5-2020

Development of Wearable Sensors for Gait Analysis

Jorden Smyth

Development of Wearable Sensors for Gait Analysis

A thesis submitted in partial fulfillment of the requirement
for the degree of Bachelor of Science with Honors in
Physics from the College of William and Mary in Virginia

by

J. Daniel Smyth

Accepted for Honors

Advisor: Prof. William Cooke

Prof. Keith Griffioen

Prof. Dennis Manos

Prof. Jim Deverick

Williamsburg, Virginia

May 4, 2020

Contents

Acknowledgments

I would like to take this opportunity to thank my advisor, Dr. William Cooke, for giving me this opportunity and for guiding me in my research and helping me to create a product that I am truly proud of. I also deeply appreciate my parents for supporting me and encouraging my love for learning. Special thanks to Jesse Smyth for reading my thesis before I did, my quarantine group (Evan Laughlin, Cairo Cairo, Jonathan Silberstein, and Kiera McKay) for keeping me sane, and the entire Physics department for inspiring me and teaching me so much during my time at William and Mary.

List of Figures

Abstract

In an ongoing experiment being conducted at The Williamsburg Landing by The Center for Balance and Aging Studies (CBAS), gait analysis is being performed on senior citizens in order to identify gait characteristics that are predictive of an increased likelihood to fall. This thesis describes the design and analysis of wearable sensors meant to assist the Williamsburg Landing study by increasing the efficiency and breadth of data collection. These sensors collect distance data from the foot to the ground over the course of multiple steps and return an approximation of the average step cycle for the subject. From my analysis of the sensor data, I was able to determine key gait characteristics such as the step clearance and foot angle. Additionally, I created a mathematical gait model to compare with my data, using input parameters based on the subject's gait. I found that my model called for an additional damping term in order to agree with my data, suggesting that the leg swing during a step is more controlled than previously expected. Improving the efficiency and reliability of data collection in this experiment is important, as determining fall likelihood is a crucial step in preventing falls that are incredibly dangerous to senior citizens.

Chapter 1

Introduction

Studies have found that one in three seniors older than 65 suffer from a fall in any given year. These falls account for 86% of all hip fractures, an injury with a mortality rate of around 30%. [3, 6] These distressing statistics have been the motivation for many gait and balance studies in the past. Studies such as the Berg Balance Scale test [8, 6] involve mostly subjective measurements of the subjects' competency in completing tasks such as standing up, turning around, or standing on one foot. While these tests give an idea of the subjects' individual capabilities and fall risk based on their balance, they do little to collect reliable and useful data that can be applied to others. Beginning in 1973, studies began using wearable sensors, and have seen success collecting and using gait and balance data to predict which participants are at elevated risk of falling. [2, 4] These studies used a variety of sensors including accelerometers and gyroscopes attached at the hip, thigh, calf, and foot, as well as pressure sensors, and had varying levels of success. Figure 1.1 shows the wearable sensor setup and data from a study conducted using gyroscopes at key joints. This study measured thigh, calf, and foot angular displacement using these sensors, and compared data to their video tracking.

At Williamsburg Landing, The Center for Balance and Aging Studies is currently researching gait, using video analysis to study the gait of seniors at risk for falling.

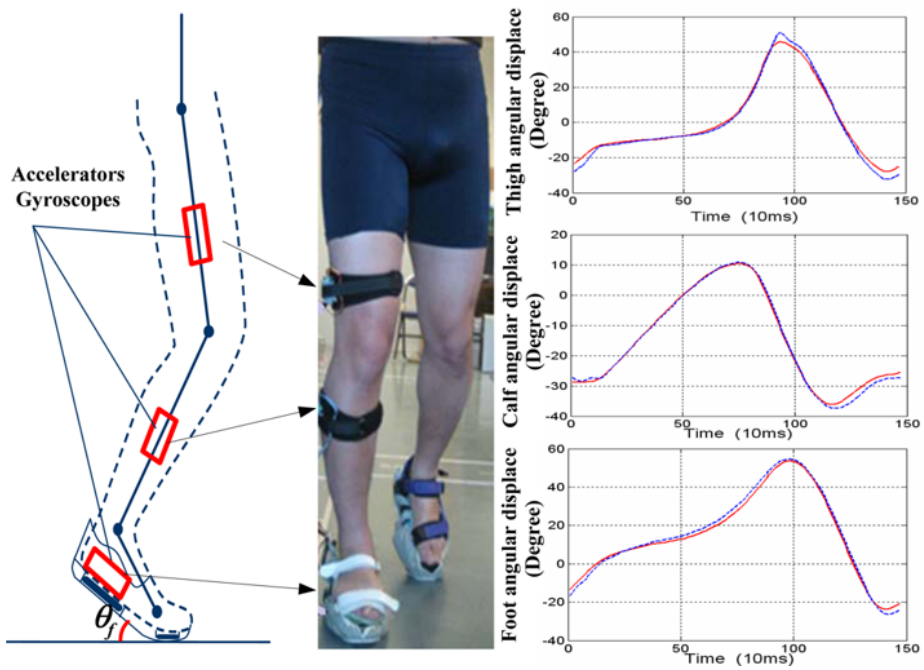


Figure 1.1: Previous wearable sensor data. This shows the setup and data from a previous wearable sensor gait study using gyroscopes to measure thigh, calf, and foot angle displacement [1]

Their current setup is shown in figure 1.2 and involves recording the subjects using video cameras to the side and front as they walk along a course and perform various tasks, such as stepping over a block or walking while reciting something from memory. Each subject has small black 'blobs' attached to their legs at the toe, ankle, knee, and hip which can be tracked in the videos to record the locations of these points in each frame. From this data, information such as step height, length, and width can be calculated. While this technique has many benefits such as collecting and storing a lot of vital gait data, it is also an inefficient and time consuming method since frame by frame video analysis is a tedious process. Due to changes in lighting and visibility of the blobs, the software parameters must be edited for each video to avoid missing blobs or picking up on blobs that are not attached to the subject. This dramatically reduces the rate of data analysis for the Williamsburg Landing experiment. My project is motivated by a desire to reduce this inefficiency.

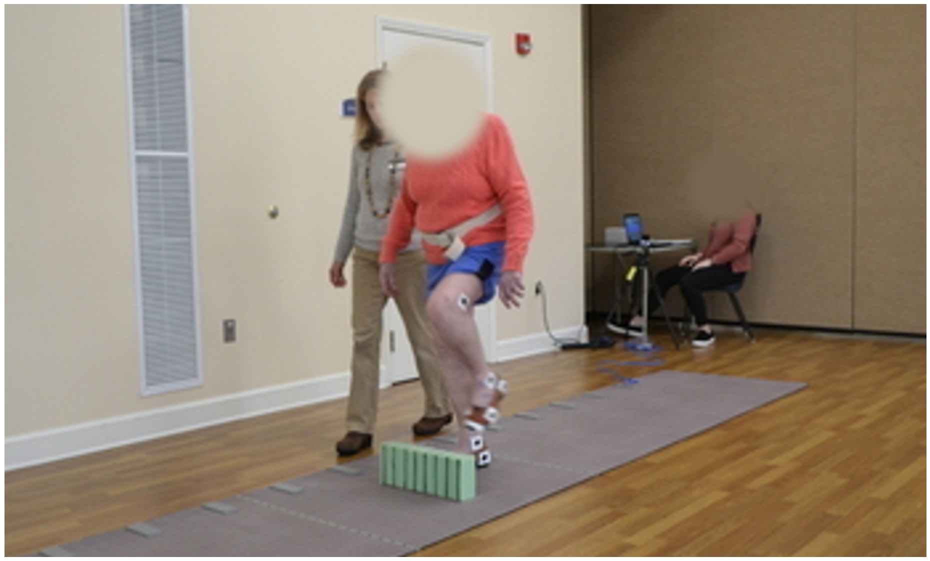


Figure 1.2: The experimental setup for the Williamsburg Landing research. Black dots shown on the subject's legs are used for video gait tracking

This thesis describes the development of wearable sensors to be used in this on-going study to collect gait data and predict falls among senior citizens. This study is looking to obtain a few vital pieces of information including step clearance during the swing phase as well as foot angle at the start and end of a step. Step clearance during the swing phase is determined by the distance from the ground of the lowest part of the foot at the lowest point of its swing. Essentially, it is the height of the largest object that could be placed in a subject's path that would not cause them to trip. In order to be useful for the study, my sensors should be cheap, efficient, and easy to use. To satisfy these constraints while also collecting useful data, I decided to use a time of flight sensor (ToF) to collect distance readings from the foot to the ground throughout the gait cycle. The sensor I used was the Adafruit VL53L0X time of flight sensor, a cheap ($13.95) and precise distance sensor, in conjunction with a Raspberry Pi Zero to record and store data.

After selecting and calibrating my sensor, I designed a method for attaching it to my foot and collecting data while walking normally. The sensor returns a measurement of the distance from my toe to the ground, along the angle of my foot, every 33ms. I collected multiple data sets on my own gait and was able to extract my step clearance relatively easily. For further data analysis I used two separate methods: video tracking and mathematical gait modeling. Video tracking took a form similar to that used by the Williamsburg Landing team. I tracked the locations of various points on my legs, then analyzed the output and compared it with my sensor readings. My mathematical model was based on modeling the leg as a driven double pendulum. The motivation behind this model was to gain a deeper understanding of the gait cycle, as well as to extract the calf angle at all points in the hopes of eventually measuring the subjects foot flex (angle between shin and foot).

