Department of Mechanical and Mechatronics Engineering

MTE 546: Gait Initiation Detection

Professor Carol Hulls

Group #4:

Adam Sequeira (20511490)

Lok Kan Chan (20466306)

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Introduction

A large research topic in Biomechanics is rehabilitative technology to enhance or restore lower limb motor functions. Examples of these technologies include exoskeletons and active prosthetics. [1] It is common for the rehabilitative technology to be equipped with advanced control algorithms that will help the patient achieve basic tasks. A common theme among this research topic is integrating wearable sensors to que the activation of the control algorithms. The merit in implementing wearable sensors are to better improve the human interaction with the technology, in other words, the ability to detect human intent. [1]

During the winter term of 2018, the student Curtis Chan is participating in the course KIN 472 which is a Self-Directed Study in Biomechanics that involves a research project for that relevant field. The overall goal of the research project is to develop an algorithm to detect human intent to begin walking using wearable sensors such as accelerometers and gyroscopes.

When attempting to detect the intention of walking, it is important to understand the different states that human progresses through when beginning to walk. A state that would be pertinent to this task is the position of the center of mass of a patient. The importance of the center of mass will be further explained in the next section of this report. The center of mass of a human is however, unobservable when it comes to ambulatory rehabilitative technology. Meaning, there exists no wearable sensor that can directly detect the center of mass of a patient. The objective of this project is then to develop an algorithm to estimate the position of the patient's center of mass using two different types of wearable sensors.

Background

In this section, supplementary information will be provided for the reader to better understand terminology and reasoning behind the algorithm development. The specific two areas that will be further explained are biomechanics of walking and the relevant sensor fusion techniques to solve the problem.

Biomechanics of Walking

In the world of biomechanics and clinical rehabilitation, gait analysis which is the systematic analysis of locomotion is used for "pretreatment assessment, surgical decision making, postoperative follow-up, and management of both adult and younger patients." [2] Gait analysis has yielded developments in describing the process of how a human walks which is known as a Gait Cycle. [2] This has allowed clinicians to diagnose the patients issues by examining gait patterns and implementing the appropriate correction programs. [2] Gait analysis has also allowed the advancement in bioengineering technology to evaluate the kinematics of the human body, which leads to the ability to quantify joint angles, angular velocities etc. [2] The gait cycle of a human can be shown below in Figure 1

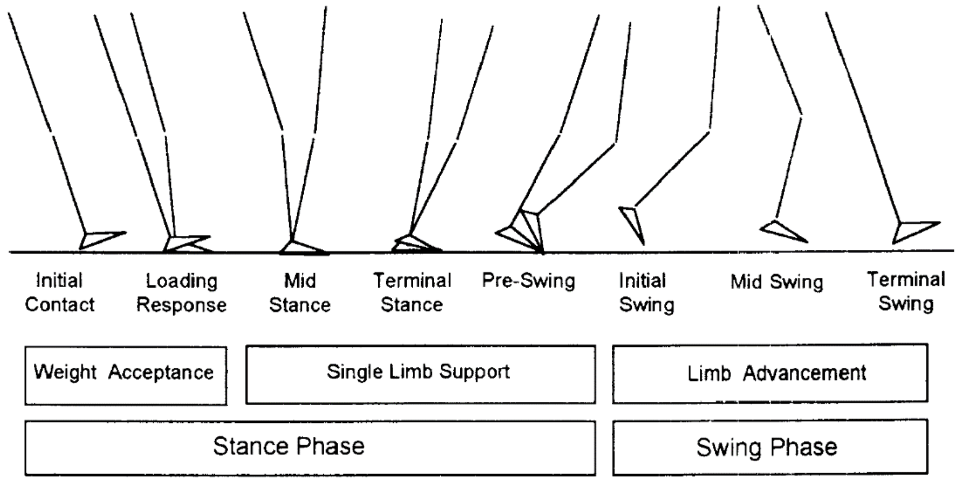


Figure 1: Gait Cycle Illustration [2]

As seen in Figure 1 the gait cycle illustrates different states that the human is in during the act of bipedal locomotion. The clear definition and classification of the different states has paved the way for wearable sensors to be used to track patient gait patterns. An example of such application is using foot pressure sensors to detect the initial contact at the heel or the terminal stance phase. [1] This is highly applicable to technology such as lower limb exoskeletons and other rehabilitative technologies as this can also provide feedback and pertinent information to the tasks that they are trying to achieve.

