Design of a terrain detection system for foot drop

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Design of a Terrain Detection System for Foot Drop

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Submitted in partial fulfillment of the requirement for the

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In
Mechanical Engineering

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OCTOBER 2012
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Design of a Terrain Detection System for Foot Drop

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Acknowledgments

I would like to start by thanking my family for their constant and loving support. From kindergarten to high school they have been responsible for showing me just what hard work is. They have given me all the opportunities in the world and I just hope I can make them proud.

As for this project, I think it is the longest single project I have ever worked on. It has introduced me to some of the most inspiring and hardworking people in the Rochester area, and honestly without their help I would not be here today. This project really started two long years ago when I asked Dr. Lamkin-Kennard if she had any co-op positions. At the time she didn’t, but she did point me in the direction of Dr. Elizabeth DeBartolo. I cannot overstate just how important Dr. DeBartolo has been for this journey. With her constant pressure and positive attitude, she single handedly placed me into the MS program, and has not stopped pushing me forward since. It has been a wild ride and I am happy for the opportunity to work with such a passionate teacher.

I would also like to thank my Committee members Dr. Lamkin-Kennard, Dr. Gomes, and Dr. Walter for your patience, and help throughout this project.

I would also like to thank J.J. and all of the other clinicians and students at the Nazareth Physical Therapy Center. Observing your work has directly lead to the creation of anything that I have accomplished with this project.

I would like to thank Dr. Barbano for his initial idea for creating an improved brace, and really being a driving force behind collaboration between RIT and RGHS.
I would also like to thank the Rochester Orthotics Lab for providing me with a very knowledgeable staff to talk to. Your experience and guidance really helped shape the boundaries of the project and really made it feasible.

Thank You
Abstract

The ankle foot orthotic (AFO) has been around for centuries. They were created to augment functionality of an ankle damaged due to injury or disease. A common reason a patient might be prescribed an AFO is a condition called foot drop. Foot drop can be caused by many conditions, but the most common reason is a stroke. Foot drop can be characterized by the inability to raise and/or lower a patient’s foot. This incapacitation of the patient’s foot leads to unnatural gaits and joint fatigue, as well as increasing the patient’s likelihood of tripping and becoming seriously injured. Hard plastic AFOs that hold a patient’s foot in a neutral position are the current standard for combating foot drop. These AFOs come in many different shapes and sizes, which emphasizes the wide variety in functionality of someone with foot drop. Unfortunately, the restrictive nature of the AFO can cause unnatural movements in the patient’s foot; these unnatural tendencies are more exaggerated when walking down stairs and ramps, as the natural gait is to land toe first, the opposite of what the brace allows the patient to do. The purpose of this project is to create a sensor system for an AFO to help identify varying terrain. In the future this information can then be made to control an active AFO.

Each terrain type will be first measured by a pair of simple infrared range finder, attached on the lower leg, one range finder looks ahead of the user and the other looks straight down at the ground. Models for the ground conditions can be established by representing each with Fourier series created using RANdom Sample Consensus (RANSAC). RANSAC coefficients will be scaled off the rate of data coming in and gait speed. Each model has a period term so the data can easily be scaled to match the pattern of walking regardless of pace. Gait speed will be measured using the downward facing ankle-mounted
rangenfeinder, but with a threshold to determine when the foot is in contact with the ground. Once this initial set-up is completed, the system can take in data live and provide a prediction of the type of ground the patient is walking over, using pattern recognition techniques. The hope for this project is that if the system can accurately predict the change in ground type from, for example, level walking to walking down a ramp, an AFO could then be made to adjust itself, giving the patient a more natural gait, even when encountering adverse conditions. A byproduct of constantly using a patient’s own gait to measure ground type is the ability to track a patient’s changing gait over time, giving therapists a valuable new tool for tracking progress in a patient.
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1. Background

1.1. Motivation

There is a large population of patients in today’s health care system who suffer from a common symptom, foot drop. The quality of life that one loses with foot drop is immeasurable. Any advancement that could alleviate some of the patients’ day-to-day hassles would be a project worth tackling. Returning to being independent after someone has suffered a stroke is merely a dream for many patients; thus, to return to them some extra mobility through the use of an improved brace is a worthwhile goal.

With this in mind, the design and creation of a more versatile ankle foot orthotic would be of great use. The problem at hand can be split into two major portions: the physical brace, an AFO that can react to different ground types; and a control system for identifying these ground types, which is the main focus of this project. Originally the brace design was thought to be the easier of the two questions to answer. Upon further inspection, it was determined that a much more useful question to answer was, in fact, that of the control system. With a simple system for identifying ground types available, not only is the idea of an improved AFO made feasible, but such a system could also allow for constant monitoring of a patient’s gait cycle, which provides invaluable information for therapists in constructing physical rehabilitation exercises.
1.2. Basics of Gait Cycle

Foot drop is only a symptom; it is the inability to dorsiflex and in more severe cases to plantarflex the foot that causes problems with walking (Figure 1.1). Without dorsiflexion the foot can drag on the ground, which inevitably leads to tripping and over-exertion of the hip and knee in an attempt to compensate for the new height that the foot must reach to clear the ground (Figure 1.2). Without plantarflexion, the foot is unable to push off from the ground, thus decreasing forward progression of the whole body.

Foot drop can be caused by many different diseases, such as polio, multiple sclerosis, cerebral palsy, and stroke [1], all of which affect neurological functions or are

![Figure 1.1. Dorsiflexion/plantarflexion example](image)

![Figure 1.2. Gait cycle illustration](image)
muscular disorders. There are 6.5 million stroke survivors each year and 20% of them suffer from a lasting symptom of foot drop [2].

Walking is the cyclical motion of our legs as we shift our weight from one foot to the other in an attempt to progress forward. This cyclical process as viewed from a single foot is called the gait cycle. The gait cycle can be split into two major functions: the stance phase, where the foot is initially planted and then pushes off; and the swing phase, where the toe is pulled up towards the shin and hovers over the ground while swinging to its next destination [3]. The foot has two kinds of motion during this cycle, dorsiflexion and plantarflexion. Dorsiflexion is the motion of the foot being brought closer to the shin; plantarflexion is the movement of the foot being pointed towards the ground [3].

The ankle foot orthotic or AFO is the most common brace or treatment issued to someone suffering from foot drop. The main goal of an AFO is to replace the functionality of a damaged ankle or foot. The sheer number and diversity of AFOs on the market, discussed later, is representative of how widely the patient base varies. It also

Figure 1.3 Example Ankle Foot Orthotic
shows how broad of a diagnosis foot drop can be. The modern and most common AFO consists of a custom-fitted plastic leg brace resembling the bottom half of a foot cast (Figure 1.3). This brace rigidly holds the patient’s foot in place, not allowing it to dorsiflex or plantarflex. An AFO is generally designed to be worn for a day, but for comfort most people will also wear a compression sock to protect their leg from the abrasive AFO.

AFOs’ rigidity is what allows them to replace the function lost due to foot drop. AFOs allow patients to walk; without them they would trip and fall, or would be left unable to truly progress forward. The common complaint about AFOs is their lack of natural movement. During a gait cycle, the ankle does not stay still, and so in that sense the brace does a poor job imitating human locomotion. This premise will be the basis of much of the work to come.

1.3. Customer Interviews

When this project began, it was identified that most AFO-related projects have settled on a particular actuator first. Patients’ input on what they thought they needed in an AFO was not solicited. With this in mind, our approach to the problem involves first preforming a needs assessment, getting input from AFO users and clinicians, and making design choices based on this knowledge.

Our pool of potential AFO users to interview was relatively limited. It is important to note that this means that although all the people interviewed had foot drop, these particular AFO users might not be the best candidates for testing a device such as ours. Nine people were interviewed and asked questions relating to their AFO. All people
interviewed were at least six months post-stoke, and IRB approval was secured before conducting the interviews. Clinicians and an orthotics specialist were also interviewed for their insights on their long-term interactions with patients and their AFOs, and AFO construction. A list of the general questions asked of the patients can be seen below.

- Do you have any specific complaints about your AFO?
- Do you have any specific compliments about your AFO?
- How many AFOs have you had?
- How long have any of your AFOs lasted?
- What kind of hinges have your past or present AFOs had?
- If you could remove material from your AFO, where would you remove it from?

The following is a list of target customer specifications. Again, this is not a list of attributes directly associated with the population that was interviewed for the study, but a list of patient attributes that would be ideal if this device were ever to be tested.

- Problems with plantar/dorsi flexion (i.e., has foot drop)
- Limited complications such as toe curling or ankle rolling
- Able to respond
- Well into recovery (at least 6 months)
- Currently able to walk unassisted with an AFO

1.3.1. Customer Needs

Interviews were conducted with nine AFO users. While this was by no means a large sample, it is also important to note that the patients interviewed exhibited a wide variety of impairments, and any common themes between patients should be taken as a widespread problem.

All patients had negative or indifferent comments about how their AFO fits inside of a shoe. A common response to this problem by the patients was to request a reduction in the amount of material in the AFO. In addition to fitting in a shoe better, patients saw
removing material as a way to add more flexibility to their brace. Although this was an idea common to multiple patients, it is important to note that most clinicians did not recommend this, as it would reduce the lifespan of the brace, which can be up to six years, as well as reduce the effectiveness of the brace. The differing comments by patients and doctors is an important takeaway because it demonstrates the need for stiffness, as expressed by clinicians, and the desire for more flexibility, expressed by patients. The issue of combining both qualities into once device is a very common engineering problem.

All but one patient stated that they were unable to get their AFO on unassisted. However, it should be noted that most of the patients are older and exhibit high dependency on others for other tasks as well. While this was a common problem, it seems like it would be best solved with a second device.

Another key fact gained from the interviews was the complaints about the surface that contacts the patients’ legs. Common issues were stickiness, excessive sweating, and development of sores. Most patients have to wear extra high socks to avoid skin contact with the plastic AFO.