Eventually, I was able to determine the step clearance, initial and final foot angle, and a prediction of the foot angle at all points of the step from my sensor data. From my model, I found that without additional damping terms, it did not line up well with the tracked output. This suggests that leg movement is a bit more controlled than we originally predicted, since there must be some muscle use or internal resistance to account for the need for this term.

Chapter 2

Technology Theory and Calibration

2.1 Section Overview

Before collecting data, I needed to make sure that any data I collected was reliable and that my sensor could register and record data with enough speed and accuracy to use while walking. First, I set up and did background research on my sensor. After finding that the sensor readings can be offset by multiple factors, I decided to do an initial calibration before beginning data collection. I calibrated the sensor for distance by collecting data at various known distances to generate a fit for the output. Lastly, my sensor will not always be directed perpendicular to the floor, so I calibrated the angle measurement of the sensor to ensure that it was still precise over a range of angles.

2.2 Time of Flight Sensor

The VL53L0X time of flight sensor works by sending out a 940nm infrared signal in a small cone and then determining the distance using the phase shift of the returning signal. It is rated for distances from 50mm to 2m and can function with a variety of ranging modes. For my data collection, I communicated with the sensor using I^2C protocols run from a Raspberry Pi. After establishing a time of flight object, I utilized the imported VL53L0X libraries in Python to collect data. The provided libraries had various accuracy and ranging modes, in this project, I used the 30Hz continuous ranging mode. This records data every 33ms at the cost of being slightly less accurate than slower ranging modes such as 15Hz. For my sensor calibration and eventual worn data collection, I wrote code in Python to record and store in an array the distance and time of measurement (since the start of data collection) for an inputted number of data points.

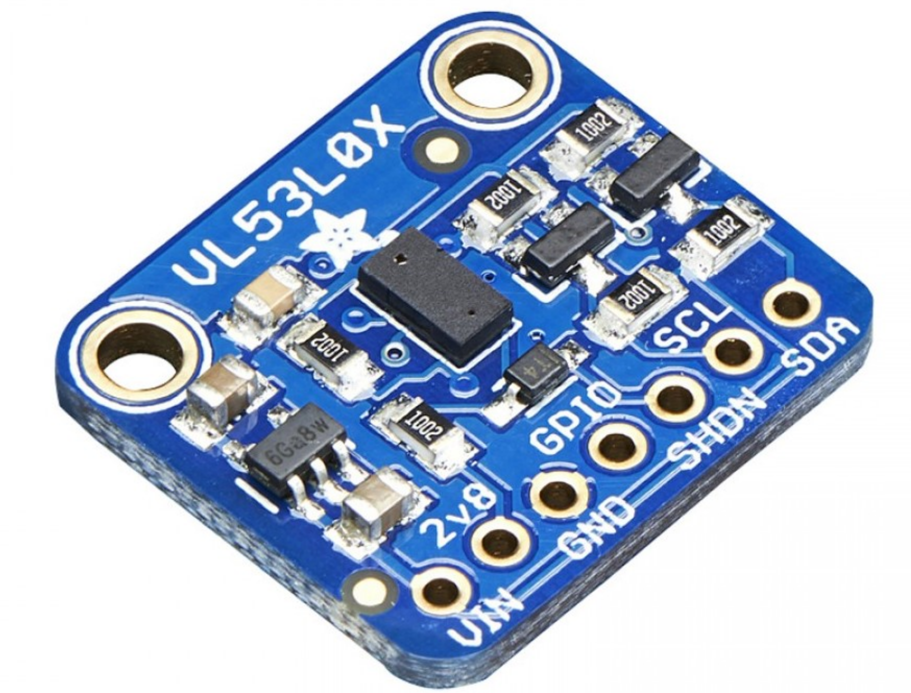


Figure 2.1: Adafruit VL53L0X time of flight sensor. I selected this sensor for my data collection due to its small size and accurate data collection from 50mm to 2m.

I now had a functioning time of flight sensor, however, due to factors such as ranging distance, voltage drift, and temperature drift, the VL53L0X readings can still be offset by anywhere from 10mm to 30mm. This was not a problem, as long as I could determine the offset, and adjust the results accordingly. Also, since the VL53L0X sensor is not rated for distances closer than 50mm, it was especially important for me to test and calibrate the range below 50mm since my sensor could be slightly closer to the ground at times.

2.3 Distance Measurement Calibration

To calculate the sensor offset and confirm the it was consistent below 50mm, I collected data for known distances and fit the output, returning an equation which mapped my measured results onto the actual distance. To accomplish this, I secured the sensor in place as shown in Figure 2.2 and adjusted the position of its target using a translation stage.

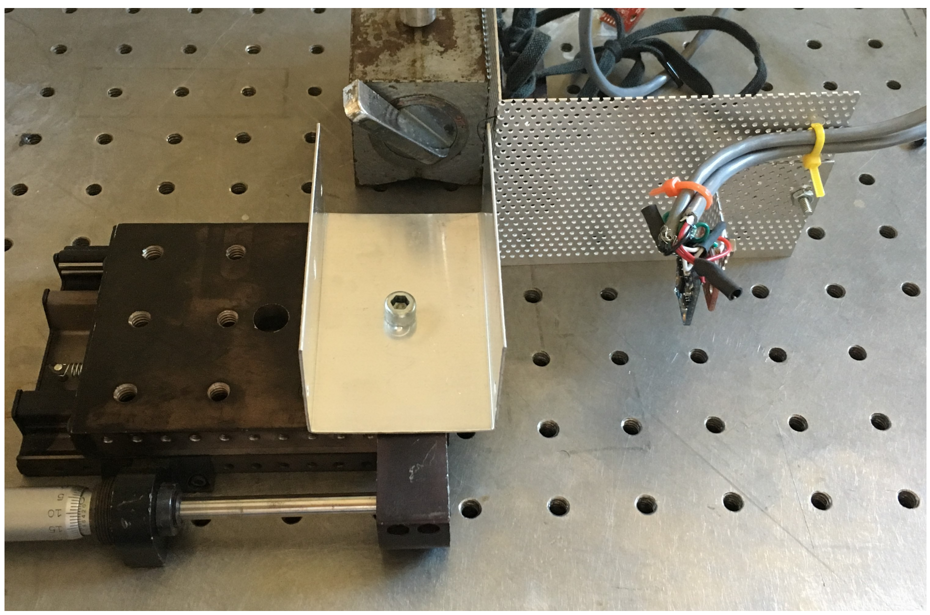
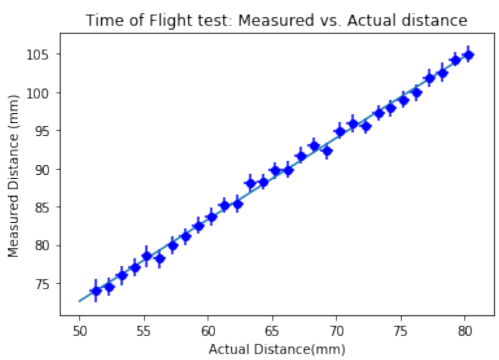


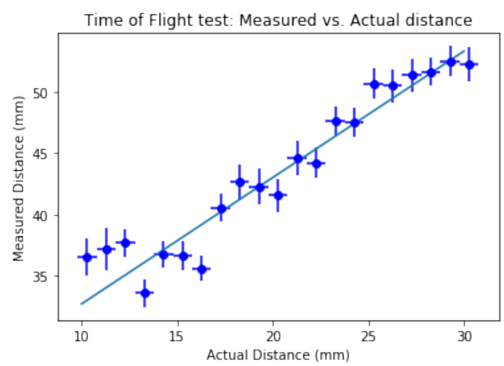
Figure 2.2: Distance Callibration setup. The time of flight sensor is mounted in place on the right, while the translation stage on the left allows for accurate measurement of the actual distance between the sensor and the plate.

I recorded 100 data points per millimeter increment as I moved the target towards the sensor and calculated the mean and standard deviation of these points. The plots in Figure 2.3 show my data from this test. I tested distances ranging from $10mm$ to $80mm$ and found that the sensor was precise to within approximately $\pm 1mm$ for distances over $35mm$ from the sensor, and to $\pm 2mm$ in the range from $20mm$ to $35mm$. I fit this data linearly and used the fit to convert my measured distance into the actual distance using equation 2.1.

$$Actual(mm) = \frac{Measured(mm) - 19.15mm}{1.068} \tag{2.1}$$



(a) Ideal Sensor range: 50mm to 80mm



(b) Sensor Breakdown Range: 10mm to 30mm

Figure 2.3: Actual distance vs Sensor Measurement (mm) for ideal and breakdown ranges on the sensor. Each point represents the mean of 100 data points with error bars of one standard deviation. This data is used to convert between my measured data to actual distance

2.4 Angle Measurement Calibration

In order to be confident in my collected data, I also tested the sensor at various angles to the ground since the VL53L0X sensor will not always be measuring distance at a 90° angle to the ground. When measuring someone's gait, the sensor will measure the distance from the sensor to the ground along the angle of the foot as shown by the red line in figure 2.4, rather than the vertical distance of the foot.