There also exists an analysis for gait initiation which is the model that is of interest to this project. The gait cycle in Figure 1 illustrates a patient who is already in motion, the following diagram shown in Figure 2 will outline the process of gait initiation.

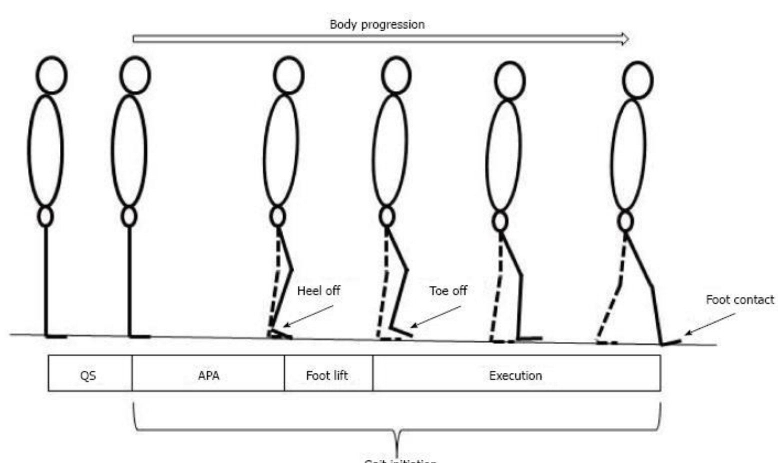


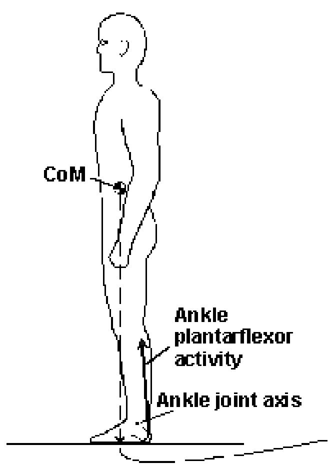
Figure 2: Gait Initiation Cycle

Like the regular gait cycle, the gait initiation cycle classifies definitive states of the process of a person beginning to walk. Referring to Figure 2, the abbreviations “QS” and “APA” refer to quiet standing and anticipatory postural adjustment. [3] Quiet standing specifically refers to the state at which a human is standing with no intention to move. However, human equilibrium is inherently unstable such as an inverted pendulum and will experience small perturbations while attempting to remain erect. [3] Anticipatory postural adjustment is a shift in the center of mass before heel off to take the first step. [4] There exists several metrics to detect gait initiation, such as APA and flexion of the hip and knee. [4]

To reiterate the relevance of detecting the position of the center of mass of the patient, it is a method of classifying at which state the patient is in during the gait initiation cycle. More specifically, in this project the center of mass detection will be used to classify whether the patient is in quiet standing or anticipatory postural adjustment.

Sensor Fusion Technique

IMUs or inertial measurement units are devices that contain both accelerometers and gyroscopes to measure both the linear acceleration, orientation and angular velocity of a body. One of the major advantages of using an IMU as opposed to separate accelerometers and gyroscopes is that the data from the full set of IMU data can be used to determine other aspects of the intention to walk.



The IMU is attached to the hip, the two main parameters extracted from the imu is the orientation of the hip as well as the linear acceleration in the two-dimensional plane.

The Kalman filter is an algorithm that takes in different sets of data which contain noise and other forms of inaccuracies, and by estimating a joint probabilistic distribution of the two sets of data, it can generate a combined set of data with more accuracy and less noise.