The most common and the most dangerous complaints of our patients concerned stairs and ramps. Specifically, while descending stairs and ramps, the patients would complain about feeling unstable, and all attributed it to the performance of their AFO. The natural inclination is to walk down with the toe leading (plantar flexion), but the AFO prevents the foot from moving in this way. As a result AFO users must lean their weight out over their foot to get their toe down, which leads to the feeling of instability. This is also
backed up by observations made in the clinic, as walking up and down stairs is a very common exercise to do during a physical therapy session. It is important to note that although the patients’ conditions vary widely, this complaint was unanimous and independent of the kind of brace the patient used. A list of necessary range of motions for the different ground types can be seen in Table 1.1

Table 1.1 Range of Motion

<table>
<thead>
<tr>
<th>Metric</th>
<th>Units</th>
<th>Test</th>
<th>Importance (1-4)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sit to Stand</td>
<td>70°- 85°</td>
<td>Detects and allows for adequate motion of the ankle while attempting to stand from a seated position</td>
<td>4</td>
<td>[4]</td>
</tr>
<tr>
<td>Stairs Ascent</td>
<td>82°- 58°</td>
<td>Detects and allows for freedom of the ankle so the patient could walk with successive foot motion up and down a flight of stairs</td>
<td>3</td>
<td>[5]</td>
</tr>
<tr>
<td>Stairs Descent</td>
<td>82°- 45°</td>
<td>Detects and allows for freedom of the ankle so the patient could walk with successive foot motion up and down a flight of stairs</td>
<td>3</td>
<td>[5]</td>
</tr>
<tr>
<td>Inclined Surface Ascent</td>
<td>82°- 46°</td>
<td>Detects and allows for motion of the foot during descent or ascent of a ramp</td>
<td>2</td>
<td>[5]</td>
</tr>
<tr>
<td>Inclined Surface Descent</td>
<td>60°- 80°</td>
<td>Detects and allows for motion of the foot during descent or ascent of a ramp</td>
<td>2</td>
<td>[5]</td>
</tr>
<tr>
<td>Level Surface</td>
<td>75°- 45°</td>
<td>Patient does not drag his/her foot on the ground</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
1.4. Project Goals and Challenges

The original goal for this project was to create a physical brace that would allow for better traversing of stairs and ramps for a patient with foot drop. While descending ramps and stairs the foot naturally plantarflexes to meet the changing ground level, but while wearing an AFO this kind of motion is restricted. The brace to be designed was going to be made variable so that if it were aware of a change in ground type it could allow the patient to plantarflex their foot, which would make their gait more natural. This brace was to be made universal so that any of the patients that the project had access to would be able to test out the device.

The problem with this idea is the sheer size of the patient base. A brace of this kind, if it were to be made, would have to be custom fit to the needs and specifications of a single patient. Even the idea of fitting it to a specific individual requires knowledge outside the scope of this project. The difficulty of producing an AFO, let alone an AFO that changes at some point, cannot be overstated. Thus, the goals of this project were altered to help a greater number of people, as it was observed that the control system for such a device would be far more useful than the brace itself. If the motivation behind the project was to help as many people as possible, the goals of this project needed to be changed to reflect that fact.

The revised goal of this project is to create a detection system to determine if a patient with foot drop is walking over a specific kind of terrain—a ramp, stairs, or level ground—and if they are ascending or descending. The system will have as a part of its construction an automatic way to learn a patient’s gait pattern over said types of ground
conditions. It will then apply this knowledge to a predictive model to determine what kind of ground condition the patient is about to step on prior to the heel strike. It is important that this happen pre-heel strike as the aforementioned brace needs to be given time to change into its secondary mode for ascending or descending ramps and stairs.
2. Preliminary Research

2.1. Ankle Foot Orthotics

A table of the AFOs that will be investigated in this section is provided.

Table 2.1 AFO Metric Chart

<table>
<thead>
<tr>
<th>AFO</th>
<th>Metric</th>
<th>Spec</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hard Plastic AFO</td>
<td>Mass</td>
<td>.3-.6 (kg)</td>
<td>[6]</td>
</tr>
<tr>
<td>Bioness AFO</td>
<td>Mass</td>
<td>.1 (kg)</td>
<td>[7]</td>
</tr>
<tr>
<td>i-AFO</td>
<td>Maximum braking torque</td>
<td>10 (Nm)</td>
<td>[8]</td>
</tr>
<tr>
<td></td>
<td>Mass</td>
<td>990 (g)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Movable angle</td>
<td>−45° to +45°</td>
<td></td>
</tr>
<tr>
<td>Air Muscle AFO</td>
<td>Maximum pulling torque</td>
<td>171.7 (Nm)</td>
<td>[9]</td>
</tr>
<tr>
<td></td>
<td>Mass</td>
<td>1.3-1.7 (kg)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Movable angle</td>
<td>−10° to +35°</td>
<td></td>
</tr>
<tr>
<td>Pneumatic Power Harvesting AFO</td>
<td>Maximum power generation</td>
<td>10(W)</td>
<td>[6]</td>
</tr>
<tr>
<td></td>
<td>Mass</td>
<td>1 (kg)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Movable angle</td>
<td>−9° to +15°</td>
<td></td>
</tr>
</tbody>
</table>

2.1.1. Commercially Available AFOs

Only in the last two decades have there been real strides made in full replacement of the function of the lower limb, with a solid brace. These braces are called ankle foot orthotics (Figure 2.1). Most commercially available AFOs are passive in that they only support the foot and add no energy to the system. Most are made from thermosetting plastics and are molded to fit the patient’s own leg. These AFOs are light and rigid. This rigidity has been identified as a possible hindrance to patients’ adoption of their
new AFOs, as it can cause an unnatural gait by not emulating the movements of a healthy ankle.

In addition to rigid orthotics, there are also other solutions to the problem of foot drop that attempt to give small shocks (5V max) to the peroneal nerve, causing dorsiflexion [11]. This form of therapy is commonly known as electrical stimulation [11], and an example of such a device can be seen in Figure 2.2. Electrical stimulation is considered to be a viable replacement for the AFO [11], but the devices are not without their problems; they are expensive, considered an invasive technology, and the long-term effects of electrical stimulation are unknown. These devices are also contraindicated in many patients [7]. For example, the peroneal nerve is not always in an appropriate spot where electrical stimulation could work without discomfort, electrical stimulation should not be used on anyone with a heart condition or any kind of pacemaker, and the leg being stimulated should not have any recent fracture or dislocation. While these types of devices are considered active AFOs, they are outside the planned scope of this project [7].

2.1.2. Experimental AFOs

Active AFOs that have been created for research are abundant, but most have been hindered by their need to be tethered to a computer or external power supply.
Additionally, they are usually too complicated to bridge the gap as a commercially viable alternative to the inherently simple passive AFOs.

An “i-AFO” (Figure 2.3) was constructed in 2010 by researchers at Yamagata University, in Japan [8]. Its purpose was to better control the gait of a patient who had flaccid paralysis of the ankles. “i-AFO” used a rotational braking system to variably dampen the system. This particular AFO was in its third generation and was still too bulky to fit into an unmodified shoe, but it was still useful in that it helped to show the advantages that can be achieved by dampening alone.

In 2008, a more complex AFO (Figure 2.5) was created by Svensson and Holmberg from Halmstad University. The AFO was created to help patients walk up an inclined surface, stairs, or flat ground. They used a magneto rheological-type dampener. This type of dampener is variable, i.e., it provides various levels of dampening based on voltage. During the swing phase the AFO would lock up, thus holding up the foot, and during the stance phase the AFO would release its hold [5]. This AFO was important because its goal was to recreate a normal gait cycle, even when being used on inclined surfaces. The power supply
for this AFO is not mentioned in the paper, so the practical effectiveness of this kind of damper is hard to measure.

Air muscles are not new, but their excellent strength-to-weight ratio has renewed interest in the technology during recent years. In 2005 air muscles were used by University of Michigan researchers to create an AFO [9] (Figure 2.4). It tackled the problem of plantar flexion, which is the motion opposite typical foot drop. The AFO was successful in that it did generate plantarflexion, but it was never tested on patients and the AFO had to be tethered because of computational and air supply limitations. The AFO was later adapted to include dorsiflexion, but the added air muscles made it impossible to wear a shoe at all.
Researchers at UIUC recently developed an AFO (Figure 2.6) that used a bladder to generate all the air pressure needed for the AFO, calling it the Pneumatic Power Harvesting Ankle-Foot Orthosis [6]. This AFO used a very small piston to mechanically lock the foot into a preferable position. This AFO is self-contained and relies purely on the mechanical action of walking to trigger its different states. Unfortunately the design was bulky and there was no variability: the device was either on or off.

2.2. Human Gait Analysis

Models of the foot are invaluable in the design of an AFO. Using a simplified 2-D approach, approximate models of the ankle-foot joint, as well as simple actuators, have been made in the past. The effects of foot drop on the gait cycle have also been simulated. By generating an accurate model of the injured system it should be possible to add on simplified models of an AFO so that any effects on the gait could be predicted. Thus far this has only been done to illustrate how a pre-decided actuator would have to work, and has not been used for comparison. [3]

Human gait analysis is currently confined to a laboratory. The technology has come a long way in its relatively short life span, but the emphasis has always been on more
precise and more accurate data, which has made the state of the art more and more
cumbersome to implement. Video motion capture is currently considered the best way to
evaluate joint angles and positioning of body parts. With the use of reflective markers and
expensive tracking systems human gait tracking has become more accessible, but as stated
before study is still confined to the laboratory. Examples of these gait studies can be found
in [12-18].

However, not all research is moving in this direction. Some studies have used
gyroscopes or accelerometers to determine gait percentage, but because of accelerometer
and gyroscope drift their accuracy is currently questionable, and the data is really only
useful for predicting relative angles between sensors. It is also important to note that all of
these studies use video capture to evaluate the systems. Examples of accelerometer-based
gait studies can be found in [19-25].

As the number of usable measuring systems in the motion capture field have
increased, so have the ways in which the coordinate systems of these devices have varied
[19]. However, because the coordinate system was often left out of the final report on each
device, the usefulness of most of the published data to this study was limited. A useful
study [19], which reported not only input joint angles but also the coordinate system,
included angle data of 20 adults (9 male, 11 female), whose ages ranged from 27–72. In
terms of its population, this study is useful to our dynamic analysis of ankle momentum in
Chapter 3 Gait Analysis, because it represents the forces that someone with foot drop
would not be producing, or the forces an AFO would have to replace. This study also
addressed the importance of using a standardized coordinate system, also explained later in Chapter 3.

2.3. Terrain Detection

Currently, terrain detection seems to be limited to the field of robotics. Three-dimensional scanning with laser scanners, infrared scanners, or live video is not uncommon in the field of self-navigating robotics. These techniques require a relatively powerful computer to accurately predict upcoming terrain in real time. There has been some investigation of simpler means of terrain detection, but this is often limited to object avoidance rather than terrain mapping. The current path that terrain detection is taking is much like human gait analysis: As time goes on, the field has become more complicated and more accurate, but little thought has been given to simple classification of different types of terrain into broad families. Examples of such studies can be found here [26 - 33].