I set up the sensor on a rotation stage as shown in figure 2.5a, then recorded 100 distance readings every 2° while using an accelerometer to measure the actual angle

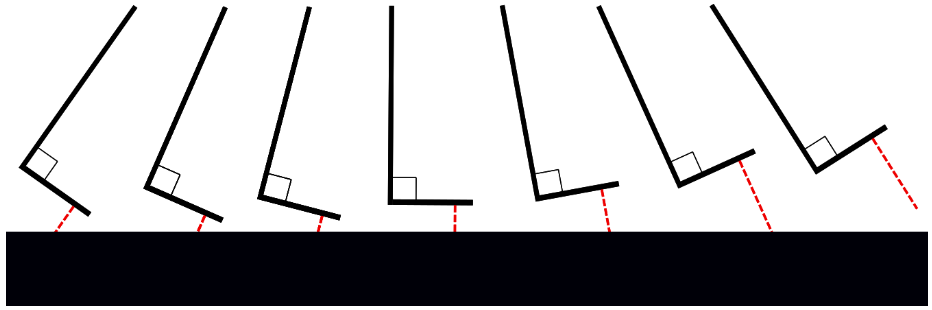


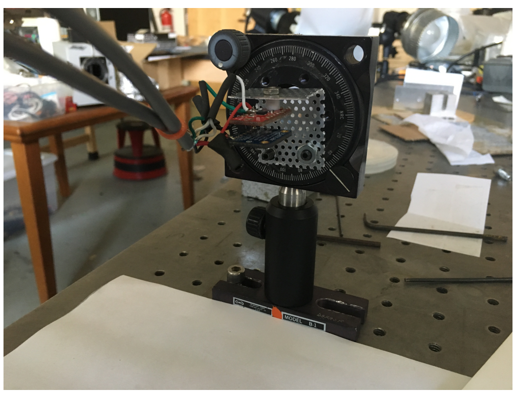
Figure 2.4: Angle convolution graphic. The distance that the sensor reads is represented in red, it is determined by both the height and angle of the foot.

between the sensors and vertical using equation 2.2.

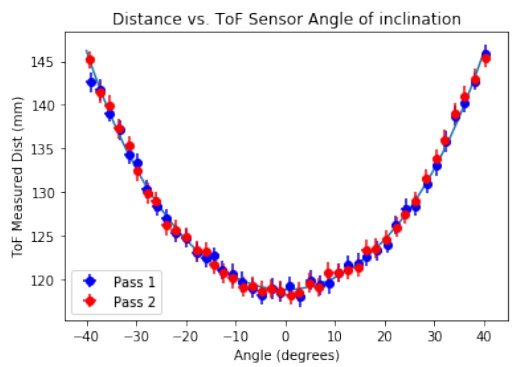
$$\theta = \arccos\left(\frac{\vec{V_0} \cdot \vec{V}}{\mid V_0 \mid\mid V \mid}\right) \tag{2.2}$$

In this case, $\vec{V_0}$ is the accelerometer measurement when measuring vertically and $\vec{V}$ is the accelerometer output vector at a given point. I took data at 2° increments ranging from -40° to 40° and plotted and fit the mean data as shown in figure 2.5b. This shows that the distance readings are still precise with varying angles. With knowledge of the foot angle, therefore, I could calculate the vertical foot distance at any point using a combination of equations 2.1 and 2.3, which gives my fit for the angle data.

$$D(\phi) = \frac{D_0}{\cos 0.9\phi} \tag{2.3}$$



(a) Angle testing setup



(b) Angle testing data

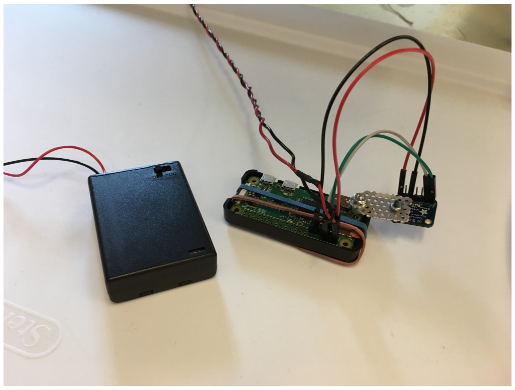
Figure 2.5: Angle testing Setup and Data. Left shows the time of flight sensor (blue) mounted on a rotation stage with an accelerometer (red) to accurately collect distance measurements at 2° increments. Right shows data points used to calculate a relationship between angle and measured distance.

Chapter 3

Data Collection

Having fully tested and calibrated the sensors, the next step was to collect actual gait data. My goal was to create a design which could collect accurate gait data while also not inhibiting my steps or altering my gait. Gait data in this case took the form of distance measurements recorded every 33ms from my toe to the ground, measured at the angle of my foot at the given time. The red line in figure 2.4 represents the distance that the sensor measures at any point in a step. As shown here, the output was affected by angle as well as vertical distance, which was something I dealt with when analyzing my data

To begin collecting data, I first transitioned to using a Raspberry Pi Zero, which I powered using a battery pack (figure 3.1a), and connected to remotely from my laptop using Putty software to execute my code on the Pi. I then connected the Pi and the sensor to my foot using rubber bands to secure the Pi case. (Figure 3.1b) While this setup was rough, it was effective for the purpose of collecting preliminary data because it was easy to set up, wireless, and did not restrict my movement while walking. To collect data, I secured the sensor-Pi system to my foot and ran code from my laptop which told the Pi to wait a 5 seconds, then collect 500 data points. Once the data collection started, I walked normally for about 15 seconds until the sensor had finished recording data. I collected data on various occasions with the



(a) Full sensor setup

(b) Sensor on foot

Figure 3.1: Sensor Setup for Gait Data Collection. Left shows my sensor setup with the Pi and battery pack. Right shows my sensor attached to my floor using rubber bands as a prototype method of attaching the sensor.

goal of extracting data that was consistent between steps and could be used to give a generalized idea of what one step cycle looked like for an individual. My raw distance sensor data for nine consecutive steps is shown in figure 3.2. This demonstrated that the sensor was picking up relatively consistent data between steps, so to get a mode accurate picture of my step cycle, I began analyzing my data.

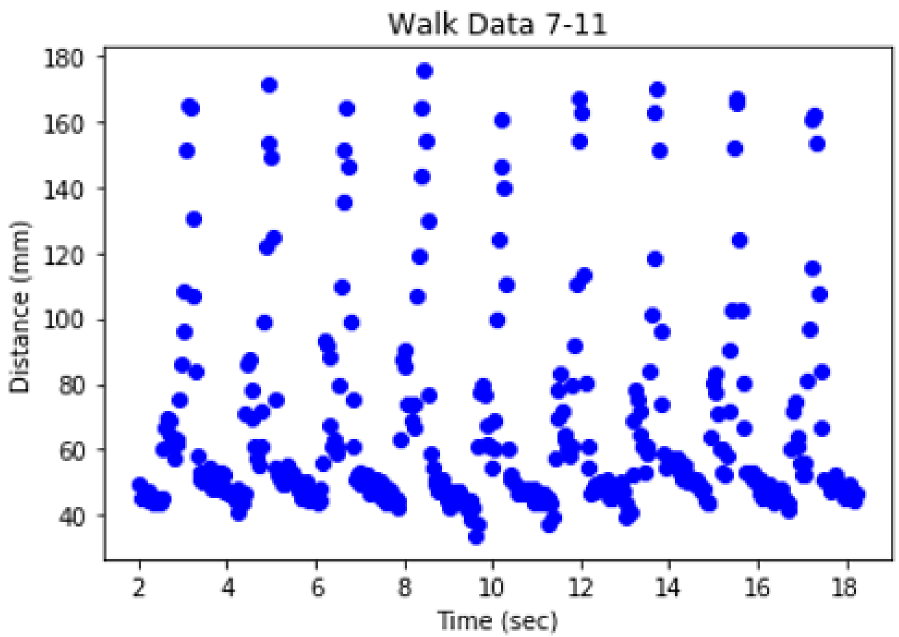


Figure 3.2: Raw sensor data from July 11th, 2019. This shows distance (mm) vs Time (s) for nine consecutive steps while wearing the sensor, taking data every 33ms.