Implementation of Experiments

Sensor Model

The sensor used for the data collection and trials was supplied by the University of Waterloo Neuro Rehabilitation Engineering Lab. The IMU is a Shimmer3 EXG Unit, which has a sampling rate of 256 Hz, includes an accelerometer and gyroscope, as well records data via Bluetooth to a smart phone app interface. The sensors can export the recorded measurements into a '.dat' file which can then be imported into MATLAB directly. Furthermore, there was no need to develop a sensor function as the Shimmer3 EXG Unit can output calibrated measurements which are already converted into the desired units. For example, the calibrated accelerometer will output measurements in m/s^2 directly.

However, to properly implement the Kalman Filter, the white noise of the accelerometer and gyroscope still need to be characterized. To achieve this, the IMU was left to sit on a desk for roughly 10 seconds and record no acceleration or angular velocity. Any other non-zero value in the measurements can be classified as expected white noise. The results of the noise characterization for the accelerometer and gyroscope are shown below in Figure 3 and Figure 4 respectively.

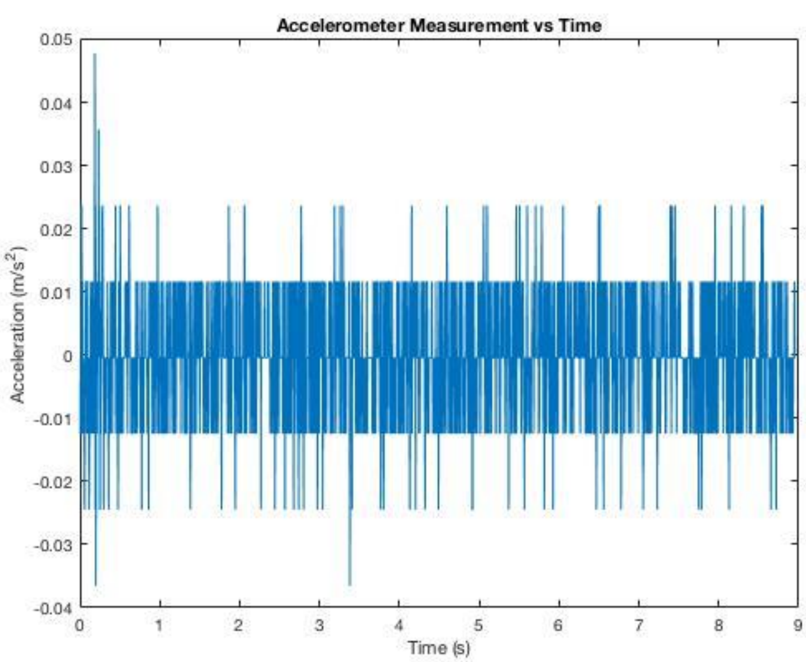


Figure 3: Noise Characterization for Accelerometer

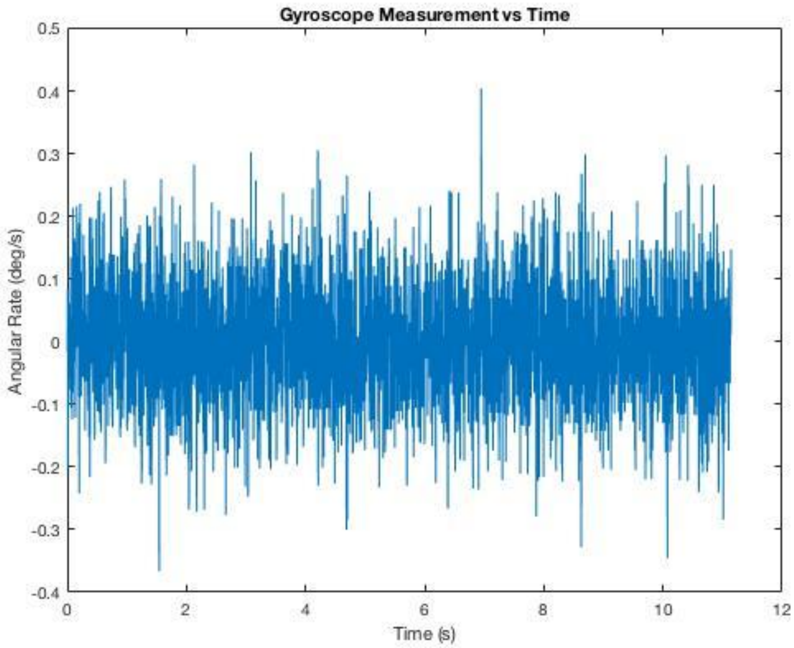


Figure 4: Noise Characterization for Gyroscope

Using the collected data and importing into MATLAB, the data can be processed and a standard deviation for both sensors can be extracted. Since the noise is chosen to be modeled as zero-mean Gaussian noise, the variance can be easily found by squaring the standard deviation. The corresponding variances are then 8.5019×10^{-5} and 0.0095 for the accelerometer and gyroscope respectively.

Data Collection

As mentioned previously, the center of mass of the human is modeled as an inverted pendulum. The center of mass of a human in standing posture is typically around the hip. [3] Therefore, using a strap which is an accessory of the Shimmer sensor kit, the sensor is tied around the test subjects waste as shown below in Figure 5.

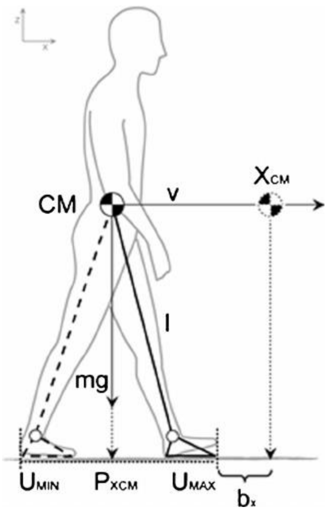
Figure 5: Experimental Set Up

One type of trial will consist of recording the test subject in quiet standing for roughly 7 seconds, however it should be noted that only 5 seconds of the trial will be processed for results. The target for 7 seconds is to ensure that at least 5 seconds of data is available for processing. Quiet standing requires the test subject to stand freely with no intentional swaying and without moving their feet. A total of 10 trials of quiet standing is recorded.

