different controllers show a linear relation between ankle angle and speed. At faster speeds, more plantar flexion is observed. The biological ankle for this specific dataset does not show such trend\(^2\). However, Winter did report similar trend in his biological dataset as what’s observed in the intrinsic controller\([15]\).

Statistical significance testing is listed in Table 4.3. The result shows that, for confidence interval of 95\%, there is no statistical difference between intrinsic and the hybrid controller. Furthermore, it also shows that for this particular dataset, there is no statistically significant differences between the prosthetic ankle and the biological one.

<table>
<thead>
<tr>
<th>Speed</th>
<th>Bio VS Int</th>
<th>Bio VS EMG-Int</th>
<th>Int VS EMG-Int</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0 m/s</td>
<td>-5.1370, 3.5200</td>
<td>-5.0622, 3.5947</td>
<td>-4.2538, 4.4032</td>
</tr>
<tr>
<td>1.25 m/s</td>
<td>-4.3664, 7.1758</td>
<td>-4.3170, 7.2252</td>
<td>-5.7217, 5.8206</td>
</tr>
<tr>
<td>1.50 m/s</td>
<td>-3.4484, 11.2914</td>
<td>-2.6259, 12.1139</td>
<td>-6.5475, 8.1924</td>
</tr>
</tbody>
</table>

Table 4.3: Tukey HSD testing result showing 95\% confidence difference interval for toeoff angle for all three speeds.

\(^2\)This particular biological ankle dataset also has larger variance in measured toe off angle than the prosthetic ankle. This further suggests that the biological data set is not very accurate.
Figure 4-6: Comparison of measured average toeoff angle for three speeds from three datasets.

**Percent time at which peak power occurs**

Percent of gait cycle at which peak power occurs for each speed is shown in Figure 4-7. Since the biological data set is misaligned, comparison between the biological and the prosthetic ankle for this parameter cannot be made. Table 4.4 shows the result from Tukey HSD test for 95% confidence interval, it is shown that there is no statistical differences between the intrinsic and the hybrid controller for all three speeds.

However, it is worth comparing the relative differences within the ankle type itself. It was observed by Winter [15] that timing at which peak power occurs does not vary with speed. This trend is observed in the biological data set. Although the biological dataset is misaligned per percent gait cycle, the relative timing between different speeds can still be compared assuming the error is consistent through all trials. Table
4.5 shows the significance testing result for each ankle. With 95% confidence, it is shown that there is no statistical significance in peak power timing across speeds for the biological ankle dataset. In addition, the error margin for the biological ankle dataset is relatively small. Similar trend is observed in the prosthetic ankle but with larger variances, especially in the hybrid controller case than the intrinsic controller case. This large error range is expected because myoelectric signal is non-stationary and non-repeatable, as shown in Figure 3-2. Thus it is difficult to use it as command signal to produce repeatable results. Myoelectric signal is only repeatable in the qualitative sense.

![Timing of Peak Power VS Speed](image)

Figure 4-7: Average timing at which peak power occurs for all three speeds.
### ANOVA Significance Testing

One-way ANOVA was used to compare statistical significance between the three data sets for the above four parameters. The differences were then further analyzed with a Tukey HSD follow-up procedure. Tukey HSD follow up results have already been presented in earlier sections. Table 4.6 lists all the p-values obtained from ANOVA. The p-value represents the probability that the mean values from all three datasets are the same. Aside from toe-off angle, all the other parameters show that there is significant difference between the datasets. For net work and peak power, this is expected due to the fact that the biological ankle dataset is misaligned. Both ankle net work and peak ankle power is highly dependent on the alignment of datasets. For peak power, the prosthetic ankle can be better tuned to match the biological data result.

