BME 512 Project **Alex Kyu**

Gait Classification Analysis

Introduction

A lot of devices nowadays can perform step detection, whether that be a Fitbit or even your smart phone. However, in the context of prosthetics this could be very useful for post-processing annotation of data. Especially if additional features relating to different parts of the gait cycle could be extracted, then these annotations could be used for model development for neural networks. Various movements and sensor outputs could then be used to predict which state of the gait cycle the user is in and predict future movement.

Walking, specifically, can be broken down into several states: heel strike (HS), flat foot (FF), toe off (TO), and mid swing (MS). If walking data can be broken down into these four (or possibly more) states, then prosthetics or exoskeletons can be programmed with preset motions to step through a finite state machine, allowing users to smoothly walk with a given intention. Currently, a lot of research is being done with the use of EMGs and accelerometers to classify these various states, using very periodic data. However, while walking can be quite periodic, it can also be quite nonperiodic and time variant (or shift variant), especially with changing terrain and obstacles. For example, for walking specifically, people speed up, slow down, or even stop depending on the who they walk with, what they are walking on, and other factors such as schedule, etc. This changes a lot of the sensor readings and measurements, specifically acceleration, become inconsistent between various walking speeds.

All these varying factors makes the segmentation of gait more important to making walking using a prosthetic or exoskeleton more dynamic and responsive to user intentions. The goal of this project was to use the subjects knee angle and linear acceleration to determine the more difficult phase changes: heel strike and toe off. The other two phases, flat foot and mid swing, are usually more distinct and can be recognized at the peaks of the knee angle signal (Figure 1).

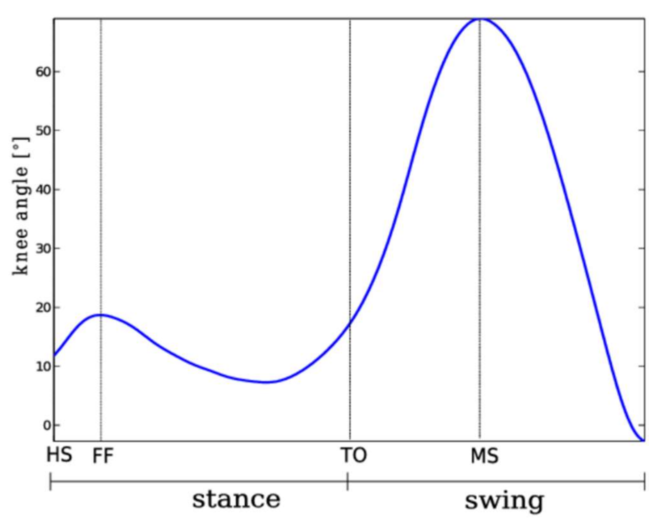


Figure 1: Knee angle throughout one cycle of the gait cycle. There are four phases shown here: Heel strike (HS), Flat Foot/Stance Phase (FF), Toe Off (TO), and Mid Swing/Swing Phase (MS) [1].

Methods

I. Data Acquisition

Data was collected using a leg brace as shown in Figure 2. The knee angle was measured by an absolute encoder (the AMT22) which was calibrated to be 0 degrees when standing straight up. An IMU (BNO055) is shown on the left to measure the inertial forces from the subject's thigh. This was used to measure linear acceleration specifically. An IMU was not attached to the shank because that wouldn't capture user intention in the case of a transfemoral prosthetic. These sensors were connected to an Arduino Micro which was connected to a laptop. Ideally, the data would have been sampled at 100 Hz or higher, but due to the communication protocols used between the microcontroller and the sensors, and the Serial communication from the micro to the laptop, data was collected as fast as possible which ranged from 50-100 Hz and was later resampled after filtering.