A second type of trial will consist of recording the test subject purposely swaying with their feet planted. The process is like the quiet standing trials, however only 5 trials were recorded since the intentional postural sway is expected to be evidently different from the quiet standing trials. The value of the second trial is for visual comparison between quiet standing and postural sway.

Algorithm Development

This technique involves modelling the system as an inverted pendulum. This is shown in the figure below.



As shown in the figure above, the small approximation is appropriate for this model as the angle between PxCM and l are relatively small. For this reason, a Kalman filter is used over an extended Kalman filter.

For the specific application the states are defined as

$$x_k = \begin{bmatrix} \theta \\ \dot{\theta} \end{bmatrix}_k$$

Where both theta and theta dot represent the angular position and velocity of the placement of the sensor.

Assuming a constant velocity model the matrix A is defined as

$$A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$$

The measurements or sensor inputs are as follows

$$z_k = \begin{bmatrix} \ddot{x} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} g \sin \theta \\ \dot{\theta} \end{bmatrix} = h$$

The following state space matrices are as follows:

$$B = \begin{bmatrix} \Delta t \\ 1 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

Ultimately from the estimate angular position generated by the kalman filtering algorithm the center of mass position can be extrapolated by the following:

$$CoM\ Position = l\sin(\theta)$$

From the Kalman filtered data a neural network can be setup to learn the appropriate mappings from an accelerometer and gyroscope data to an appropriate fused system. The reason this might be useful Is since it might be easier to implement in real-time in the future. The rational being that once the neural network is trained, it simply requires an accelerometer and gyroscope input and it can instantly map It to an appropriate center of mass position. The major limitation of this approach being that it might require a large amount of data,

Outside of the scope of the project would be to implement an artificial neural network for classification. The threshold for sway being one of the many inputs which would look at specific targets and learn whether there is an intention to walk based on said inputs.