2.4. Gaps in Literature

The major gap in the literature was the lack of a design process. Previous research relied heavily on an assumed actuator, and thus there has been no published investigation into the best actuator for the AFO. Additionally any investigation to see if there was a common problem that most AFO users were aware of was limited at best. This project interviewed medical professionals and patients to determine some common problems they had witnessed with their own AFOs or in prescribing AFOs. The interviews gave insight into the problems faced by a broader range of patients, making this research more applicable to a larger population.
The problem identified by the interviews is also an area of limited research, namely an AFO that adapts to changing terrain. Developers of all of the AFOs studied are investigating methods by which the AFOs could change their stiffness over time. The focus of this project, then, is to determine when that change should occur, by building a terrain detection system. Other terrain detection systems exist, but they are far too slow and complicated to work in this small application. They focus on robotic movement, and therefore require more information about the approaching terrain than just identifying a type of terrain.
3. Gait Analysis

3.1. Quasistatic Analysis

This analysis will focus on the moment at the ankle during a normal swing phase. This is important to our study because it will provide a good estimation of the lower bound on forces that an AFO would need to replace, assuming the ankle is no longer functioning, and that the motion is slow enough for rotational inertia effects to be discarded. The assumptions for this analysis were:

- 2D system
- Only swing
- No resistive forces associated with the joints
- No dynamic effects

Healthy adult gait data from [19] was used in conjunction with Foot characteristics which are summarized in Table 3.1, representing a 50th-percentile man. These values could easily be changed to accommodate a specific user base. Figure 3.1 represents the given coordinate system that is associated with [19].

Table 3.1 Foot Data [34]

<table>
<thead>
<tr>
<th>Link Mass $m_f$ (kg)</th>
<th>Link Length $L_f$ (m)</th>
<th>Distance to COM $a_f$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swinging Foot</td>
<td>1.67</td>
<td>0.15</td>
</tr>
</tbody>
</table>
To find the static moment associated with the ankle it is first necessary to find the angle between the ankle and level ground. The pelvic angle ($\theta_P$) is measured with respect to level ground and the hip angle ($\theta_H$) is based off of the pelvic angle so it is possible to work out the ankle angle with respect to level ground. This is shown in Figure 3.2 and Equations 3.1 - 3.5

$$\theta_{XOA} = 180^\circ - \theta_P + 90^\circ + \theta_H$$  \hspace{1cm} (3.1)

$$\theta_{XAB} = \theta_{XOA} - \theta_N$$  \hspace{1cm} (3.2)
\[ \theta_{XBC} = \theta_{XAB} + 90^\circ + \theta_F \]  

(3.3)

\[ \theta_{XBC} = 180^\circ - \theta_P + 90^\circ + \theta_H - \theta_N + 90^\circ + \theta_F \]  

(3.4)

\[ \theta_{XBC} = -\theta_P + \theta_H - \theta_N + \theta_F \]  

(3.5)

The result of this expression can be seen in Figure 3.3, and represents the angle of the ankle with respect to level ground during the swing phase of the gait cycle. Now that the angle is known we can do a moment analysis using the center of mass and Figure 3.4 as our free body diagram. The results of this can be seen in Figure 3.5 a maximum moment of .9 Nm about the ankle represents that moment that would need to be replaced during the swing of a foot moving with minimal acceleration.

Figure 3.3 Angle of Foot to Ground \( \theta_{XBC} \)
Figure 3.5 Quasistatic Moment about the Ankle
3.2. Dynamic Analysis of Gait

A secondary analysis was performed to determine the dynamic force that an AFO would need to provide during the swing phase. This was done as a way to find the upper bound on the moment that could be expected. The assumptions for this analysis were:

- 2D system
- Only swing
- No resistive forces associated with the joints

This analysis requires more anthropometric data than the quasistatic analysis, which is shown in Table 3.2. These values could easily be changed to accommodate a specific user base. A schematic is shown in Figure 3.6.

Table 3.2 Body Characteristics [34]

<table>
<thead>
<tr>
<th>Link No.</th>
<th>Corresponds to</th>
<th>Link Mass $m_i$ (kg)</th>
<th>Link Length $L_i$ (m)</th>
<th>Distance to COM $a_i$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Stationary Calf</td>
<td>3.37</td>
<td>0.473</td>
<td>0.186</td>
</tr>
<tr>
<td>2</td>
<td>Stationary Thigh</td>
<td>7.02</td>
<td>0.441</td>
<td>0.188</td>
</tr>
<tr>
<td>3</td>
<td>Swinging Thigh</td>
<td>7.02</td>
<td>0.441</td>
<td>0.253</td>
</tr>
<tr>
<td>4</td>
<td>Swinging Calf</td>
<td>3.37</td>
<td>0.473</td>
<td>0.287</td>
</tr>
<tr>
<td>5</td>
<td>Swinging Foot</td>
<td>1.67</td>
<td>0.15</td>
<td>0.076</td>
</tr>
</tbody>
</table>
In this analysis the legs will be broken up into five links (Figure 3.6). Each link’s angle is measured with respect to vertical, as shown. Using the healthy adult gait data from [19] and LaGrange’s method, the moment about the z-axis on the foot at the ankle is calculated.
LaGrange’s method is a very powerful systematic approach to solving dynamic mechanical systems by differentiating the kinetic and potential energies of a system. LaGrange’s method will output the necessary force for these energies to arise. LaGrange’s method is summarized in Equation (3.6).

$$\frac{d}{dt} \left( \frac{\partial T}{\partial \dot{q}_i} \right) - \frac{\partial T}{\partial q_i} + \frac{\partial R}{\partial q_i} + \frac{\partial V}{\partial q_i} = Q_i$$

To find the total kinetic energy of the system, it is first necessary to find the velocity of each link’s center of mass. To do this we will use the geometry of the links and differentiate to get the velocity of each link.

$$x_1 = a_1 \sin \theta_1$$

$$y_1 = a_1 \cos \theta_1$$

Figure 3.6 Diagram of double leg single support model positive rotation
\[ x_2 = a_2 \cos \theta_2 + l_1 \cos \theta_1 \quad (3.9) \]
\[ y_2 = a_2 \sin \theta_2 + l_1 \sin \theta_1 \quad (3.10) \]
\[ x_3 = a_3 \cos \theta_3 + l_2 \cos \theta_2 + l_1 \cos \theta_1 \quad (3.11) \]
\[ y_3 = a_3 \sin \theta_3 + l_2 \sin \theta_2 + l_1 \sin \theta_1 \quad (3.12) \]

The remaining locations can be generated by following the pattern set by the previous equations.

\[ v_i^2 = \left( \frac{dx_i}{dt} \right)^2 + \left( \frac{dy_i}{dt} \right)^2 \quad (3.13) \]
\[ T_i = \frac{1}{2} m_i v_i^2 \quad (3.14) \]
\[ T_1 = \frac{1}{2} m_1 (a_4 \dot{\theta}_1)^2 \quad (3.15) \]
\[ T_2 = \frac{1}{2} m_2 \left( (a_2 \dot{\theta}_2 \sin \theta_2 + l_1 \dot{\theta}_1 \sin \theta_1)^2 + (a_2 \dot{\theta}_2 \cos \theta_2 + l_1 \dot{\theta}_1 \cos \theta_1)^2 \right) \quad (3.16) \]
\[ T_3 = \frac{1}{2} m_4 \left( (a_3 \dot{\theta}_3 \sin \theta_3 + l_2 \dot{\theta}_2 \sin \theta_2 + l_1 \dot{\theta}_1 \sin \theta_1)^2 \right. \\
\[ \left. + (a_3 \dot{\theta}_3 \cos \theta_3 + l_2 \dot{\theta}_2 \cos \theta_2 + l_1 \dot{\theta}_1 \cos \theta_1)^2 \right) \quad (3.17) \]
\[ T_4 = \frac{1}{2} m_4 \left( (a_4 \dot{\theta}_4 \sin \theta_4 + l_3 \dot{\theta}_3 \sin \theta_3 + l_2 \dot{\theta}_2 \sin \theta_2 + l_1 \dot{\theta}_1 \sin \theta_1)^2 \right. \\
\[ \left. + (a_4 \dot{\theta}_4 \cos \theta_4 + l_3 \dot{\theta}_3 \cos \theta_3 + l_2 \dot{\theta}_2 \cos \theta_2 + l_1 \dot{\theta}_1 \cos \theta_1)^2 \right) \quad (3.18) \]
\[ T_5 = \frac{1}{2} m_5 \left( (a_5 \dot{\theta}_5 \sin \theta_5 + l_4 \dot{\theta}_4 \sin \theta_4 + l_3 \dot{\theta}_3 \sin \theta_3 + l_2 \dot{\theta}_2 \sin \theta_2 \right. \\
\[ \left. + l_1 \dot{\theta}_1 \sin \theta_1)^2 \right. \\
\[ \left. + (a_5 \dot{\theta}_5 \cos \theta_5 + l_4 \dot{\theta}_4 \cos \theta_4 + l_3 \dot{\theta}_3 \cos \theta_3 + l_2 \dot{\theta}_2 \cos \theta_2 + l_1 \dot{\theta}_1 \cos \theta_1)^2 \right) \quad (3.19) \]
\[ T = \sum_{i=1}^{5} T_i \quad (3.20) \]
Once we obtain the total potential energy, we can use the geometric information that we gained in solving for velocity to make our potential energy calculations simple.

\[ V_i = gm_i(y_{imax} - y_i) \]  
\[ V_1 = gm_1(a_1 - a_1 \cos \theta_1) \]  
\[ V_2 = gm_2(a_2 + l_1 - a_2 \cos \theta_2 - l_1 \cos \theta_1) \]  
\[ V_3 = gm_3(a_3 + l_2 + l_1 - a_3 \cos \theta_3 - l_2 \cos \theta_2 - l_1 \cos \theta_1) \]  
\[ V_4 = gm_4(a_4 + l_3 + l_2 + l_1 - a_4 \cos \theta_4 - l_3 \cos \theta_3 - l_2 \cos \theta_2 - l_1 \cos \theta_1) \]  
\[ V_5 = gm_5(a_5 + l_4 + l_3 + l_2 + l_1 - a_5 \cos \theta_5 - l_4 \cos \theta_4 - l_3 \cos \theta_3 - l_2 \cos \theta_2 - l_1 \cos \theta_1) \]  
\[ V = \sum_{i=1}^{5} V_i \]

Assuming there are no resistive forces (such as a damper)

\[ R = 0 \]

Because we are interested only in what is happening to link 5, we will only need to solve this equation once in terms of link 5, meaning:
Finally, differentiating and simplifying Equation 3.6 yields the moment equation for joint 5.

\[
M_5 = a_5m_5 \left( \ddot{\theta}_1 l_1 \cos(\theta_1 - \theta_5) + \ddot{\theta}_2 l_2 \cos(\theta_2 - \theta_5) + \ddot{\theta}_3 l_3 \cos(\theta_3 - \theta_5)
+ \dot{\theta}_4 l_4 \cos(\theta_4 - \theta_5) + a_5 \ddot{\theta}_5 - \dot{\theta}_1^2 l_1 \sin(\theta_1 - \theta_5)
- \dot{\theta}_2^2 l_2 \sin(\theta_2 - \theta_5) - \dot{\theta}_3^2 l_3 \sin(\theta_3 - \theta_5)
- \dot{\theta}_4^2 l_4 \sin(\theta_4 - \theta_5) + g \sin(\theta_5) \right)
\]

To get meaningful data out of this equation, gait data was taken from [19]. The data's coordinate system for each angle is different from our model. Figure 3.7 represents