<table>
<thead>
<tr>
<th>Speed/p-value</th>
<th>net work</th>
<th>peak power</th>
<th>toe off angle</th>
<th>percent per peak power</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0 m/s:</td>
<td>3.0897e-09</td>
<td>0.0322</td>
<td>0.8741</td>
<td>9.2416e-11</td>
</tr>
<tr>
<td>1.25 m/s:</td>
<td>8.5662e-14</td>
<td>0.0226</td>
<td>0.7734</td>
<td>2.0019e-25</td>
</tr>
<tr>
<td>1.50 m/s:</td>
<td>1.9398e-11</td>
<td>0.0010</td>
<td>0.2352</td>
<td>3.8249e-22</td>
</tr>
</tbody>
</table>

Table 4.6: Anova testing p-value results.
Summary for level ground walking

Results show that prosthetic ankle controlled by the hybrid controller and the intrinsic controller both exhibit biomimetic characteristics. Measured ankle angle, torque and calculated ankle power all qualitatively resemble what is seen in biological ankles. Due to misalignment in the biological ankle, it cannot be determined if the prosthetic ankle is similar to the biological ankle in terms of net work, peak power and percent time at which peak power occurs. However, the dataset does show that the prosthetic ankle toe off angle is similar to the biological ankle dataset.

The data also shows the hybrid controller can achieve similar mean values as the intrinsic controller in terms of net ankle work, peak power, toe off angle and percent time at which peak power occurs. The myoelectric controller shows large variances for all the parameters examined. This is expected because myoelectric signal is non-stationary and subject to change. The reason the hybrid controller can achieve similar mean values as the intrinsic controller is because the $T_{\text{measured}}^3$ term for positive feedback dominates the control loop. In order to improve the hybrid controller, the myoelectric signal needs to be improved. The mapping between EMG signal amplitude and command torque gain should be binned into levels rather than a simple linear mapping.
4.2 Stair Ascent and Descent

The thesis work also used myoelectric signal to switch between different modalities in the intrinsic controller, which is similar with what’s been done in previous studies[1, 7]. The difference between this hybrid controller and study done by Au et. al. is that for stair descent, the user can control the amount ankle angle deflexion by modulating the amount of time the ankle stays in swing phase. The Au et. al. design deflects the ankle to a fixed plantar flexion angle. Thus for stairs of shallow or deep rises, the Au et. al. design cannot adjust accordingly. In addition, the hybrid controller can assist user to walk up stairs by letting the user to command push off torque. This functionality is absent in both the particular intrinsic controller used in this thesis and in Au e. al’s design.

The following results show how well the ankle behaves during stair ascent and descent in terms of ankle angle, torque and power.

4.2.1 Stair descent

Subject can switch between 'level ground/stair ascent' mode and 'stair descent' mode in the intrinsic controller by flexing gastrocnemius muscle during swing phase of the gait cycle. In order to test the robustness of threshold detection algorithm, subject was instructed to walk down a set of stairs and flex the muscle to trigger stair descent mode at every step. The same task was repeated but this time the subject was instructed to not flex the muscle. Ensemble average of ankle angle, torque and power is calculated for 10 gait cycles of subject walking down the stairs flexing the muscle and 6 gait cycles down stairs without flexing the muscle and shown in Figure 4-8.

Of the 10 gait cycles the subject was instructed to switch the controller to stair descent mode, the subject was able to make the switch all 10 times successfully. Similarly, of the 6 gait cycles the subject was instructed not to switch the controller to stair descent mode, no false switches were made.

As shown by the ankle angle plot, with the hybrid controller, the subject can command the ankle to plantar flex during swing phase of the gait cycle, restoring a
more normative gait. Thus the hybrid controller is an improvement of the particular intrinsic controller \(^3\) used in this thesis.

### 4.2.2 Stair ascent

Of the particular intrinsic controller used in this thesis, during stair ascent, no plantar flexion torque is exerted by the ankle to assist the user at push off. With the hybrid controller, the user can command ankle torque by flexing the muscle. To test how well the hybrid controller works, 10 gait cycles of subject walking up the stairs flexing the muscle to command torque and 10 gait cycles without flexing the muscle is measured. The ensemble average of ankle angle, torque and power for the two scenarios is plotted.