Results

To understand the effectiveness of the Kalman Filter, a sample calculation of the individual sensors attempting to estimate the tilt angle was performed and plotted for comparison. As mentioned before, the integration of the gyroscope measurements alone will return the tilt angle of the IMU. The integration is performed using cumulative trapezoidal numerical integration via MATLAB. The tilt angle using only the accelerometer is found using the inverse sin function. The comparison plot is shown below in Figure 6.

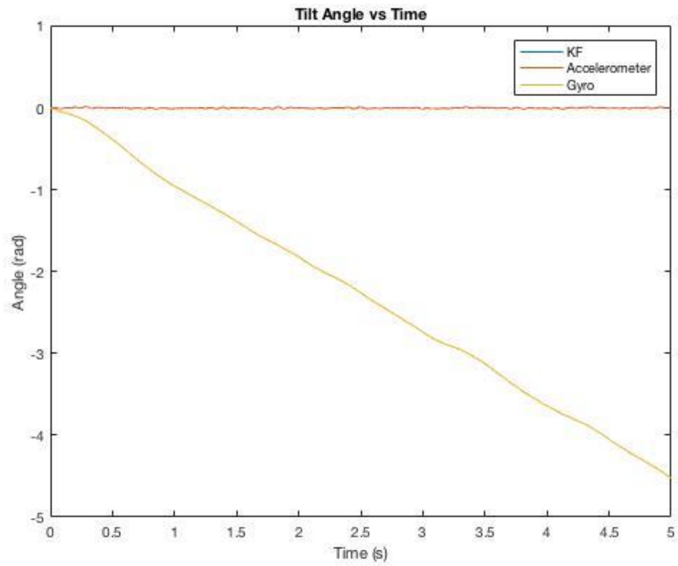


Figure 6: Comparison of estimated tilt angles from the Kalman Filter, Accelerometer, and Gyroscope for quiet standing trial

As seen in Figure 6, the first noticeable difference is the gyroscope measurement. As predicted, the drift is incredibly evident as the integration of the noise over time causes massive errors in angle prediction. The Kalman Filter estimate and the accelerometer estimate are evidently more in sync, however due to the drift of the gyroscope in the plot, it is difficult to see any differences. Therefore a sub plot of only the Kalman Filter and the accelerometer is created below in Figure 7.

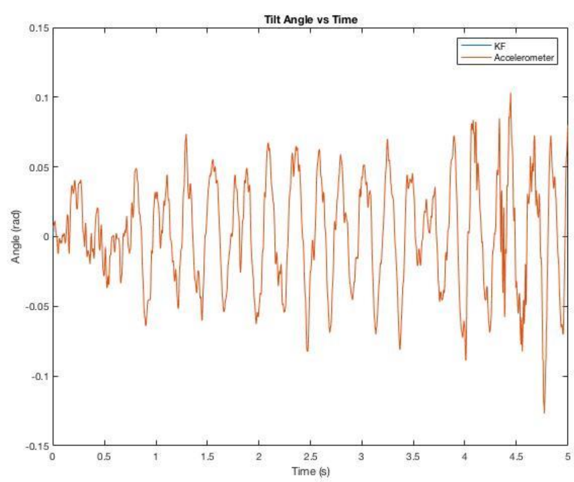


Figure 7: Comparison of Kalman Filter and Accelerometer Tilt Angle Estimate for quiet standing trial

The accelerometer appears to be incredibly like the Kalman Filter estimate, implying that perhaps the accelerometer alone can estimate the tilt angle. This can be attributed to the fact that the perturbations of quiet standing occur at low frequencies. As mentioned previously, the accelerometer is advantageous in low frequencies and the gyroscope is advantageous in higher frequencies.

Using the Kalman Filter estimated tilt angle, the estimated center of mass can be extracted and plotted for one of the trials as shown below in Figure 8.