Figure 3.7 Diagram of double leg single support model positive
their coordinate system, and Equations 3.33–3.37 represents the necessary shifts that must be made to the data.

\[ \theta_1 = 180 - (\theta_a - \theta_b) \]  
\[ \theta_2 = \theta_b + 180 \]  
\[ \theta_3 = \theta_c \]  
\[ \theta_4 = \theta_c - \theta_d \]  
\[ \theta_5 = 180 - (\theta_e + \theta_d - \theta_c) \]  

(3.33)  
(3.34)  
(3.35)  
(3.36)  
(3.37)

Once the angles have been shifted and a gait speed has been established, polynomial lines can be fit to the data so that the resulting curves (Figure 3.8) can be differentiated to yield speed (Figure 3.9) and acceleration. All these results are fed into the equation for \( M_5 \). For usability and convenience in future work, the angular velocity of the healthy ankle joint has been plotted (Figure 3.9), because it provides a good estimation for the timing and an upper bound on the speed at which an actuator would need to perform.
Figure 3.8 Shifted to Consistent Coordinate System and Fit to Polynomials
Figure 3.9 Angular Velocity of the Ankle Joint

The plot in Figure 3.10 of M₅ is shown below. This plot shows that the maximum torque that an AFO would have to withstand during swing is somewhere around 3 Nm. This fits with our quasistatic analysis (Figure 3.11), as the inertial forces increase the torque necessary to move the foot.
Figure 3.10 Dynamic Analysis of Moment $M_5$ about the Ankle Joint during Swing Phase

Figure 3.11 Quasistatic Analysis of Moment about the Ankle due to Gravity and Positioning
3.3. Terrain Detection Feasibility Model

The purpose of this section is to utilize the existing pendulum model and angle conversions to test the feasibility of an ankle mounted distance sensor. By looking at this data the kind of differences to be expected from an ankle mounted distance sensor can be determined, as well as the range of distance sensor that would be necessary to measure the upcoming ground. Figure 3.12 - Figure 3.13 represents the starting conditions and terrain profiles being considered for this feasibility study, namely walking on level ground, down stairs, and down a ramp. Kinematic data for level walking and down ramp were taken from [19]. Data for down stairs was limited so the data from down ramp was used and only the ground profile was changed. It is important to note that each case starts out on level ground and is only able to observe the initial step over the intended ground type.

Figure 3.15 represents the length of the red line, or the distance being measured, for each case. It
is important to note that a difference between the terrain profiles is noticeable when the feet start to swing out over the new terrain (approximately 40% of the gait cycle), and that the distances measured range from 20cm to 80cm. Another observation is that if the sensors in the experiment had been pointed out further in front of the legs the detection of a different terrain would happen sooner.

Figure 3.15 Distance Detected From Different Walking Cases
4. Experimental Method

4.1. Introduction

This section outlines the tools and procedures used for collecting voltage data to be tested by our algorithms. In this project three attempts are made at comparative experiments, each testing a different way to characterize the data: while recording just a single IR sensor, recording the IR sensor and a piezo electric plate, and recording two different kinds of IR sensors. The purpose of these experiments was to improve upon the automation of the characterization of the data (Table 4.1). As such, the procedures for each experiment are very similar.

Table 4.1 Experiment Sensor Summary

<table>
<thead>
<tr>
<th>Experiment #</th>
<th>First Sensor</th>
<th>Second Sensor</th>
<th>Ground Type Identification</th>
<th>Predictions Successful</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run 1</td>
<td>IR: GP2Y0A02YK</td>
<td>N/A</td>
<td>Yes</td>
<td>Not Attempted</td>
</tr>
<tr>
<td>Run 2</td>
<td>IR:GP2Y0A02YK</td>
<td>Piezo electric plate</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Run 3</td>
<td>IR:GP2Y0A02YK</td>
<td>IR:GP2D12</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

4.2. Devices Used

Voltage data for each experiment was recorded using a personal measurement device, PMD-1208LS, shown in Figure 4.1. The data was stored on a laptop for later processing. On channel one in each experiment was a Sharp GP2Y0A02YK infrared range finder, shown in Figure 4.2, which...
has an effective measuring range of 20 to 150cm. Both devices were attached to a Fitness Gear calf/shin support brace. The first experiment had no added sensor. The second experiment had a piezo electric plate, harvested from a 87dB piezo Radio Shack pulse buzzer model 273-080 shown in Figure 4.3, attached to channel two of our PMD-1208LS. For the third experiment, a second infrared range finder was attached to channel two in place of the piezoelectric plate. This is a digital range finder, the Sharp GP2D12 shown in Figure 4.4. Its effective range is 10–80cm: at 10cm the device switches from high to low, while the device will not pick up anything beyond 80cm. Figure 4.5 shows the full system assembly.

4.3. Device Wiring and Layout

The wiring layouts of the three experiments can be seen in Figure 4.6- Figure 4.8. It is important to note that the PMD-1208LS is connected to a PC through a USB-b cable. Once the device has been wired together, it can be attached to the Fitness Gear Adjustable Calf/Shin Support as shown in Figure 4.9.
Figure 4.5 Proper Brace Attachment
Figure 4.6 Experiment 1 Wiring Diagram
Figure 4.7 Experiment 2 Wiring Diagram
Figure 4.8 Experiment 3 Wiring Diagram

IR Sensor 1
GP2Y0A02YK-9

IR Sensor 2
GP2D12-8
Figure 4.9 Sensor Attachment for (a) Experiment 1: Single IR Sensor, (b) Experiment 2: Single IR Sensor and Piezoelectric plate in shoe, and (c) Experiment 3: Two IR Sensors
4.4. Walking Scenarios

Once the devices have been attached and correctly installed, data was collected for a variety of scenarios:

- Level walking: Recorded for approximately 20 seconds. Avoided walking right next to walls or chair legs, as these objects might be picked up by the sensor.
- Up and down stairs: Recorded a flight of stairs, ensuring that the leg without the device leads, as this will likely be the case for someone with an injured leg.
- Up and down ramps: Recorded for approximately 20 seconds up or down a ramp.
- Long walk, multiple terrain types to be differentiated (e.g., down ramp, up ramp, level, upstairs, level).
5. Terrain Characterization Method

5.1. Introduction

At the core of this project is the need to automatically fit repetitive data to a model as the data are being collected. This section describes a straightforward method to develop a model based on previously collected full data sets. This chapter presents the methods and techniques used to characterize the training data sets, as well as the thought process behind the model type and algorithm choice. A description of the prediction algorithm is presented in Chapter 7.

5.2. Fourier Series

A Fourier series uses harmonic sin and cos combinations to form a curve. This curve is completely repeatable along a scalable period. Much like a polynomial fit, a Fourier series’ order can be increased to produce tighter fit characteristics. Figure 5.1 shows that, by increasing the order of the function, the Fourier series is better able to approximate the shape of the square wave. As with other fitting methods, it is entirely possible to overfit data. If the order of the equation is increased too much, it also can add unnecessary complications to the fit itself.

Figure 5.1 Fourier Series Example (A) 1st order, (B) 2nd order, (C) 3rd order, (D) 4th order
The reason that a Fourier series is used for the model fitting in this project over other types of models (e.g., polynomial) is that a patient’s gait speed is expected to fluctuate but the observation from the perspective of the ankle should remain the same. Thus, by employing a model that is inherently capable of scaling itself in the time domain, we can eliminate complexity in our system, which is very important for a system that will eventually be portable.

In this analysis, we are using a fourth-order Fourier approximation. Third- and fifth-order approximations were attempted and their results can be seen in Figure 5.2.

---

**Figure 5.2 Fourier Order Comparison**

<table>
<thead>
<tr>
<th>Order</th>
<th>RMS Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>3rd</td>
<td>0.049</td>
</tr>
<tr>
<td>4th</td>
<td>0.033</td>
</tr>
<tr>
<td>5th</td>
<td>0.025</td>
</tr>
</tbody>
</table>
The third-order approximation is not as accurate as the fourth- and fifth-order approximations. When comparing the fourth to the fifth, we see that there is really no considerable difference in accuracy. However, the fifth-order approximation adds to the computational time required to predict the approaching terrain type. For each data point an additional two calculations per point are necessary, which is a 20% increase in calculations per point. Thus, a fourth-order Fourier series approximation will be used, the general form of which can be seen in Equation (5.1). The $a_i$ and $b_i$ terms are the Fourier coefficients; $t$ is time; and $w$, which is the period of the curve.

$$f(t) = a_0 + a_1 \sin(tw) + b_1 \cos(tw) + a_2 \sin(2tw) + b_2 \cos(2tw) + a_3 \sin(3tw) + b_3 \cos(3tw) + a_4 \sin(4tw) + b_4 \cos(4tw)$$

(5.1)

It is important to note that when the fitting occurs, the data that the curves will have been fit to do not necessarily start at time = 0 or a particular common point in the gait cycle. It is necessary to be able to time-shift our curves. To do this we will be using the angle sum-difference formulas, shown in Equations (5.2) and (5.3).

$$\sin(\alpha \pm \beta) = \sin \alpha \cos \beta \pm \cos \alpha \sin \beta$$  

(5.2)

$$\cos(\alpha \pm \beta) = \cos \alpha \cos \beta \mp \sin \alpha \sin \beta$$

(5.3)

Time $t$ in Equation (5.1) will be split into time and an offset $t_0$, as shown in Equation (5.4). The sum-difference formulas can be used to separate and calculate new time-shifted Fourier coefficients, the result of which can be seen in Equations (5.5). Examples of the separated coefficients can be seen in Equations (5.6) and (5.7).
\[ f(t) = a_0 + a_1 \sin((t + t_0)w) + b_1 \cos((t + t_0)w) + a_2 \sin(2(t + t_0)w) \\
+ b_2 \cos(2(t + t_0)w) + a_3 \sin(3(t + t_0)w) \\
+ b_3 \cos(3(t + t_0)w) + a_4 \sin(4(t + t_0)w) \\
+ b_4 \cos(4(t + t_0)w) \]

(5.4)

Using the angle addition relations shown in (5.2) and (5.3) and algebraic manipulation, yields:

\[ f(t) = a_0 + (a_1 \cos(t_0w) - b_1 \sin(t_0w)) \sin(tw) \]
\[ + (b_1 \cos(t_0w) + a_1 \sin(t_0w)) \cos(tw) \]
\[ + (a_2 \cos(2t_0w) - b_2 \sin(2t_0w)) \sin(2tw) \]
\[ + (b_2 \cos(2t_0w) + a_2 \sin(2t_0w)) \cos(2tw) \]
\[ + (a_3 \cos(3t_0w) - b_3 \sin(3t_0w)) \sin(3tw) \]
\[ + (b_3 \cos(3t_0w) + a_3 \sin(3t_0w)) \cos(3tw) \]
\[ + (a_4 \cos(4t_0w) - b_4 \sin(4t_0w)) \sin(4tw) \]
\[ + (b_4 \cos(4t_0w) + a_4 \sin(4t_0w)) \cos(4tw) \]

(5.5)

\[ a_{1t_0} = a_1 \cos(t_0w) - b_1 \sin(t_0w) \]

(5.6)

\[ b_{1t_0} = b_1 \cos(t_0w) + a_1 \sin(t_0w) \]

(5.7)

A graphical representation of what these new coefficients allow us to do can be seen in Figure 5.3 Time-shifting Example. (a) is the initial sequence of non–time-shifted Fourier curves, (b) shows the curves being shifted to a common low point, (c) shows the effect of scaling by gait period.
5.3. **RANSAC**

RANSAC stands for RANdom SAmple Consensus [35]. It is a model-fitting algorithm developed for fitting models to noisy or inconsistent data. It works by first fitting a random sub-sample of points to a model, then comparing the rest of the data to this model and

---

**Figure 5.3** Time-shifting Example

**Figure 5.4** RANSAC Example (a) Original data Set (b) Blue inliers; Red outliers; Line is the accepted model
determining a set of inliers. If this set is sufficiently large enough, its error is calculated and compared among other models that have passed the initial criteria. The best model at the end of this process is then reported as the model for that data set. This process has been illustrated in Figure 5.4.