Chapter 4

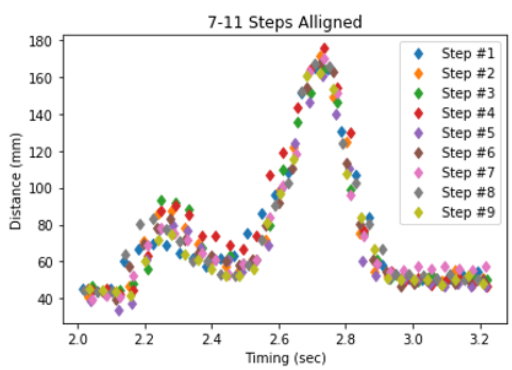
Data Analysis

4.1 Overview

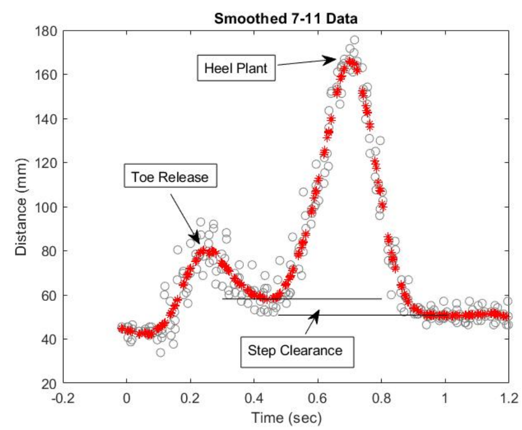
Having reached a point in my research where I had successfully recorded gait data using a prototype of my wearable sensor, my next goal was to extract as much information as possible from the data. The Williamsburg Landing is most specifically interested in the step clearance and the foot angle at the start and end of the step, but I hoped to extract more information using additional techniques such as video gait tracking and mathematical modeling.

4.2 Initial Analysis

To get a clear picture of what a general step looks like, I overlapped the nine steps from figure 3.2 using auto-correlation, then took a smoothing average of the overlapped steps to output a representation of one average step shown in figure 4.1b. This figure shows two peaks, with a dip in between. The time between these peaks represents the section of each step where my foot is not in contact with the ground. This is called the swing stage and it is the gait component that the Williamsburg Landing study is most interested in, as the majority of fall incidents occur during this stage. As I mentioned previously, the two most important pieces of information for me to obtain are the step clearance and foot angle. By comparing this step data to slow motion footage of my gait, I determined that the clearance is represented in my step data by the low peak at around 0.5 seconds in figure 4.1b. From this we can determine the clearance by subtracting the initial height of the sensor (obtained from the right side of the step data) from the measurements at this low peak. The approximate step clearance is shown in this figure as the distance between the two solid lines.



(a) Auto-Correlated step data



(b) Smoothed step data

Figure 4.1: July 11th step data alligned. Left shows Distance (mm) vs Time (sec) for the nine steps alligned using auto-correlation. Right shows a smoothing average of these steps to generate an idea of what an average step cycle looks like.

For my step data shown in these figures, I calculated a step clearance of $7.96 \pm 4.4mm$. To confirm my results for step clearance, I examined frames from a video I took of these steps. I converted the pixels to a distance in millimeters using the objects of known length, and then counted the pixels between my foot and the ground to confirm that it was within the range of my measured clearance.

The step data shown in these figures was more complex than I expected and provided much more information than was needed to determine the step clearance. This suggested that it was possible to determine more about the wearers gait from further analysis. To accomplish this, I took two separate approaches. First, I compared my sensor readings to data I collected from a video of my gait, and second, I created a mathematical gait model in order to parametrize my gait and observe how my model differs from my measured gait.

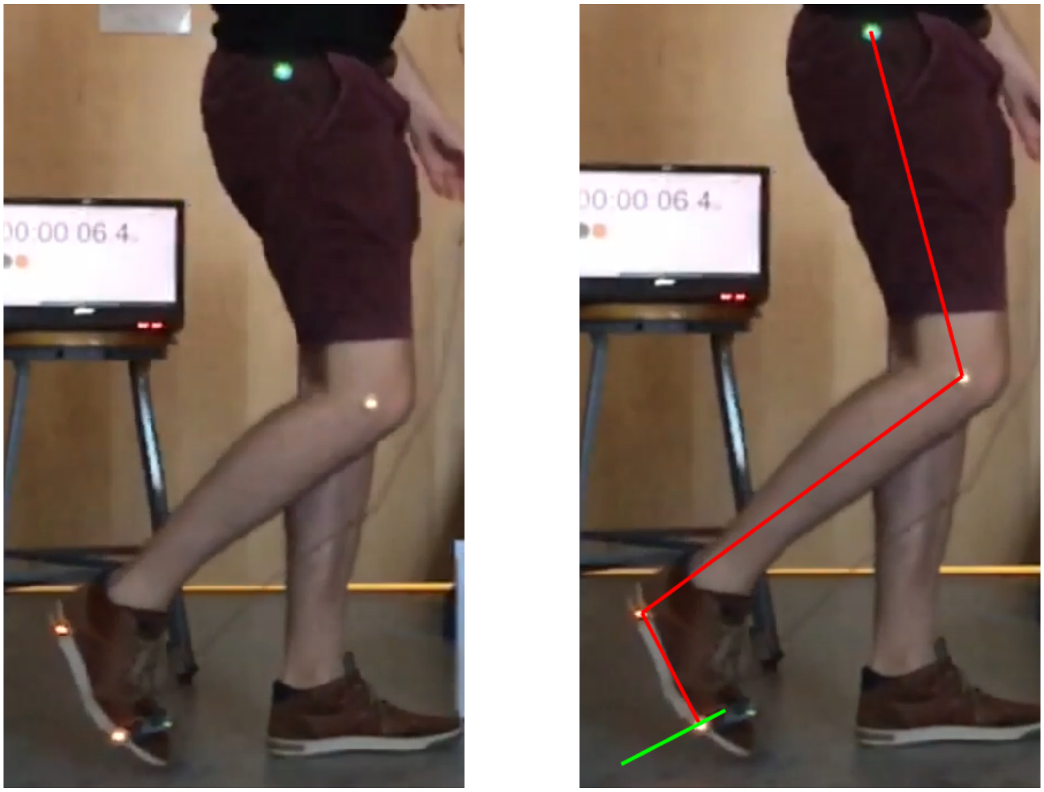
4.3 Further Analysis: Video Tracking

4.3.1 Video Tracking

Initially, when taking data, I recorded videos of my gait which I could observe later to determine what sections of my gait matched up with my sensor data. This quickly evolved into a more advanced approach inspired by the Williamsburg Landing experiment. I attached lights to my leg at my hip, knee, heel, and toe and recorded myself at 240 frames per second while collecting time of flight data. These lights, or 'blobs', on my legs acted as trackers which I could identify using a Python script which I edited to detect and record the coordinates of the blobs in each frame of the video. This left me with data for the pixel location of my leg joints for a walk cycle, as well as accompanying sensor data from my time of flight sensor.

My goal was to use this pixel data to further my understanding of the functional form of the time of flight output. To achieve this, I imported my tracked data into Matlab, as well as the data for my video frames, and used it to create a stick figure model of my leg (shown in figure 4.2b) which appears on top of my leg as I walk. From this model I was able to calculate the angles of all my leg segments at any point in my step, as well as a predicted sensor output which I could use to compare with my actual data.

Figure 4.3 shows my predicted sensor reading output from my tracked points. I calculated this in Matlab using equation 4.1 which outputs the distance from my toe to the floor along the path perpendicular to the foot (see the green line in figure 4.2b. In this equation, floorHeight refers to the lowest measured toe position and



(a) 'Blobs' for video tracking (b) Tracked stick figure

Figure 4.2: Video tracking using lights attached to legs. Left shows the lights placed at key locations on my leg to be picked up by tracking software. Right shows a tracked model stick figure and predicted time of flight for the same frame.

1.515 is the pixel to mm conversion. The tracked step data in figure 4.3 has a similar general form to that of my sensor data from figure 4.1b. It shows two peaks at the start and end of the swing phase, as well as a valley in between from which the step clearance was calculated. The first peak represents the point where the toe is released from ground, and the second represents the point where the heel plants. However, while the general forms are similar, the comparative heights of the peaks are vastly different. Additionally, the predicted data did not line up with the sensor data taken concurrently with the video (figure 4.4). This was especially interesting and led me to consider what could be causing this inconsistency between measurements on different days, as well as between the measurements and the predicted data.

$$Dist = 1.515 \frac{floorHeight - T_y}{cos(\phi_3)} \tag{4.1}$$

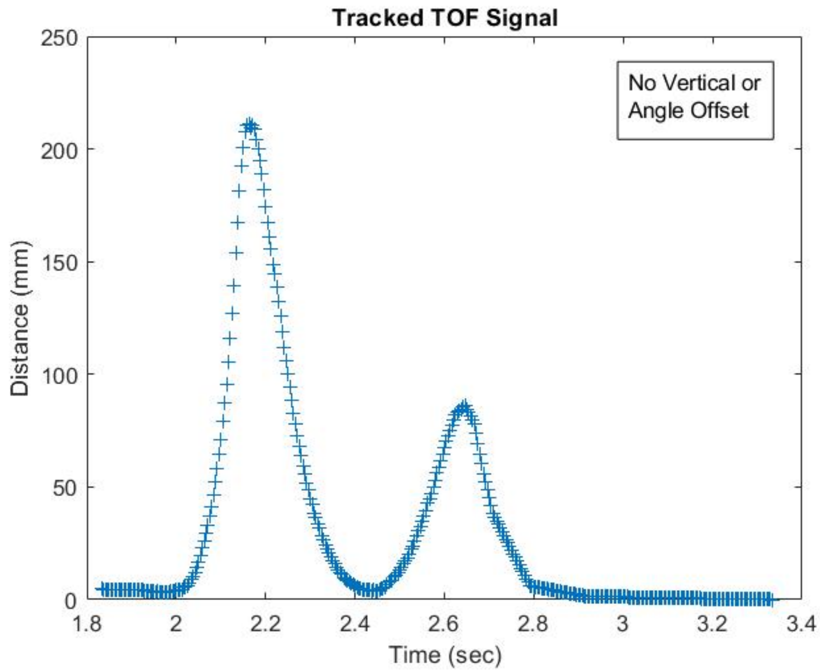


Figure 4.3: Predicted sensor reading without offset. This shows the predicted sensor reading output by my tracked gait model with no vertical or angle offset on the sensor.