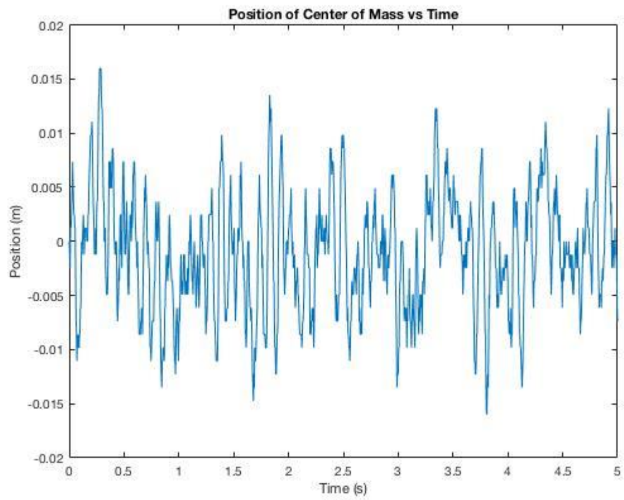


Figure 8: Sample Center of Mass Position Estimate for quiet standing

The Kalman Filter estimates the perturbation to be roughly around +/- 1.5 cm which seems reasonable during quiet standing. Further investigation will be discussed later in this section when all trials are considered and a threshold can be determined.

The same sample calculations and plots were created for the intentional postural sway trials. The plots are shown below in Figure 9 and Figure 10.

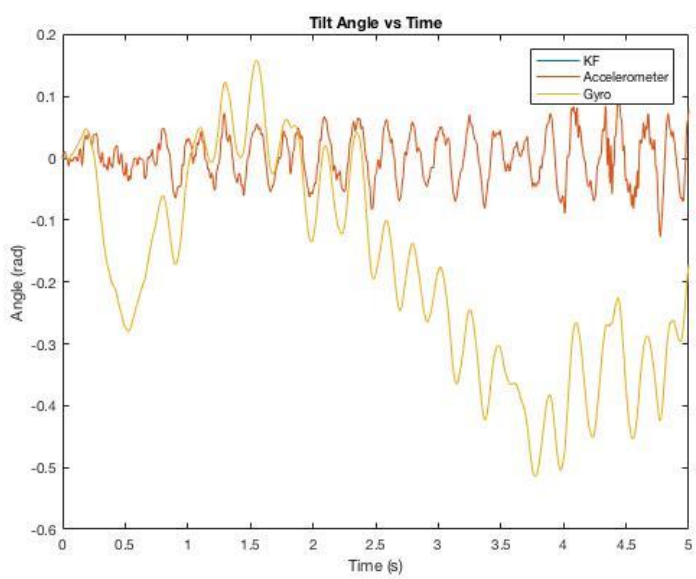


Figure 9: Comparison of estimated tilt angles from the Kalman Filter, Accelerometer, and Gyroscope for intentional postural sway trial