\(^3\)There are other intrinsic controllers that can detect stair descent mode to varying degree of robustness.
in Figure 4-9. As shown, the prosthetic ankle using the myoelectric driven controller can plantar flex and provide push off power to assist user ascend stairs.

Figure 4-9: Ankle angle, torque and power measured using the hybrid controller during stair ascent.
Chapter 5

Conclusions and Future Work

5.1 Conclusion

The goal of the thesis is to implement a hybrid controller that can maintain similar biomimetic characteristics of existing intrinsic controller but at the same time give user more control over ankle behavior. Specifically, This thesis explored the feasibility of using myoelectric signal to 1) modulate the gain of command torque during push off of the gait cycle; and 2) use myoelectric signal to switch between level ground walking and stair descent mode in the intrinsic controller. Using the six measurements: ankle angle, torque, net work, peak power, toe off angle and percent time at which peak power occurs, results show that the hybrid controller can maintain the biomimetic characteristics as the original intrinsic controller.

The hybrid controller provides the following benefits: 1) It gives user some control of ankle behavior. The user can command the amount of torque exerted during push off by controlling how hard to flex the muscle. As an improvement to the intrinsic controller used by this thesis, the ankle exhibits a more biomimetic gait pattern during stair ascent. 2) The user can switch between level ground walking and stair descent mode. The ankle plantar flexes at a fix rate. By control the time the ankle is in the air, the user can control the amount of plantar flexion in the ankle.
5.2 Improvements and Future Work

**Improvements:** As shown in the result, the user does not have fine tuned control over ankle torque exerted at push off. Following improvements need to be made to improve the project:

1) The myoelectric signal quality needs to be improved. Myoelectric signal quality is poor mainly because during walking, the contact between the fabric electrode and the skin is constantly changing. As a result, lots of motion artifact is observed. One way to improve the signal quality could be to use implantable EMG sensors instead of measuring surface EMG. The technique used to process the myoelectric signal could be improved. The method used by this thesis is the standard method. Alternative methods reported in literature includes whitening the signal, use adaptive Wiener filtering, PCA, ICA, various pattern recognition techniques using a combination of time and frequency domain features, etc. The author had attempted using some of the aforementioned methods, but did not observe much improvement than the standard method. More time is needed to test and improve the signal processing method. However, if myoelectric signal quality can be improved through better measuring techniques, it’d be more effective in getting more information from obtained signal than using extravagant processing techniques.

2) The mapping between command torque gain and EMG signal amplitude should not be linear. Since EMG signal amplitude is non-stationary with large variances, it should be binned into different levels and map to torque gain based on the levels of contraction.

**Alternative approach:** A more interesting and biomimetic approach of using myoelectric signal to modulate ankle push off torque is to process EMG using Sanger-Zajac model as done by Krishnaswami et. al. [12] to obtain muscle activation level. Upon calculating muscle activation, the result can be used in Hill’s muscle model to estimate force and joint torque assuming the residual limb muscle functions similar to muscles in non-amputated bodies. In this case, Krishnaswami et. al.’s neuromuscular
leg model could be used to estimate joint torque using real time EMG \(^1\).

**Clinical Values:** Ferris et. al. found clinical values in studying EMG morphology changes before and after using EMG proportional torque control with patients wearing orthosis [5]. In addition, they found that in amplifying the relation between muscle activation and proprioceptive feedback can improve muscle coordination and balance. The prosthetic ankle used in this thesis uses positive feedback and larger than normal gain parameters to command ankle torque. Similar studies to what Ferris et. al. had done could be conducted with ankle-foot prosthesis users once fine tuned mapping between EMG and torque can be achieved. Proportional myoelectric torque control may help prosthetic users to improve muscle coordination and have more intuitive interaction with prosthetic ankle because it provides a direct link between the user's nervous system and the prosthesis, and it also augments the movement errors related to inappropriate muscle activation patterns.

\(^1\)In this case close loop torque control should be used instead of positive feedback to control the ankle.
Bibliography