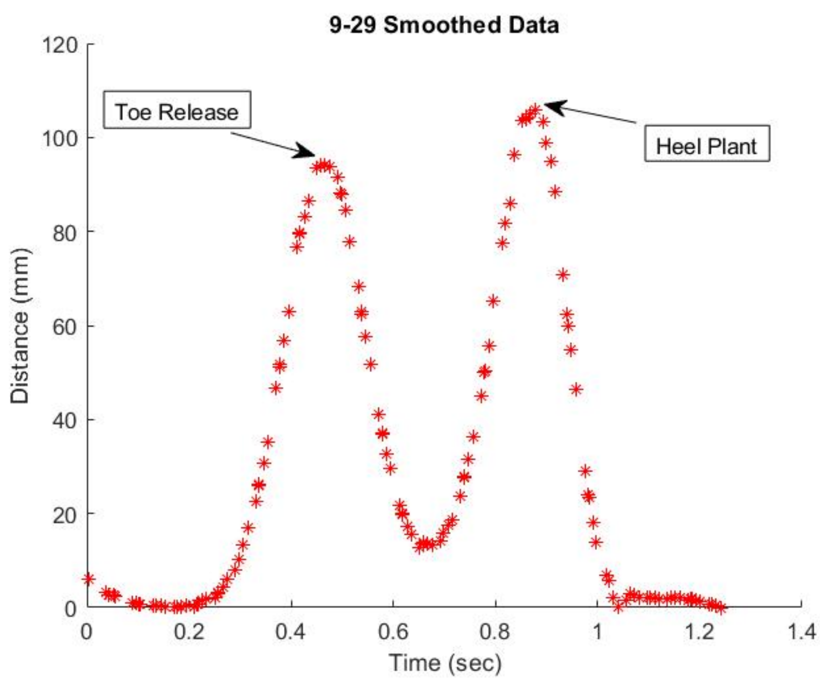


Figure 4.4: Smoothed step output from September 29th, 2019. This shows step data for five consecutive steps taken concurrently with my video.

4.3.2 Sensor Angle Offset Calibration

To test what could be causing this dramatic difference, I added two parameters to shift my predicted output: a vertical offset and an angle offset. The vertical offset shifts the sensor to a more realistic position above my foot, while the angle offset is a change to the angle of the sensor which was previously assumed to be directly perpendicular to my foot. Equation 4.2 shows my new calculation for the sensor reading over my recorded step. After adding a 40mm (26.4pix) vertical offset, I found that with a ϕ_{offset} of 20 degrees, the new sensor output looked like figure 4.5, which now clearly resembles the data collected during this video shown in figure 4.4.

$$h = \text{Vertical Sensor Offset}$$

$$\phi_{tot} = \phi_3 + \phi_{offset}$$

$$F_0 = \text{Floor Height}$$

$$Dist = \frac{F_0 - T_y + hcos(\phi_{tot})}{cos(\phi_{tot})} \tag{4.2}$$

Clearly, small shifts in the offset angle have large affects on the time of flight output, meaning that in order to get useful data, we must first know the offset angle of the sensor for each set of data. To easily and accurately determine the offset angle in each case, a simple calibration must be done before each data set is taken. My method for this calibration and determining the offset angle is to first measure the distance from the subject's toe to the sensor, then have the subject step on a block of known height and a tilted block of known height and angle while recording distance data. Figure 4.6 shows this general setup. Stepping on the block of known height would determine the overall offset from vertical by taking the inverse cosine of the known height over the measured height. This would not determine the direction of the offset, which would be calculated using the result from the tilted block. Using the measured height

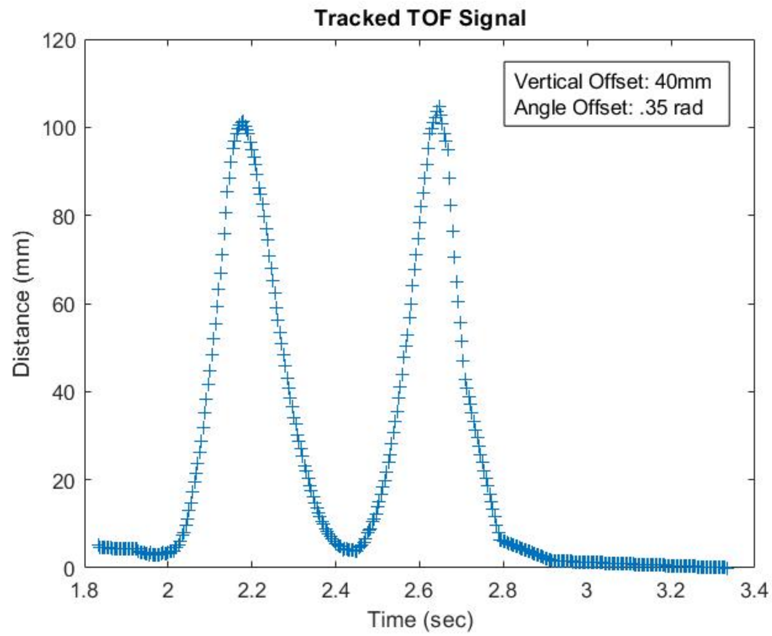


Figure 4.5: Updated predicted sensor reading. The predicted sensor reading output by my tracked gait model with a 40mm vertical offset and a .35 radian angle offset. This looks much more similar than previous output to my acutal 9-29 step data.

and angle of the tilted block, we can determine the amount of offset in the foreward or backward direction and use this to correct the time of flight data.

4.3.3 Determining Foot Angle

By using my predicted offset of 20° for the September 29th data set, I was able to determine the initial and final angles of the foot from the sensor data, since the convolution of foot height and angle is not an issue when either the toe or heel is still planted. Figure 4.7 shows the geometry used to calculate the initial and final angles of the foot for any data set given our angle offset. Equation 4.3 uses the definitions from the figure to calculate the release angle, while equation 4.4 does the same for the heel plant angle. For the tracked time of flight signals shown in figures 4.3 and 4.5, my calculation of the initial angle returns $\phi_3 = -72.76°$ for both these plots and the tracked angle of the foot at this point is $\phi_3 = -74.09°$. At the end of the

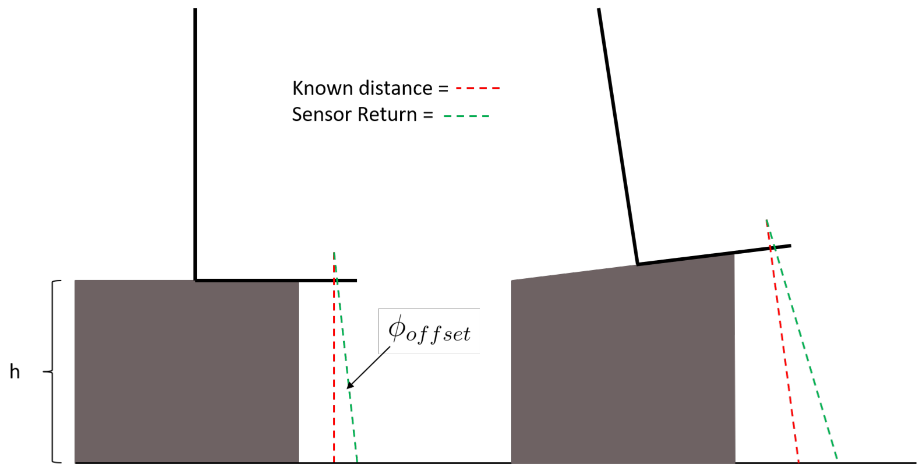


Figure 4.6: Offset angle calibration method graphic. My calibration method involves stepping on a block of known height and a block of known height and angle to determine the total offset, then the offset direction.

swing the tracked model returns a value of $\phi_3 = 18.59°$ compared to a calculated ϕ_3 of 18.4° from the time of flight data and the angle offset. These results confirm that the initial and final angles can be calculated from the sensor data given proper calibration. Unfortunately, due to lack of access to sensors for collecting additional data, I was unable to test this on data sets from my actual sensor.