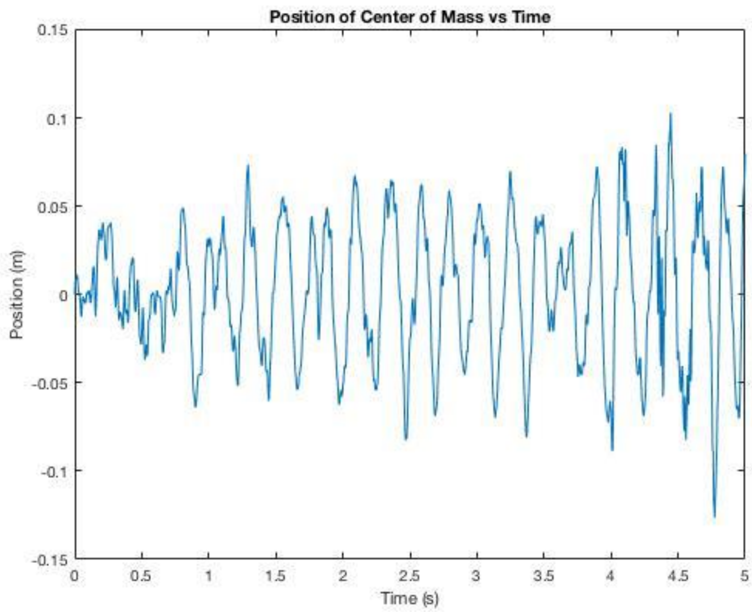


Figure 10: Sample Center of Mass Position Estimate for Intentional Postural Sway

To process the data and determine a threshold from each trial. In the likelihood that the intentional postural sway and quiet standing perturbations overlap and there is no definitive threshold, both the standard deviation and maximum deviations from true equilibrium is calculated for each trial. The data for quiet standing and intentional postural sway trials can be summarized below in Table 1 and Table 2 respectively.

Table 1: Summary of Standard and Maximum Deviation for all Quiet Standing Trials

Trial	Standard Deviation (m)	Maximum Deviation (m)
1	0.0068	0.0251
2	0.0065	0.0274
3	0.0052	0.0240
4	0.0055	0.0169
5	0.0059	0.0177
6	0.0056	0.0157
7	0.0125	0.0461
8	0.0124	0.0439
9	0.0099	0.0295

10	0.0094	0.0295
Average	0.008	0.0276

Table 2: Summary of Standard and Maximum Deviation for all Intentional Postural Sway Trials

Trial	Standard Deviation (m)	Maximum Deviation (m)
1	0.0361	0.1066
2	0.0386	0.1284
3	0.0256	0.0683
4	0.0314	0.0985
5	0.0217	0.0697
Average	0.0307	0.0943

Artificial Neural Network

An Artificial Neural Network which helps map the inputs of the accelerometer and gyro data to the fused data was developed using the neural network toolbox in Matlab. The complete set of trail data including trials not shown in the figure above were used as training data and feed into the network. The network contained a total of ten hidden layers.

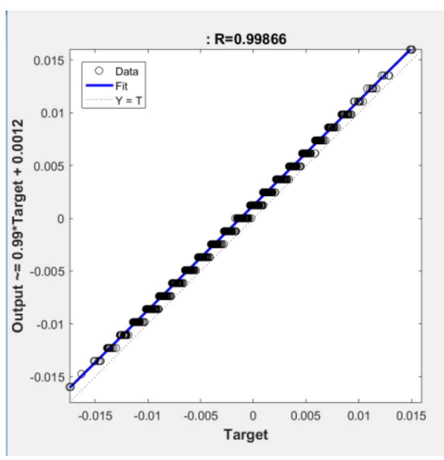


Figure 11: Performance of Trail 4 Data on ANN

As shown in the figure above, the network works quite well for Trail 4.

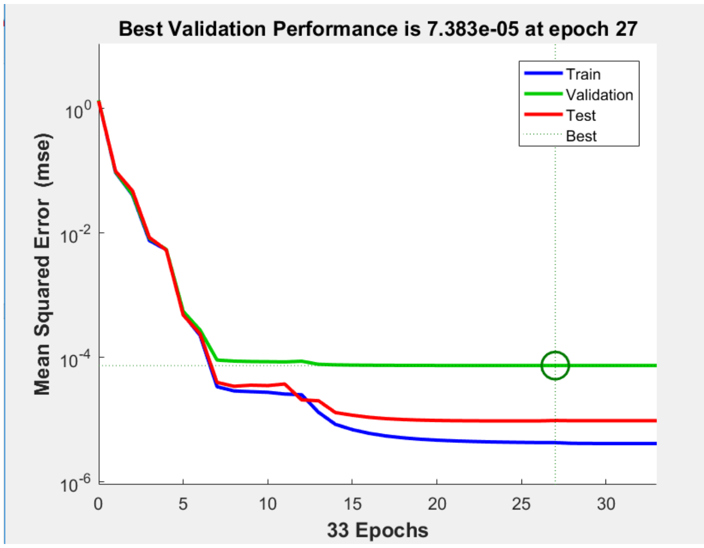


Figure 12: ANN Performance Validation

The performance of the network works quite well with a small mean squared error.