There are five key inputs to RANSAC:

1. The data to be fit
2. The minimum number of random points needed to generate a model
3. Tolerance for what will define an inlier and outlier
4. The minimum number of points in the data set that must fit the model for it to be considered
5. The number of iterations that must be completed for the algorithm to statistically produce the correct model

It is important to note that the more iterations that are completed by RANSAC, the more likely the algorithm is to produce the correct model. In addition to these values, an additional guess on the length of a gait will be used to help reduce the number of iterations necessary to produce a useful model. The generation of these values and how they will be applied to the algorithm will now be discussed.

5.3.1. RANSAC Coefficients

Table 5.1 contains a summary of the general approach taken for generating the RANSAC coefficients.
Table 5.1 RANSAC Coefficients

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tolerance</td>
<td>19%</td>
</tr>
<tr>
<td>Min Random # of Points</td>
<td>55% of # of points in a step</td>
</tr>
<tr>
<td>Min Points for Model</td>
<td>55% of # of points in data set</td>
</tr>
<tr>
<td>Number of Iterations</td>
<td>300</td>
</tr>
</tbody>
</table>

The accepted way to calculate the necessary tolerance for the RANSAC algorithm is trial and error [35]. It is generally considered an unworkable problem to determine the error analytically, as the error depends on the specific data being used and the model generated from the data. The optimal tolerance for a problem is also not very important, as changing its value has a relatively small impact on the overall outcome of the points selected.

The RANSAC algorithm calls for the minimum number of points to be used to generate a model [35]. In this case, because the data are being fit to a fourth-order Fourier series, the minimum number of points to be fit is four. This increased the number of iterations that are necessary and reduced the ability of the algorithm to produce models with all of the prominent features that the data was showing.

The number of points for a good model needs to be determined through trial and error. The goal is to eliminate models that would otherwise have better errors than a correct model because they have fewer points to cause more error [35].

The number of iterations (k) is a function of the probability of picking a good data point (w) and the number of good data points selected (n), as shown in Equation (5.8) [35].
For our purposes it is assumed that there is a 95% chance of picking a good point and our sets of good points have been observed to consist of about 110 points. According to Equation (5.8) we should complete 282 iterations. This was rounded up to 300.

\[ k = w^{-n} \]  

(5.8)

5.4. Gait Recognition

5.4.1. Introduction

A reliable way to estimate the user’s gait speed is vital to this project. In order to effectively model gaits using the RANSAC method described previously, it is important to know the subject’s gait period. This raises the question of how to estimate the speed at which someone is walking. Additionally, we need to determine how to apply this method in an on-demand manner, as opposed to after-the-fact analysis.

Three methods for applying RANSAC with gait estimation will be discussed, one analytical method and two sensor-based methods. The two sensor-based methods are detailed in Section 4.1. The analytical method is based on simple trial and error, paired with an Fminsearch technique to re-evaluate the analytical estimation. The first sensor method uses a piezo electric plate with a simple algorithm to detect foot strikes. The final sensor method uses a second IR sensor to detect foot contact with the ground.

5.4.2. Fminsearch Method

This first attempt at estimating gait period was to generate our models while manually guessing at the gait period, and running the RANSAC process multiple times until
proper input values could be established on a per-data-set basis. Unfortunately, by using a guess there was no algorithm to determine the proper method of finding the gait period, and no real estimation on how successful it was. However, when we first compared our models to live data, some algorithms using the Fminsearch function in Matlab were investigated for their ability to estimate gait speed after the fact.

Fminsearch is a minimization tool. The tool is provided with an error function dependent on some set of variables, along with initial guess values, and the tool finds the local minimum error value. In all of these scenarios we have the five-model function $f_i$. Each model function is dependent on time $t$ and period $w$, but because the time length that each function is being compared to is the same it will not be present in any of the error functions. Each function will be compared to $\bar{x}$, which represents the voltage data.

In our first case, the error function consisted of five least squares errors for each of the five models (Equation (5.9)). The error function is dependent on the individual periods of the Fourier series. This would produce five different but hopefully similar period values that could later either be averaged or used as is.

$$
error = \frac{\sum_{i=1}^{5} \sqrt{(f_i(w_i) - \bar{x})^2}}{5}
$$

Due to high sampling rates and high variability of the error function, running a single set of data consisting of only a two to three steps could take hours, so this method was not used in the final model. The length of time involved was a result to the program
attempting to investigate the relationship of five separable functions at the same time. If a less powerful tool had been investigated the outcome might have been more successful.

This problem was tackled in two ways. The first was to run each equation separately though the Fminsearch (Equation (5.10)). However, the drawback of this method was its inability to pick a consistent period. Each curve, though appearing similar around the target range, focused on wildly different periods. Thus, deciding how much further to look into the data to predict which model fit best was almost impossible.

\[
error_i = \sqrt{(f_i(w_i) - \bar{x})^2}
\]  

(5.10)

Another solution was to combine the error functions into one function so that Fminsearch would only report one value for the period, which would be the one with the lowest error all around. While this almost worked (Equation (5.11)), it often weighed heavily towards longer periods than necessary based on how the slopes combined. The run time for this algorithm was also unacceptably long, ranging in the minutes for a sample that was only 20 or so seconds long.

\[
error = \sum_{i=1}^{5} \sqrt{(f_i(w) - \bar{x})^2}
\]  

(5.11)

5.4.3. Piezo Electric Plate Method

The next approach relied on the addition of a piezo electric sensor to detect heel strike and used the data from experiment 2 described in Section 4.2. The time between heel strikes can be used to calculate the gait period directly. A sensor would need to be
added with the explicit purpose of detecting when the patient’s foot was making contact with the ground. At heel strike a pulse from the plate would be given off. This pulse could be tracked as a way to determine roughly how fast the patient was walking by looking for successive pulses at regular intervals.

The plate turned out to be too noisy due to momentum effects, with a comparison shown in Figure 5.5 and Figure 5.6. Additionally the spike would regularly fail to create a large enough pulse. This would happen, for example, when walking down stairs and ramps, because people tend to land toe first, and since the plate was not at the location making contact with the ground, the spike produced was difficult to distinguish from noise.

![Figure 5.5 Level Ground Walking Data with Minimal Momentum Spikes](image)

Figure 5.5 Level Ground Walking Data with Minimal Momentum Spikes
In order to address the false spike issue, an algorithm to identify the first maximum spike in the data set was adopted. This spike would then become the threshold height for the rest of the steps. A second step would then be defined as being a local maximum above the threshold set by the first step. During this process, the program would be searching for a new first step, which occurred when a spike was above the current first step’s voltage by more than 25%. Once a first and second step had been determined, the program would use this first period to estimate the location of the next step. A local maximum would be found in the area around this guess. If it was within tolerance, the algorithm would register this step as successfully observed, adjust the period, and take another guess. If the algorithm positively identified more steps than more failures to detect a step, it would register this as a success and the algorithm would end and return the observed value for the period. If it was not a success the algorithm would abandon the first observed step and look for a new first step. The process is repeated until it either finds an acceptable period or runs out of data, in which case the best guess on the period would be returned.
This algorithm proved very useful in that for the majority of cases it would find and report a period. It was not always the correct period, but an answer was always returned. The problem with this method was that it relied too much on having a large set of data which was not the case in scenarios, such as ascending and descending stairs where the number of stairs was limited. There was also no good way to determine when the foot was on the ground or in the air, as the first strike was not always distinct enough to be counted. This method could have been improved through the use of filters, but a better option became apparent before this was tried.

5.4.4. Secondary IR Range Finder Method

The third method of characterizing gait and predicting period was the third method outlined in Section 4.3. The addition of a second IR sensor, aimed directly down, toward the ground enabled us to quickly and accurately determine if the patient’s foot was on the ground, which not only provided the information on how fast the patient was walking, but also if the patient was standing still, a valuable piece of information not yet captured by our other sensors. The only drawback to this sensor was its occasional tendency to register false “foot off the ground” readings.

Three algorithms were written to determine the pace and the location of the target foot, as well as to determine if there was a false reading. The first took a filtered approach to the situation. False step readings typically registered as very short steps. To eliminate this effect, a piece of code that simulates the use of an RC circuit with a time constant of about 0.1 was implemented. This acted as a low-pass filter to excise the quick changes that occur when a false step is taken.
Once the data were sanitized in this fashion a cutoff voltage of .4 was used to determine the difference between the high and low voltage. The program scanned the data for matching high/low situations. A statistical analysis, consisting of computing the standard deviation and looking for outliers, was done. This usually eliminated the first step, as it had a period of inactivity within it and would negatively affect the average pace. This algorithm worked very well; its simplistic design made it very robust and eliminated the need for logic gates, which could be faulty. The only problem with this approach was that it introduced a time shift of about .03 seconds to the data due to the transience of the filter. This delay might not seem large, but when the algorithm run time is only .003 seconds for an entire data set, the .03 seconds added up.

\[ \tau = \frac{1}{RC} \]  

(5.12)
The next algorithm took a statistical approach to the problem. By finding the mean and standard deviation pace of all samples, it was able to determine outliers above and below one standard deviation. However, this method had several drawbacks. The first was that it was slightly slower than the filtered approach, because of the time required to count extra steps as well as having more steps to count to calculate the mean and standard deviation. The algorithm also produced differing results for the overall pace because it tossed out a section of step. This became more apparent when the error occurred toward the middle of a step, and could also cause the algorithm to count it as two steps if split properly.