Initial Angle Calculation

$$
\begin{aligned}
l &= L - \frac{tan(\phi_{off})}{h} \\
d &= D - \frac{h}{cos(\phi_{off})} \\
A &= \sqrt{d^2 + l^2 - 2dlcos(a)} \\
\phi_{initial} &= -\arccos \frac{1}{2Al}(-d^2 + l^2 + A^2)
\end{aligned}
\tag{4.3}
$$

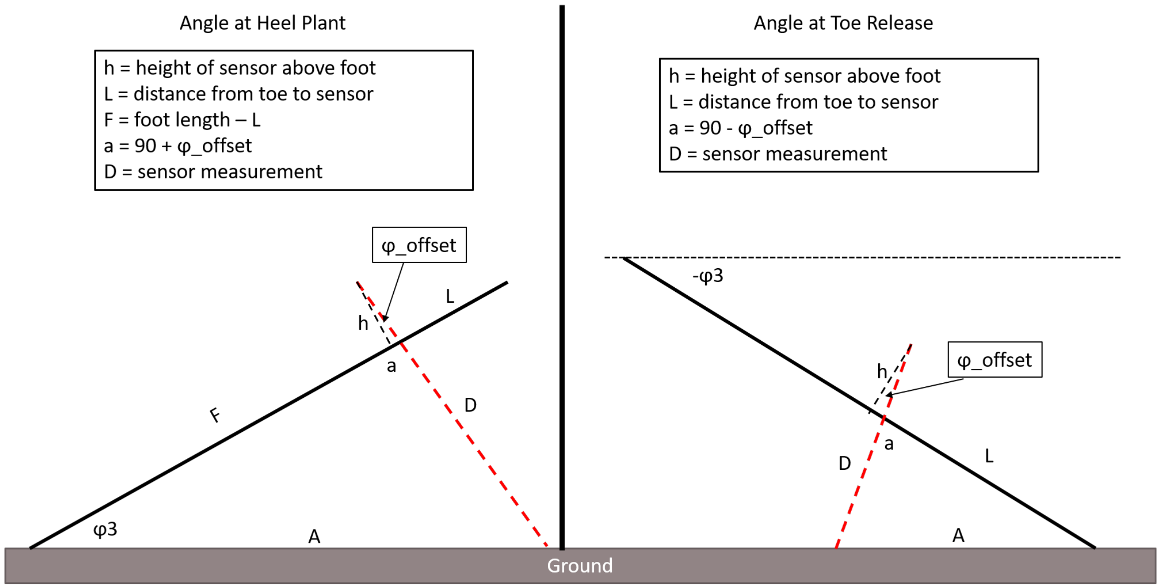


Figure 4.7: Foot geometry used for calculating the initial and final angles of the foot. The variables and definitions used here show the geometry of the heel plant and toe lift which allows me to calculate the initial and final angles of the foot.

Final Angle Calculation

$$\begin{aligned} f &= F - L + \frac{tan(\phi_{off})}{h} \\ d &= D - \frac{h}{cos(\phi_{off})} \\ A &= \sqrt{d^2 + f^2 - 2df\,cos(a)} \\ \phi_{final} &= \arccos \frac{1}{2Af}(-d^2 + f^2 + A^2) \end{aligned} \tag{4.4}$$

4.4 Further Analysis: Mathematical Modeling

4.4.1 Model Goals and Motivation

The second method that I used to extract additional gait information was to create a mathematical gait model based on a driven double pendulum. My goal with this model was to reach a point where it could output a prediction for the ϕ_2 motion and time of flight measurements which I could compare to my tracked data for ϕ_2 and measured time of flight data. Since my model assumed no resistance on the swing of the calf, the comparison of my model and my actual data would be useful because any differences between the outputs will suggest points in my gait where I used muscles or had some resistance in my step. Additionally, the calf (ϕ_2) motion for a step is needed to calculated the foot flex (angle between the top of the foot and the shin) throughout a step. With a functioning model, I could also test the effects of removing different terms from the model to see how this effects the agreement with my video tracked model.

4.4.2 Model Development

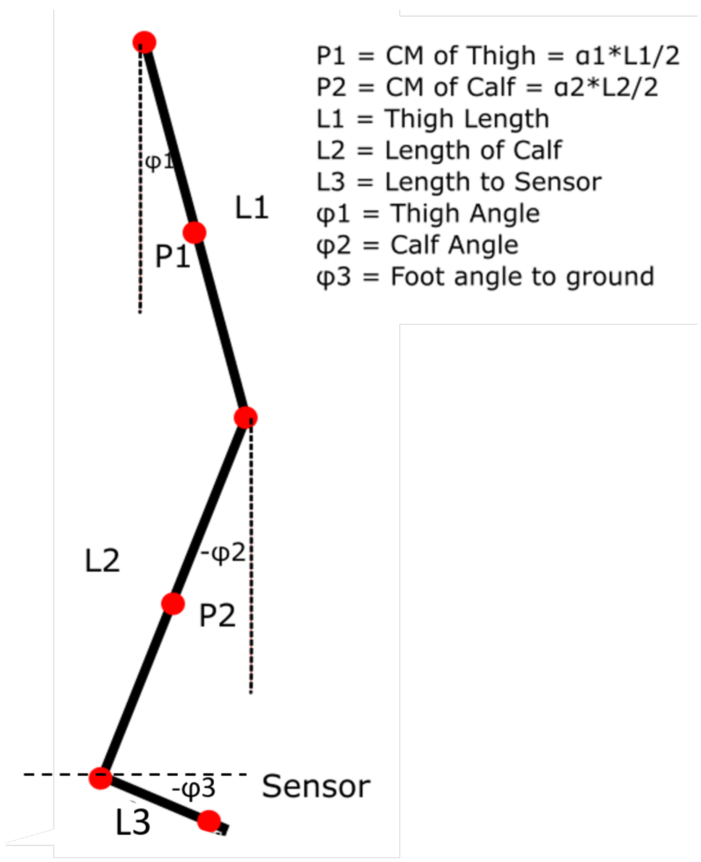


Figure 4.8: Leg parameter diagram. This graphic defines the parameters and variables which I use for my model, including leg lengths, segment angles, and segment center of mass.

Figure 4.8 shows the input parameters and variable definitions that I used for my model which are inherent to the person whose gait is modeled. To begin my model, I first calculated the Lagrangian of this system shown in equation 4.6. I then solved for the acceleration of the the calf angle ($\ddot{\phi_2}$) by finding its Euler-Lagrange equation and solving for $\ddot{\phi_2}$ as shown in equation 4.8.

$$L = T - U \tag{4.5}$$

$$\begin{aligned} L =& \frac{1}{2}m_1(\dot{x_h}^2 + \dot{x_h}\alpha_1 L_1\dot{\phi_1}cos(\phi_1) + \dot{y_h}^2 + \dot{y_h}\alpha_1 L_1\dot{\phi_1}sin(\phi_1) + \frac{\alpha_1^2 L_1^2}{4}\dot{\phi_1}^2) \\ &+ \frac{1}{2}m_2(\dot{x_h}^2 + \dot{y_h}^2 + 2\dot{x_h}L_1\dot{\phi_1}cos(\phi_1) + 2\dot{y_h}L_1\dot{\phi_1}sin(\phi_1) + \dot{x_h}\alpha_2 L_2\dot{\phi_2}cos(\phi_2) \\ &+ \dot{y_h}\alpha_2 L_2\dot{\phi_2}sin(\phi_2) + L_1^2\phi_1^2 + \alpha_2 L_1 L_2\dot{\phi_1}\dot{\phi_2}cos(\phi_1 - \phi_2)) \\ &- m_1 g(Y_h - \frac{\alpha_1 L_1}{2}cos(\phi_1)) - m_2 g(Y_h - L_1 cos(\phi_1) - \frac{\alpha_2 L_2}{2}cos(\phi_2)) \end{aligned} \tag{4.6}$$

$$\frac{\partial L}{\partial \phi_2} - \frac{d}{dt}(\frac{\partial L}{\partial \dot{\phi_2}}) = 0 \tag{4.7}$$

$$\ddot{\phi_2} = \frac{-2L_1}{\alpha_2 L_2}(\frac{\ddot{y_h}}{L_1}sin\phi_2 + \ddot{\phi_1}cos(\phi_1 - \phi_2) - \dot{\phi_1}^2 sin(\phi_1 - \phi_2) + \frac{g}{L_1}sin\phi_2) \tag{4.8}$$

To calculate the calf motion for all times, I needed to input hip and thigh motion into my $\ddot{\phi_2}$ equation. After initially trying to guess solutions and adjust parameters based on fits, I decided that using my tracked hip and thigh motion from my video would return more useful data to compare. To input my tracked hip and thigh motion, I first plotted and fit the vertical hip motion for frames 519 through 620 in my video. These frames represent the swing stage of my gait from toe release to heel plant. The fitted hip motion is given by the equation 4.9 which has a second derivative of $-.010521\frac{frames}{pix^2}$, which I used for my model input parameter. The negative sign here stems from the fact that the video frames count pixels in the y direction starting with zero at the top.

$$Y_h = 0.00526(frame)^2 - 6.139(frame) + 2099.49 \tag{4.9}$$

For the driving ϕ_1 equation, I calculated the angle of my thigh for each frame and plotted it in figure 4.9, this plot shows the tracked ϕ_1 compared with a fitted cosine function. I used the fitted cosine function (equation 4.10) as my driving ϕ_1 input.