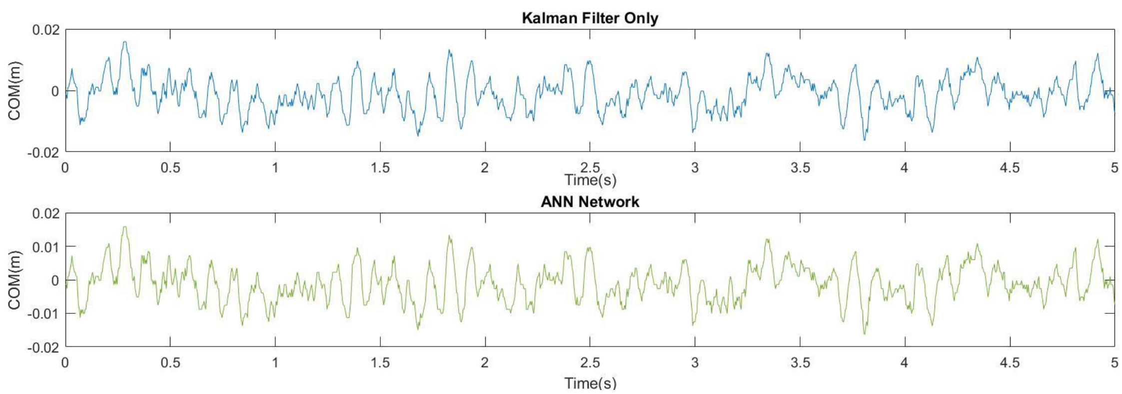


Figure 13: Trail 1 COM position compared to ANN

When looking at KF vs ANN data it can be shown they map quite well to each other, it is important to note that this set of trial data was not used in the training of the network.

The major limitation of this approach is that the data collected may not include enough training data to have a robust and accurate network. The other issue Is that the set of trails only included two possibilities, quiet standings and intentional swaying. To have a more accurate mapping in the future it likely that more outcomes should be analyzed.

Conclusion & Recommendation

In conclusion, it was determined that the Kalman filter is an effective tool in fusing data from the accelerometer and gyroscope. As shown in Figures 3,4 the raw data as compared to Figure 8 a substantial amount of noise and other inaccuracies have been removed and filtered. Ultimately, the sway from quiet standings was calculated from the Kalman estimates. The maximum and standard deviations for from quiet standing were also calculated and determined for each trail. This data is one of the criteria to be used in determining the intention to walk which is outside the scope of this project.

Some recommendations for the future of this project would be to have a better method of categorizing the threshold of sway. This would ideally include trials on multiple individuals in real time and analyse the maximum deviation of sway just before the intent to walk. Some other recommendations could be to include other sensors such as a pressure sensor on the foot which is able to calculate deviation from quiet standing based on the measurement of force.

Works Cited

[1] D. Novak, P. Reberšek, S. M. Maria De Rossi, M. Donati, J. Podobnik, T. Beravs, T. Lenzi, N. Vitiello, M. C. Carrozza and M. Munih, "Automated detection of gait initiation and termination using wearable sensors," *Elsevier,* vol. Medical Engineering & Physics, no. 35, pp. 1713-1720, 2013.

[2] G. F. Harris and J. J. Wertsch, "Procedures for Gait Analysis," *Physical Medicine and Rehabilitation,* vol. 75, no. 2, pp. 216-225, February 1994.

[3] R. Martinez-Mendez, M. Sekine and T. Tamura, "Detection of anticipatory postural adjustments prior to gait initiation using inertial wearable sensors," *Journal of Neuroengineering and Rehabilitation,* vol. 8, no. 1, pp. 1-10, 2011.

[4] J. A. B. Valencia, J. J. R. Pasaye and F. J. Pérez, "Tilt Measurement based on an Accelerometer, a Gyro and a Kalman Filter to Conrol a Self-Balancing Vehicle," *2013 IEEE International Autumn Meeting on Power Electronics and Computing (ROPEC),* pp. 1-5, 2013.