The final algorithm looked for too-small steps and attempted to mend the data by setting a minimum length for a step. Depending on which part of the gait cycle the algorithm detects the error in, the algorithm will take actions to fix the problem if a step falls beneath this threshold. While this algorithm has to relook at sections of the data, it has proven to be faster than having to deal with an extra step later at the mean and standard deviation area of the code. It does not add any delay to the data, and is good for determining specifically when the foot is on and off the ground. This final algorithm was eventually selected as the algorithm to use. A flow chart of its parts and logic gates can be seen in Figure 5.8. This algorithm reports not only the number of data points that can be seen in a single step, but also reports the location of the steps within the data. This will be useful later because the models will need to be time-shifted back to a common area. This process will be discussed in further detail in the modeling section of this paper.
Figure 5.8 Logic Flow Chart
6. Results


Each characterization method will be analyzed for its ability to reliably produce unique and similar models from different sets of data. The important numbers here will be mean and standard deviation of the Fourier coefficients produced. Table 6.1 shows the Fminsearch coefficients and a plot of these curves can be seen in Figure 6.1.

Table 6.1 Experiment 1 Model Results

<table>
<thead>
<tr>
<th></th>
<th>Level Walking</th>
<th>Descending Stairs</th>
<th>Ascending Stairs</th>
<th>Descending Ramp</th>
<th>Ascending Ramp</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>a0</td>
<td>1.7314</td>
<td>0.036</td>
<td>1.7674</td>
<td>0.055</td>
<td>1.882</td>
</tr>
<tr>
<td>a1</td>
<td>-0.413</td>
<td>0.038</td>
<td>-0.8048</td>
<td>0.061</td>
<td>-0.6051</td>
</tr>
<tr>
<td>b1</td>
<td>0.1255</td>
<td>0.029</td>
<td>0.0605</td>
<td>0.069</td>
<td>0.116</td>
</tr>
<tr>
<td>a2</td>
<td>-0.0667</td>
<td>0.029</td>
<td>-0.2609</td>
<td>0.045</td>
<td>-0.3043</td>
</tr>
<tr>
<td>b2</td>
<td>-0.0573</td>
<td>0.017</td>
<td>0.0947</td>
<td>0.052</td>
<td>-0.0077</td>
</tr>
<tr>
<td>a3</td>
<td>-0.1064</td>
<td>0.018</td>
<td>-0.0533</td>
<td>0.039</td>
<td>-0.0645</td>
</tr>
<tr>
<td>b3</td>
<td>-0.0821</td>
<td>0.014</td>
<td>-0.0447</td>
<td>0.026</td>
<td>0.0029</td>
</tr>
<tr>
<td>a4</td>
<td>-0.0748</td>
<td>0.007</td>
<td>-0.0242</td>
<td>0.015</td>
<td>-0.006</td>
</tr>
<tr>
<td>b4</td>
<td>0.0032</td>
<td>0.017</td>
<td>-0.0297</td>
<td>0.028</td>
<td>-0.0197</td>
</tr>
<tr>
<td>w</td>
<td>4.6902</td>
<td>0.283</td>
<td>4.4016</td>
<td>0.324</td>
<td>4.2268</td>
</tr>
</tbody>
</table>

w - 4.9935  0.2

The results of this portion of the experiment give us some insight into the plausibility of the system as a whole, but this experiment does not use any form of true automation and instead relies on post-processing of existing data sets. As such, this experiment does not say
anything about the reliability of the process other than that it is possible to produce unique Fourier coefficients for different types of terrain. It is important to note that while no comment can be made on the reliability of the process from this experiment, it is important that each coefficient in the set is unique from one another. This was determined by observing that none of the sets of coefficients are within a standard deviation of one another, as shown in the boxplots of the individual coefficients and their standard deviations in Figure 6.2. Although the coefficients are different, Level Walking and Down Ramp seem to be very similar. It is also important to note that while computing the average values for each coefficient a few outliers have been identified, as shown in the boxplots in Figure 6.2. An outlier was defined as being more than 75% away from the mean value. This caused a difference between means in the boxplots and means in the charts.
Figure 6.2 $a_0$-$b_4$ Probability distribution
6.2. Characterization of Curves Piezo Electric Plate

The experiment that used the piezo electric plate was useful to comment on the reliability of the process of generating models as it was a fully automated algorithm. The time shifting was all done using Fminsearch to find the common low point to synchronize the equations. The results of this are shown in Table 6.2, with mean and standard deviation of the Fourier coefficients reported.

Table 6.2 Experiment 2 Model Results

<table>
<thead>
<tr>
<th></th>
<th>Level Walking</th>
<th></th>
<th>Descending Stairs</th>
<th></th>
<th>Ascending Stairs</th>
<th></th>
<th>Descending Ramp</th>
<th></th>
<th>Ascending Ramp</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>a0</td>
<td>1.5553</td>
<td>0.022</td>
<td>1.7843</td>
<td>0.274</td>
<td>1.8376</td>
<td>0.03</td>
<td>1.6346</td>
<td>0.093</td>
<td>1.8976</td>
<td>0.025</td>
</tr>
<tr>
<td>a1</td>
<td>-0.4631</td>
<td>0.019</td>
<td>-0.7047</td>
<td>0.416</td>
<td>-0.4041</td>
<td>0.129</td>
<td>-0.5337</td>
<td>0.027</td>
<td>-0.245</td>
<td>0.024</td>
</tr>
<tr>
<td>b1</td>
<td>-0.0429</td>
<td>0.019</td>
<td>-0.0309</td>
<td>0.227</td>
<td>0.0624</td>
<td>0.039</td>
<td>-0.0891</td>
<td>0.051</td>
<td>0.1281</td>
<td>0.019</td>
</tr>
<tr>
<td>a2</td>
<td>-0.1618</td>
<td>0.01</td>
<td>-0.3016</td>
<td>0.261</td>
<td>-0.287</td>
<td>0.075</td>
<td>-0.1342</td>
<td>0.007</td>
<td>-0.054</td>
<td>0.029</td>
</tr>
<tr>
<td>b2</td>
<td>-0.0248</td>
<td>0.009</td>
<td>0.041</td>
<td>0.098</td>
<td>-0.0308</td>
<td>0.041</td>
<td>0.0014</td>
<td>0.024</td>
<td>-0.0242</td>
<td>0.01</td>
</tr>
<tr>
<td>a3</td>
<td>-0.1385</td>
<td>0.013</td>
<td>-0.0956</td>
<td>0.144</td>
<td>-0.0776</td>
<td>0.029</td>
<td>-0.1253</td>
<td>0.032</td>
<td>-0.0959</td>
<td>0.012</td>
</tr>
<tr>
<td>b3</td>
<td>-0.0235</td>
<td>0.004</td>
<td>-0.0055</td>
<td>0.055</td>
<td>0.027</td>
<td>0.013</td>
<td>-0.0285</td>
<td>0.016</td>
<td>-0.0444</td>
<td>0.007</td>
</tr>
<tr>
<td>a4</td>
<td>-0.0642</td>
<td>0.01</td>
<td>-0.0214</td>
<td>0.051</td>
<td>-0.0446</td>
<td>0.065</td>
<td>-0.0596</td>
<td>0.015</td>
<td>-0.0633</td>
<td>0.006</td>
</tr>
<tr>
<td>b4</td>
<td>0.0408</td>
<td>0.005</td>
<td>-0.0086</td>
<td>0.059</td>
<td>-0.0205</td>
<td>0.028</td>
<td>0.0429</td>
<td>0.013</td>
<td>0.0134</td>
<td>0.008</td>
</tr>
</tbody>
</table>

The results of this experiment show that it is possible to automate the curve-fitting process. With the exception of Descending Stairs, which had the most variability by far, the average values and

Figure 6.3 Descending Stairs with erroneous models
standard deviations are distinct. With Descending Stairs (Figure 6.3), erroneous models were selected. These models, however, do not significantly impact the average model that is produced. The significance of this is that a single training run cannot be used to determine the overall model.

Part of the problem is that the algorithm is detecting false gait speeds (Figure 6.4). The multiple spikes cause the algorithm to look at false intervals for models, which ends up generating bad models. A way to eliminate these spikes could be to use a larger plate, covering more of the foot, or adding some filtering to the spikes to eliminate the smaller spikes.

Despite these few bad models, the results are overall still useful Figure 6.5 shows the terrain curves and Figure 6.6 shows the boxplots of the Fourier coefficients. It is important to note the similarity between level walking and walking down a ramp. Because of the inaccuracy of the step detection, predictions for this data set were never completed.
Figure 6.6 $a_0$-$b_4$ Probability Distributions
6.3. Characterization of Curves Second IR Sensor

The experiment that used the second IR sensor to detect heelstrike is capable of producing reliable results as a fully automated algorithm. The time shifting in this experiment used the known position of the foot to determine the optimal shifting time; this is significant because it adds to the uniqueness of each curve. The statistical results of the fitting are shown in Table 6.3.

Table 6.3 Experiment 3 Model Results

<table>
<thead>
<tr>
<th></th>
<th>Level Walking</th>
<th>Descending Stairs</th>
<th>Ascending Stairs</th>
<th>Descending Ramp</th>
<th>Ascending Ramp</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>a0</td>
<td>1.4863</td>
<td>0.014</td>
<td>0.9436</td>
<td>0.122</td>
<td>1.6519</td>
</tr>
<tr>
<td>a1</td>
<td>-0.2016</td>
<td>0.096</td>
<td>-0.5163</td>
<td>0.163</td>
<td>0.0299</td>
</tr>
<tr>
<td>b1</td>
<td>-0.3267</td>
<td>0.11</td>
<td>0.3562</td>
<td>0.091</td>
<td>0.1089</td>
</tr>
<tr>
<td>a2</td>
<td>0.0275</td>
<td>0.077</td>
<td>0.1575</td>
<td>0.114</td>
<td>0.0054</td>
</tr>
<tr>
<td>b2</td>
<td>-0.1153</td>
<td>0.045</td>
<td>-0.0363</td>
<td>0.101</td>
<td>0.1209</td>
</tr>
<tr>
<td>a3</td>
<td>0.0741</td>
<td>0.068</td>
<td>-0.0555</td>
<td>0.053</td>
<td>0.0486</td>
</tr>
<tr>
<td>b3</td>
<td>-0.0219</td>
<td>0.044</td>
<td>0.0315</td>
<td>0.09</td>
<td>0.0098</td>
</tr>
<tr>
<td>a4</td>
<td>0.0431</td>
<td>0.034</td>
<td>-0.0399</td>
<td>0.048</td>
<td>-0.013</td>
</tr>
<tr>
<td>b4</td>
<td>0.0051</td>
<td>0.032</td>
<td>-0.0198</td>
<td>0.06</td>
<td>-0.0685</td>
</tr>
</tbody>
</table>

The results of this experiment show again the validity of automating the system. With the addition of improved gait detection the standard deviations are significantly reduced. A very important factor shown by this data is the importance of time shifting. Previously all models were time shifted.