$$\phi_1 = -0.46cos(\frac{\pi(frame - 398)}{200}) \tag{4.10}$$

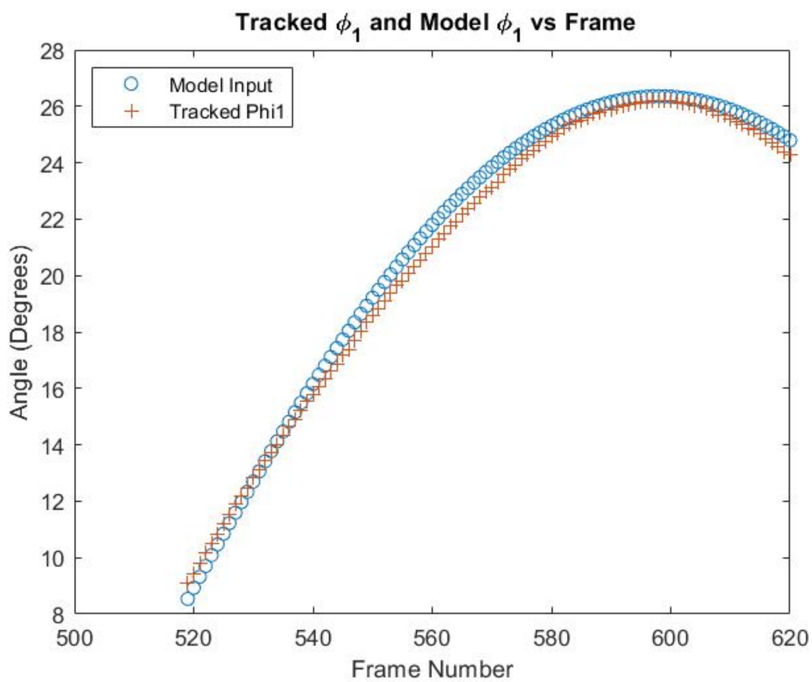


Figure 4.9: Tracked vs. fitted ϕ_1 motion. I used the fit shown here in blue as my input for thigh motion in my model, using my tracked thigh swing allowed for more reliable data comparisons.

Once the hip motion and thigh rotation were updated, the only remaining adjustable input parameter was the calf center of mass, α. While this is technically a measured value, it is hard to know exactly where it falls. From my research, I found that a good guess for the center of mass of the calf-foot system would be about 58% the length of the calf [7], closer to the foot. Using 1.2 (60% down the calf) for my value of alpha, I ran my updated model in Matlab to output a predicted ϕ_2 angle to compare with my tracked ϕ_2 values.

4.4.3 Model Analysis

The output of my model as well as the tracked ϕ_2 values are shown in figure 4.10. From this plot it is clear that my model predicts a significantly faster swing than we observe, this is confirmed in figure 4.11 where we see their compared time derivatives. The fact that my model predicts a faster swing than is known to occur suggests that it is missing some key information about the calf swing. This discrepancy could be caused by the use of muscle during the swing stage to control the calf swing, as well as joint tension which causes resistance and prevents the calf from swinging past the angle of the thigh. To improve the model from here I looked at the shape of the tracked ϕ_2 curve and noticed two points where the behavior diverges from my prediction. In figure 4.11 at approximately frame 550, the rate of change evens out drastically compared to the tracked motion, then, around frame 615, it begins to sharply decrease. From this I concluded that the addition of a damping term which scales with ϕ_2 velocity and proximity to ϕ_1 could be added to improve my model. Unfortunately I did not have time to do further testing on my model to see the effects of a damping term.

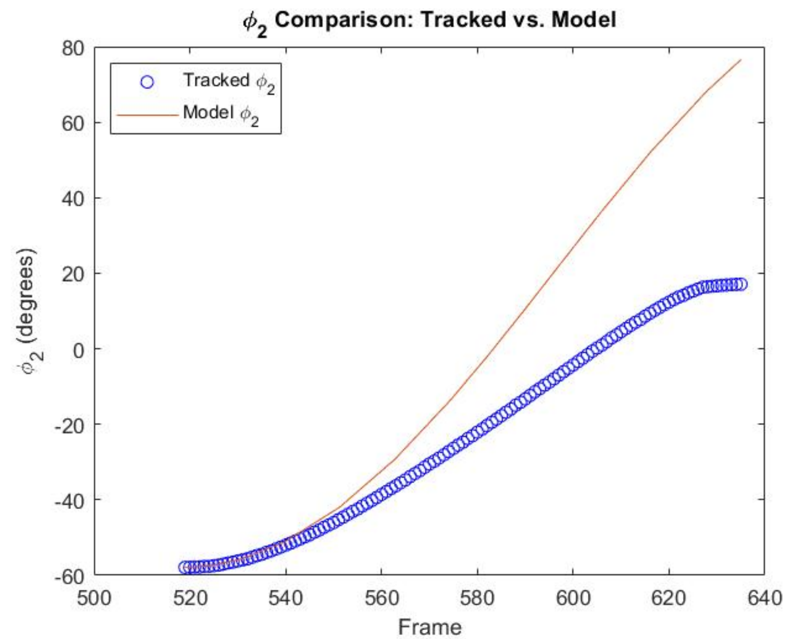


Figure 4.10: Tracked vs Model ϕ_2 output. This shows my model swinging to a greater angle than the tracked data, suggesting the need for a damping term.

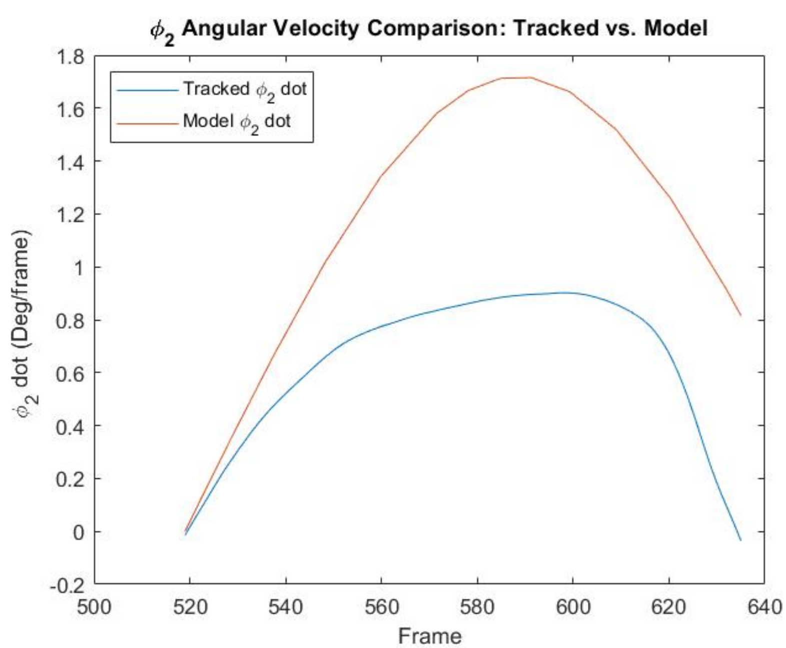


Figure 4.11: Tracked vs Model $\dot{\phi_2}$ output. This shows where the model velocity diverges from actual leg velocity. The shape of the tracked velocity curve could be informative for where a damping term is needed.

4.4.4 Term Comparison

In addition to my analysis of the overall model output, I also wanted to determine how the various terms in my model effect its output in order to know more about how different parameters could effect the calf swing. Referring to equation 4.8, my differential equation for ϕ_2 now has four terms. To test the relative importance and effects of these terms, I ran my model and recorded the ϕ_2 output while removing individual terms. In all of these tests, I used an alpha value of 1.2 (60% down the calf) since this is a reasonable estimate of average location of the center of mass of the calf-foot systems [7]. Figure 4.12 shows a comparison of the modeled ϕ_2 values with various terms removed. From this plot, I determined that the $\dot{\phi}_1$ and $\ddot{\phi}_1$ terms speed up the swing of my calf, while my hip motion slows it down slightly. The $\ddot{\phi}_1$ term has the greatest effect and the hip motion has the least. Since the $\ddot{\phi}_1$ motion speeds up my model, a reduction in the magnitude of this term would likely fit my tracked data more accurately. This suggests that my model may be a better fit for subjects with less exaggerated gait, such as senior citizens, since their gait will likely be slower and have less thigh acceleration.