Figure 6.7 Gait Curve Examples
to a common low voltage in the gait cycle, which was assumed to correspond roughly to foot strike. However with the addition of the second IR sensor the time shifting was done with the knowledge of exactly when foot strike occurred. While this occurred near the low point (Figure 6.7), it was not always the low point. This variation in the start of the gait cycle is important, as it introduces a greater variability to the shape of the IR sensor curves, which can be observed in the box plots of the coefficients (Figure 6.9).

Another example of the benefits of time shifting to the exact point of foot strike can be seen when comparing Down Ramp and Level Walking in Figure 6.7. Both models have the same shape but they are significantly offset from one another due to the time shifting, as a result this method was the best of the three at producing unique models. The only problem with this method, in comparison to searching for a common minimum, occurs when the time shifting is offset. The general shape of the curves can be the same but they will not be as tightly clustered on the same values. As more data are collected this problem should be eliminated (Figure 6.8).
Figure 6.9 $a_0\text{-}b_4$ Probability Distribution
7. Pattern Recognition

Pattern recognition is a field of study in and of itself. This project uses pattern recognition to associate voltage curves created from our infrared range finders with the models discussed in Chapter 6. By estimating gait speed and then comparing error values, the algorithm is able to predict what terrain type might be ahead, before the pattern is complete. The models will be used to predict from our training data. Ground-type prediction will only be carried out on the third experiment’s (two IR sensors) data sets because it was the only data set in which steps could accurately be distinguished.

A least min squares approach was used to calculate error (Equation (7.1)). In this equation $t$ represents relative time, $w$ represents the assumed frequency at which the patient is stepping, $x$ represents the local data, and $f_i$ represents the expected value of each of the different models. The .6 in the summation represents the fact that the error equation is only looking at what it assumes is the first 60% of the gait cycle. 60% of the gait cycle was chosen because it represents the stance phase of the gait cycle.

$$\text{error}_i = \sum_{t=0}^{t+.61/w} (x(t) - f_i(t, 1/w))^2$$  \hspace{1cm} (7.1)

By computing this error for each model for a single step, the program is able to make an assessment of what kind of ground the patient is about to traverse. A successful prediction using 60% of the gait cycle represents the ability to identify the upcoming terrain by the time the AFO foot leaves the ground. This leaves enough time for a future system to make AFO adjustments within an acceptable time.
7.1. Success Rate Analysis

To judge the success rate of this method it is necessary to define what a success is. A successful prediction would be when the program is able to identify the proper ground type. Along with the percentage of correctly predicted steps, it is also necessary to report how many steps were investigated, because although the same number of trials were completed for each data set, within the data set the number of steps taken was drastically different between different ground types. The total success rate will be the number of times the program produces the correct result divided by the number of steps of that kind taken.

7.2. Predicting Ground Types

The following chart represents the percentage of correctly predicted ground types from the training data.

Table 7.1 Pattern Recognition Results

<table>
<thead>
<tr>
<th>Level Walking</th>
<th>Down Stairs</th>
<th>Up Stairs</th>
<th>Down Ramp</th>
<th>Up Ramp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct (%)</td>
<td>94.9</td>
<td>90.0</td>
<td>80.0</td>
<td>97.5</td>
</tr>
<tr>
<td># of Steps</td>
<td>98</td>
<td>50</td>
<td>50</td>
<td>80</td>
</tr>
</tbody>
</table>

The results show that there is still work to be done in improving our pattern recognition techniques. To illustrate the problems faced by the prediction algorithm at this time, examples of a correct and incorrect prediction will be shown below. Multiple wrong examples might be given if a variety of problems exist. In the legend of each plot you will see what model has been identified as the predicted model, along with what the other models looked like.
7.3. Level Walking Predictions

Level Walking had relatively good accuracy compared to the other models. When Level Walking would be misidentified it would happen because of time-shifting errors: The step registered early, causing it to look like either Ramp Up or Ramp Down. This is a very hard error to fix because it appears to be a perfect match, at least in the first 60% of the time for the other models.

Figure 7.1 Level Walking Incorrectly Interpreted as Ramp Up and Ramp Down

Figure 7.2 Data Correctly Predicted as Level Walking
7.4. Down Stairs Predictions

The plots below show that the Down Stairs predictions are often mispredicted due to variability in the voltage produced while going down stairs. The correctly identified plots in Figure 7.3 show that there is troublesome variability, which stems from the fact that the Down Stairs and Up Stairs data sets had the largest standard deviations of all the data sets.

![Figure 7.3 Data Correctly Predicted as Walking Down Stairs](image-url)
Figure 7.4 Down Stairs Incorrectly Interpreted as Level Walking and Ramp Up

Figure 7.5 Down Stairs Incorrectly Interpreted as Ramp Down
7.5. Up Stairs Prediction

The predictions for Up Stairs had the lowest correct identification rate. Figure 7.7 shows examples where the sensor registered almost a flat line that could be taken as Ramp Down. This is unfortunate because it is not so much a matter of shifting the data as the fact that occasionally, the data being read in does not resemble any of our models.

![Figure 7.6 Data Correctly Predicted as Walking Up Stairs](image)

![Figure 7.7 Up Stairs Incorrectly Interpreted as Ramp Down and Ramp Down](image)
7.6. Ramp Down Prediction

The predictions for Ramp Down were the most consistent. There was only one instance when the Ramp Down prediction was mislabeled, and much like Level Walking it appears to be a time-shifting issue, where the step is being registered early. This can be seen in the shape of the data curve.

![Data Correctly Predicted as Walking Ramp Down](image1)

![Ramp Down Incorrectly Interpreted as Ramp Up](image2)
7.7. Ramp Up Predictions

The predictions for Ramp Up are relatively bad considering that this was one of the more stable data sets. Like Ramp Down and Level Walking, Ramp Up is adversely affected by early step detection. Additionally, Ramp Up seems to be the most affected of all data sets by early step detection. This could be because the ground, being a ramp, trips the sensor at more sporadic times than other ground types.

![Figure 7.10 Data Correctly Predicted as Walking Ramp Up](image)

![Figure 7.11 Up Ramp Incorrectly Interpreted as Ramp Down and Ramp Down](image)
7.8. **Recommended Improvements**

A few key improvements could provide better accuracy to our predictions. These will be listed and explained here.

- **Probability weighting:**
  - The majority of a person's day is spent walking on level ground. Therefore, the error function could have a likelihood factor, making it much harder for level ground to be detected as anything but level ground.
  - The downside to this is that there is a chance of over-compensating and identifying all down ramps as Level Walking.

- **Time-shift models for best fit:**
  - Instead of shifting all models to obtain a minimum error for each, an initial probability check can be done to eliminate false models.
  - This can be followed by a time shift to reduce the remaining models' errors to a local minimum, which could greatly improve predictions.
  - However, there might not be enough time to complete this calculation within a single step.

- Look at full gait cycle after a step has been taken to determine if the algorithm can tell if it has made a mistake.
8. Conclusion

8.1. Characterization of Curves

This portion of the project has focused on creating a reliable way to automatically characterize repetitive voltage fluctuations created by a distance sensor while walking over a variety of terrains. This has been achieved through the use of a modified RANSAC algorithm. After being refined through two other testing phases, the algorithm now produces useful unique models to estimate what kind of terrain a patient is walking over.

8.2. Predicting Ground Types

This portion of the project has focused on predicting terrain types immediately in front of a patient. The technique is not new but its application to walking is and this highlights the need for more research into similar pattern recognition problems. While all methods scored above 80%, this system is by no means a final product, but it is a successful determination of feasibility.

8.3. Future Work

There are several important next steps for this research, the most important of which is developing this system into a truly portable platform. Once portable a brace can be made to take advantage of this information. Next this system still needs to be tested on a patient with impaired gait to ensure that their gait patterns are repeatable enough, and distinct over different terrain types, for our simple system to be able to identify a pattern. Additional modifications to improve prediction accuracy should also be investigated, such as adding a second set of sensors to the other leg or adding more sensors to a single leg to
verify data readings. It is important to note that the leg of a patient with foot drop might not be the optimal leg to take measurements from.

Another important future possibility for this research is its use in gait monitoring. Gait monitoring is currently done primarily in the lab, and shows only a brief timespan of someone walking typically in the presence of a clinician. These expensive and difficult studies can track a lot of information but it is all still confined to a laboratory. This new system will enable tracking of a patient’s gait over time in a real-world setting. The information that could be gained from constantly tracking a patient’s gait, especially if they have had an injury like a stroke and are still recovering, would be invaluable to clinicians. Not only would it provide a way to track a patient’s gait, but by generating models for these gait patterns it would provide a method to monitor large changes in a patient’s gait over time by comparing new and old characteristic curves.
References


Appendix

A.1 Data Collection Procedure

- Attaching Sharp GP2Y0A02YK to PMD-1208LS:
  - Loosen the phoenix block for channel 1 on the PMD-1208LS and insert the output voltage ($V_o$) lead of the range finder (pin out shown below) and tighten phoenix block.
  - Loosen the phoenix block for channel 3 on the PMD-1208LS and insert the ground (GND) lead of the range finder (pin out shown below) and tighten phoenix block.
  - Loosen the phoenix block for channel 30 on the PMD-1208LS and insert the constant voltage ($V_{cc}$) lead of the range finder (pin out shown below) and tighten phoenix block.

- Attaching a second sensor to PMD-1208LS:
  - Loosen the phoenix block for channel 2 on the PMD-1208LS and insert the output voltage or positive ($V_o$) lead of the sensor (pin out of Sharp GP2D12 shown below) and tighten phoenix block.

Figure A.1 GP2Y0A02Yk Schematic
Loosen the phoenix block for channel 3 on the PMD-1208LS and insert the ground or negative (GND) lead of the sensor (pin out of Sharp GP2D12 shown below) and tighten phoenix block.

If the device requires constant power (the piezo plate does not), loosen the phoenix block for channel 30 on the PMD-1208LS and insert the constant voltage (Vcc) lead of the range finder (pin out of Sharp GP2D12 shown below) and tighten phoenix block.

A.2 Software and Instillation

The package to install the PMD-1208LS is called InstaCal™. The software package used to record the voltage data was TracerDAQ™, and within TracerDAQ™ the Strip Chart function was used to save the data. Both packages can be downloaded from the Measurements and Computing website here: http://www.mccdaq.com/software.aspx.
To Install the PMD-1208LS, simply open InstaCal™ with the device plugged into the computer by its USB cord and the Plug and Play Board Detection window should appear. Once the device is installed it is important to check to see that the board is in 8 Single Ended mode and not 4 Differential. This can be done by right-clicking on the board, then selecting Configure, and selecting 8 Single Ended mode from the dropdown menu.

Now that the PMD-1208LS is installed, TracerDAQ™ must be properly configured. This package is limited to 30,000 samples per channel and can be downloaded. The sampling rates were changed around quite a bit to test the recorder's capability. The first experiment used a variety of sampling rates ranging from 100Hz to 1KHz. This was done to estimate the accuracy of the software. The second experiment used 100Hz and the third 500Hz. The settings for the sampling rate can be found under the Edit>Scan Rate/Trigger.
Settings, as illustrated below. It is important to note that the recording speed should be set below 100Hz as the sensor takes samples at roughly 40Hz.

**A.3 Post-Data Collection processing**

Once the data is gathered, it must be taken from a .txt file format to a .mat format for our program to handle it. To do this, the .txt file is first imported into Excel, which splits the values up into columns. The time-stamps the file contains for the data points are in Hr:Min:Sec.mSec format. This is cumbersome to use, so for each run the time was simply taken as 0 for the first data point, then incremented by the inverse of the frequency for the length of the data. It is also important to note that during the import process a ",DAQ Start" and a ",DAQ Stop" will be added to the first and last data points respectively and need to be removed. This is a good way to check that the data was “Stopped” and not “Paused,” because the data will contain a ",DAQ Paused” in the middle.

Once these extraneous artifacts are removed it can then be dropped into a Matlab™ array variable by simply copying and pasting the data into Matlab™. Once all the data have been dropped into one variable the variable can be saved as a .mat file. It is important to note that for the Fminsearch experiment, the time shifting was done by hand, and as such it has a different procedure in the section below.

Data Comparison Methods
Algorithm Procedure (FminSearch)

- Producing Fourier Coefficients
  - Run Script “rsacwalking4.m,” input the data array, and use best judgment on RANSAC coefficients
  - Repeat until a reasonable model and RANSAC coefficients can be found
  - Change RANSAC coefficients as needed to produce similar models

Drop results into Excel and using methods previously discussed, time-shift curves to a common low point. An example of what this looks like is shown in the figure below.

- The results of this can then be saved for statistical analysis

- Statistical Analysis
  - Compute the average Fourier coefficient value and its standard deviation
  - Compare to see if coefficients are dissimilar

A.4 Algorithm Procedure

- Producing Fourier Coefficients
  - Run Script “repeitTenTimes.m” with the array variable as the input
  - Save output of program to new .mat file for statistical analysis

- Statistical Analysis
  - Compute the average Fourier coefficient value and its standard deviation
  - Compare to see if coefficients are dissimilar

- Prediction Testing Single Type
• Run Script “Predictor” with input being the averages of the coefficients and a data set

• Repeat test with known data set types

• Save record of successful/unsuccessful identifications

• Calculate overall percentage of correct identification from each data set

• Prediction Testing Multi Type

  • Run Script “Predictor” with input being the averages of the coefficients and “long walk” data sets

  • Save record of successful/unsuccessful identifications

  • Calculate overall percentage of correct identification

A.5  Matlab

```matlab
function output = gait(fq,data)
inttol=.4;
%set up minimum number of steps between steps
sizer=size(data,1);
g=0;
fong=[0;0];
foffg=[0;0];
fonoffg=[0;0;0;0];
step=1;
on=1;
off=1;
i=1;
mison=0;
misoff=0;
mistol=1.25*fq;
fongt=0;
data=(inttol<data);

while i<sizer %search data for when the foot is on and off the ground

    if(data(i)&&on && i<sizer) %searches first for an on the ground
        if(not(misoff))
            fongt(1,1)=i;
        end
        while(on&& i<sizer)
            i=i+1;
        end
    end
```

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if data(i)  
    fongt(2,1)=i;
else  
    on=0;
end
if(i<sizer)  
    fong(:,step)=fongt;
end
end
if(not(data(i)) && off && i<sizer) %searches  
    if(not(mison))  
        foffg(1,step)=i;
    end
end
while(off && i<sizer)  
    i=i+1;  
    if not(data(i))  
        foffg(2,step)=i;  
    else  
        off=0;
    end
end
end
if(i<sizer)  
    if(foffg(2,step)-foffg(1,step)<= mistol)  
        on=1;  
        off=1;  
        misoff=1;
    elseif (fong(2,step)-fong(1,step)<= mistol)  
        off=1;
        if step>1  
            mison=1;  
            on=0;  
            step=step-1;  
            i=i-2;
        end
    else  
        mison=0;
        misoff=0;
    end
    if(not(off)&&not(on)&&not(mison)&&not(misoff))  
        step=step+1;  
        on=1;  
        off=1;
    end
end
fonoffg=[fong;foffg];
g = fonoffg(4,:) - fonoffg(1,:);  
sta = (abs(g - mean(g)) <= 2*std(g));  
g = g(sta);  
fonoffg = fonoffg(:, sta);  
g = mean(g);  
output{1} = round(g);  % average number of data points inbetween steps  
output{2} = fonoffg;  % on off ground  
end

function x = predictor(data, a0, a, b)  
% data in column array that looks like data(time, terrain voltage, step voltage)  
% a0, a, b are column vectors for the 5 different types  
% 1 Level walking  
% 2 Stairs down  
% 3 Stairs up  
% 4 Ramp down  
% 5 Ramp up  
syms t;  % time  
syms w;  % pace  
stepnum=1;  
w = [1/w 1/w 1/w 1/w 1/w] * (2*pi());  % converts from frequency and radians to period  
inc = [1 2 3 4];  
y = a0 + sum(cos((w'*inc)’*t).*(a')) + sum(sin((w'*inc)’*t).*(b'));  
fq = 1/data(2,1);  % sets the frequency of the data  
g = gait(fq, data(:, 3));  % simulates data from previous steps and reports  
w0 = g{1}/fq;  % sets the period of the function to that of the observed gait  
percentgait = .6;  % percent of gait  
while (stepnum <= size(g{2}, 2))  
    it = g{2}(1, stepnum);  % current iteration within the step  
    reltime = it/fq;  % relative time within the iteration  
    locdata = data(it:1:g{1}*percentgait+it,:);  % local time data  
    t0 = (locdata(:, 1) - reltime);  % local time shift data  
    y0 = subs(subs(y, 'w', w0, 't', locdata(:, 1) - reltime));  
    error = sum((y0 - ((locdata(:, 2))’*[1 1 1 1 1])).^2);  
    [u type] = min(error);  % reports the minimum error  
    x(stepnum) = type;  
    plot((locdata(:, 1) - reltime)’*100.*percentgait./max(locdata(:, 1) - reltime), locdata(:, 2))  
    hold all  
    plot(t0’*percentgait.*100./max(t0’*[1 1 1 1 1]), y0)  
end  
switch type  % shows which type of step is predicted  
case 1
function [a0 a1 b1 a2 b2 a3 b3 a4 b4 w] = repeitTenTimes(data)
%data in column array that looks likes data{array variable}(time,terrain
voltage, step voltage)
t=0;
i=1;
while i<=10
    %number of iterations can be changed for number of data sets being
    investigated
    fq= round(1/(data{i}(2,1)-data{i}(1,1))); %frequency of data
    g{i}=gait(fq,data{i}(:,3)); % guess on period of data points automated
    k(i)=300; % number of iterations
    l(i)=.19; % tolerance when a datum fits a model
    d(i)=round(size(data{i},1)*.55); % number of close data values required
    to assert that a model fits well based off of sizing of model
    n(i)=round(g{i}{1}*.55); % minimum number of data required to fit model
    based on number of points in a step
    e{i}=rsacwalking4(data{i},n(i),k(i),l(i),d(i),g{i}{1}); % model fit
    % temp for fourier series constants
    c0=e{i}{1}.a0;
end

axis([0 100 0 2.6]);
xlabel('Percent Gait %');
ylabel('Voltage');
pause;
hold off
stepnum=stepnum+1;

End

End
c1=e{i}{1}.a1;
c2=e{i}{1}.a2;
c3=e{i}{1}.a3;
c4=e{i}{1}.a4;
s1=e{i}{1}.b1;
s2=e{i}{1}.b2;
s3=e{i}{1}.b3;
s4=e{i}{1}.b4;
w(i)=e{i}{1}.w;

% sets fourier series constants for the function

t(i)=offseter(g{i}{2},e{i}{2},fq,w(i)); % uses a detected step to zero out the fourier series

a0(i)=c0;
a1(i)=+c1*cos(t(i)*w(i))+s1*sin(t(i)*w(i));
b1(i)=-c1*sin(t(i)*w(i))+s1*cos(t(i)*w(i));
a2(i)=+c2*cos(2*t(i)*w(i))+s2*sin(2*t(i)*w(i));
b2(i)=-c2*sin(2*t(i)*w(i))+s2*cos(2*t(i)*w(i));
a3(i)=+c3*cos(3*t(i)*w(i))+s3*sin(3*t(i)*w(i));
b3(i)=-c3*sin(3*t(i)*w(i))+s3*cos(3*t(i)*w(i));
a4(i)=+c4*cos(4*t(i)*w(i))+s4*sin(4*t(i)*w(i));
b4(i)=-c4*sin(4*t(i)*w(i))+s4*cos(4*t(i)*w(i));

i=i+1 % iterates the modeling finding
end

function [output] = rsacwalking4(data,n,k,t,d,g)
% data in column array that looks likes data(time, terrain voltage, step voltage)
% n minimum number of data requiered to fit model
% k number of iterations
% t tolorance when a datum fits a model
% d number of close data values required to assert that a model fits well
% i current iteration
% g guess on period of data points

bset=0; % best set of data
cset=0; % starting set of data
berror=100000000; % set high to trip if statment later
terror=0; % temp error
tmodel=0; % temp model
tdata=0; % temp data
bdata=0; % best data
bseed=0; % best seed number
bmodel=fit([0;1;2;3;4;5;6;7;8;9],[1;1;1;1;1;1;1;1;1;1],'fourier4'); % best model

merror=0; % model error
j=size(data,1);
ifer=0; % replacement vareable for mass if statment

while bset==0 %tests to see if any model has been found
    i=0;
    while i<k %tests to see if the number of repititions has been completed
        seed = abs(randi(j-g)); %picks a random area of the curve
        cset=sort(randi([seed,seed+g],n,1)); %picks random points within a
        period
        minliers=data(cset,:);
        mmodel=fit(minliers(:,1),minliers(:,2),'fourier4');

        mdata=mmodel(data(:,1));
        merror=abs((data(:,2)-mdata)./mdata);
        ifer=(t>merror); %tests the threshhold

        cset=linspace(1,j,j).*ifer;
        cset=cset(cset~=0);
        terror=sum(merror.*ifer)/size(cset,1);

        size(cset,1);
        if size(cset,1)>=d %test number of points in set
            if terror< berror %tests minimum error
                bset=cset; %sets the best sets
                berror=terror;
                bmodel=mmodel;
                bseed=seed;

            end
        end
    end
    i=i+1;
end

d=d*.8; %if the method fails to find a proper model the number of points
for a proper model is reduced by 80%
end

%plot(data(bset,1),data(bset,2),'*')
%plot(bmodel)
output{1}=bmodel;
output{2}=round(mean(bset));