4.5 Determining Foot Flex

The final goal of my sensor data analysis that I will discuss was to extract the foot flex at any point during a step. As I mentioned, the foot flex is the angle between the shin and the top of the foot, meaning that calculating it requires data for both the foot angle and the calf angle. Returning to my video tracked data, figure 4.13 shows my tracked data for the angle of the foot (ϕ_3) for one step. Since this data looked approximately linear, I fit it with the linear equation shown in the figure. If more testing could be done to show that this is consistently the case, I would be able to

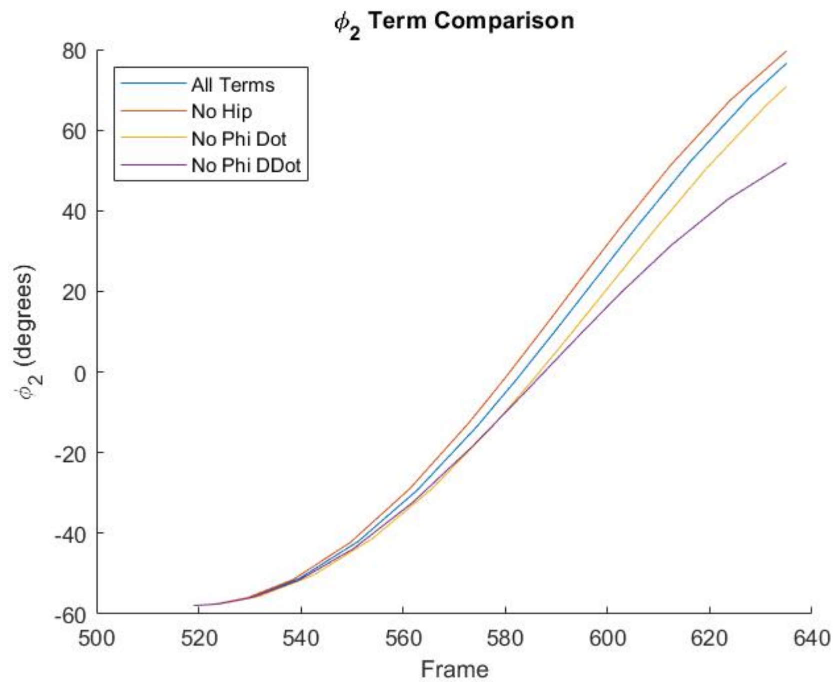


Figure 4.12: Comparison of ϕ_2 outputs with individual terms removed. The output differs based on which terms are included, showing that my hip motion slows down the swing and thigh motion speeds it up.

create a prediction for the approximate angle of the foot at all times using only my sensor data by linearly fitting the calculated initial angle and final angles. From here, if my model can be updated to a point where it matches the gait of a senior citizen to an acceptable degree, then a combination of my model data and sensor data will provide a prediction of the subjects foot flex at any time.

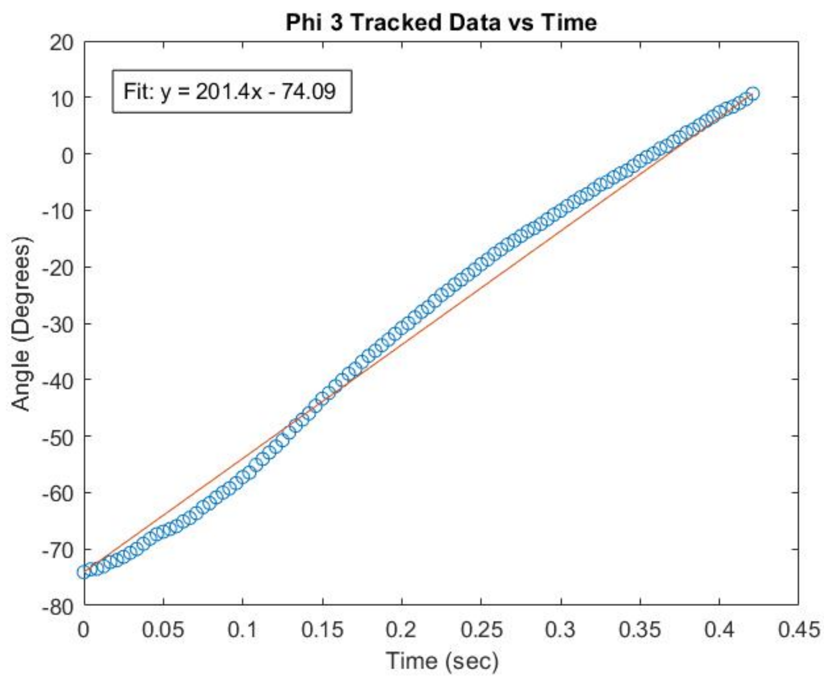


Figure 4.13: Tracked and fit data for the angle of my foot relative to the ground during the swing stage. The fit in this plot is using only the initial and final angle, demonstrating the linearity of the data and the possibility of extracting the foot angle at all times.

Chapter 5

Results and Conclusions

My main goal and motivation for this project was to assist the Williamsburg Landing team with their experiment and to improve the efficiency and breadth of their data collection and analysis. This will hopefully lead to a faster return on results on key gait characteristics which are predictive of fall likelihood. If these characteristics can be identified prior to a fall, steps can be taken such as notifying doctors and conducting gait therapy to prevent falls before they occur.

As I described, my method for assisting the ongoing study was to collect data using a wearable sensor and extract from its output the information they require and more. I found that with proper calibration prior to collection, my sensor data can be analyzed to determine the step clearance and initial and final angles of the foot for any step. These are three useful gait characteristics to the Landing experiment which can be predictive of fall likelihood. Furthermore, my analysis is promising for accurately determining the angle of the foot and foot flex at all points using a linear fit of the initial and final angle combined with my model data. While my device never got to a point where it could be utilized for this goal by the Landing, my analysis is very promising for extracting significant gait information from a simple and unobtrusive wearable sensor. Additionally, my mathematical gait model which I developed to complement my sensor data gave me insight into the nature of gait and has potential to help determine foot flex. The discrepancies between the swing speed of my model and reality demonstrated the need for a damping term to match the muscle use and internal resistance of the subjects gait. When completed, this will be useful for determining the magnitude of muscle usage and its effects on gait in general.

Chapter 6

Steps For Future Research

This project has many possible paths for continuation in future semesters, and I believe it has great potential to assist the ongoing research in the Williamsburg area as well as other gait analysis projects. Reasonable next steps for this project include collection of new data and testing of my calibration method, the addition of a second sensor to allow for angle calculation, additional modeling and model analysis to determine gait parameters, and more data analysis on existing step data.

Due to unforeseen circumstances, I was unable to collect additional data this semester and therefore could not test my methods of calibration. The first logical next step for this research is to implement the calibration method I discussed in section 4.3.2 to confirm that the initial and final angles can be found using actual data. This is a straightforward next step which would confirm the validity of my results and make my sensor more useful to the Landing study.

Adding a second sensor to the current setup would be a relatively quick and simple way to acquire a significant amount of additional data. The last thing that I accomplished with my sensors was to change the address of one sensor to allow me to run multiple sensors at once from the same Pi. I planned on adding an additional time of flight sensor to my wearable device this semester, and this would still be a useful next step for future research. An additional sensor could either be added to the other foot in order to collect data and search for discrepancies in gait between the subject's legs, or in a second location on the same foot. With this additional sensor on the same foot, and the same methods for calibration, the subject's foot angle could be calculated for any point using the difference in the measured distances.

While my model turned out to be missing some key terms, it is a solid basis for further modeling and my results showed promise for extracting gait parameters if an appropriate damping term was added. Further modeling could help determine where muscle use is occurring, and eventually could be compared to time of flight sensor data to highlight discrepancies between the model and the subjects actual gait as well as allow for calculation of foot flex. The addition of a predicted time of flight reading would be relatively simple given my tracked results for ϕ_3 being approximately linear from the initial to final angle.

Lastly, additional data extraction could take many forms. One useful path could be to use my sensor data to analyze variations between steps. Most of my current analysis has looked at taking many steps and using them to get data on what an average step looks like, but my data could also be used to show variation step to step. Looking at variations in step timing, step clearance, and foot angles between steps would be relatively simple with my data and could be useful for the Landing experiment.

Chapter 7

Bibliography

1. Tao,Weijun, et al, "Gait Analysis Using Wearable Sensors.". *MDPI, Molecular Diversity Preservation International*, 16 Feb. 2012.

2. Schwesig, René, et al, "Can Falls Be Predicted with gait Analytical and Posturographic Measurement Systems? A Prospective Follow-up Study in a Nursing Home Population.", *Clinical Rehabilitation*, vol.27, no. 2, pp.183-190 Feb. 2013

3. Schnell, Scott, et al, "The 1-Year Mortality of Patients Treated in a Hip Fracture Program for Elders." *Geriatric Orthopaedic Surgery & Rehabilitation, SAGE Publications*, Sept. 2010

4. Bugane, et al, "Estimation of Spatial-Temporal Gait Parameters in Level Walking Based on a Single Accelerometer: Validation on Normal Subjects by Standard Gait Analysis." *Computer Methods and Programs in Biomedicine*, Elsevier, 3 Mar. 2012

5. Senden, Rachel & Grimm,Bernd & Heyligers, Ide & Savelberg, Hans & Meijer, Kenneth. "Acceleration-based gait test for healthy subjects: Reliability and reference data.", *Gait & Posture.*, 2009

6. Zheng H, Zhao Y. "Sensing Movement: Microsensors for Body Motion Mea-

surement.", *Sensors.*, 2011; 11(1):638-660

7. Clauser, et al "Weight, Volume, and Center of Mass of Segments of the Human Body.", *Wright-Patterson Air Force Base, OH, Aerospace Medical Research Laboratory.*, (AMRL-TR-69-70), 1969, p. 49.

8. Berg K, Wood-Dauphinee S, Williams JI, and Gayton D. "Measuring balance in the elderly: preliminary development of an instrument.", *Physiotherapy Canada* 1989; 41: 304-311.