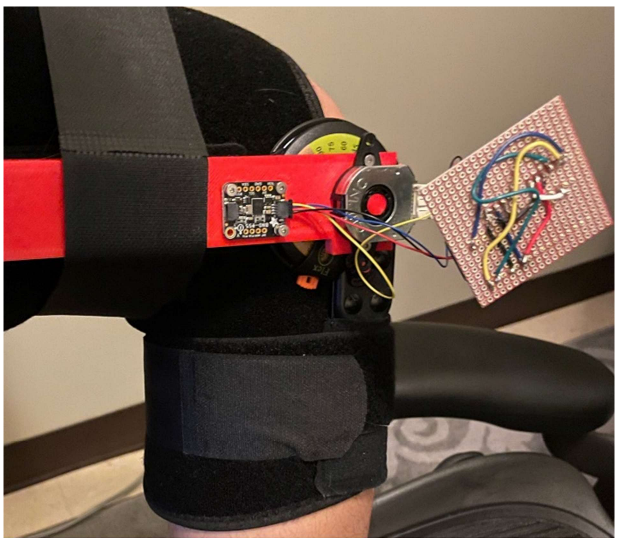


Figure 2: Data collection setup. On the left is the IMU, center is the encoder, and right is the Arduino Micro. All of this is attached to a custom, 3D printed, bar that is attached to a leg brace. The bar and brace help align the sensors to point along the thigh and shank.

With this given setup, five trials of walking were conducted, each at varying speeds, for 60 seconds. These speeds were quite arbitrary but were separated into these categories: fast (63 steps/min), fast/medium (58 steps/min), medium (54 steps/min), slow/medium (52 steps/min), and slow (45 steps/min) walking. The subject started walking at the given pace and then data acquisition started. The subject walked down a hallway which had a bend at the end of it.

In addition to these five trials, two additional trials were taken and analyzed with more abnormal and nonperiodic gait cycles to test the robustness of the designed filtering and classification process.

II. Data Augmentation and Classification

Linear acceleration data initially collected were separated into the three separate axes of the IMU. These were combined to create one singular linear acceleration (Figure 3). Then both signals' power spectrums were analyzed. Based on their power spectrums two filters were created to filter out the zero-meaned signals. The knee angle was filtered through an 8^{th} Order

Butterworth Bandpass filter with a cutoff at 0.1 Hz and 6 Hz. The linear acceleration was filtered through an 8th Order Butterworth filter with a cutoff at 4 Hz. The outputs of these signals were shifted to fix their time delay due to the filters (0.65 seconds for knee angle, 0.2 seconds for linear acceleration) and were resampled at 1000 Hz to correctly match up data points (Figure 4).

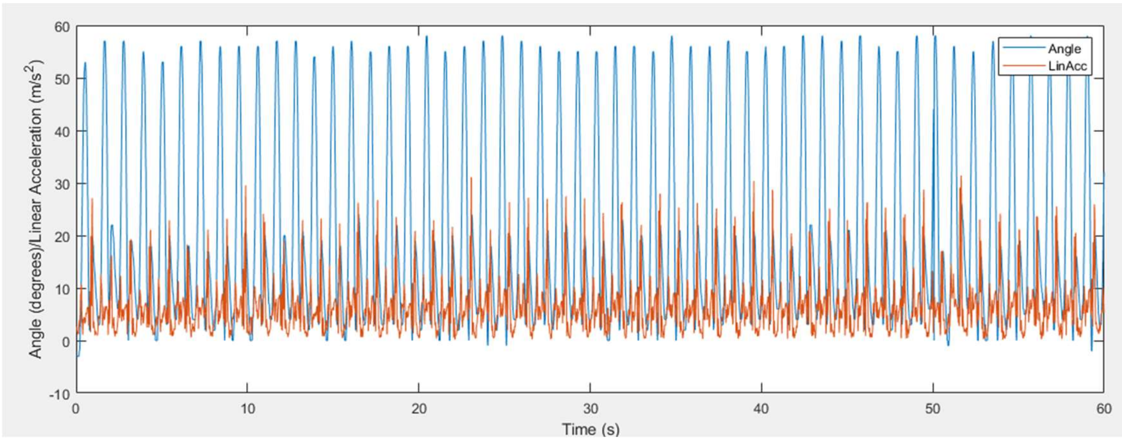


Figure 3: Original sampled data of Knee angle and Linear Acceleration.

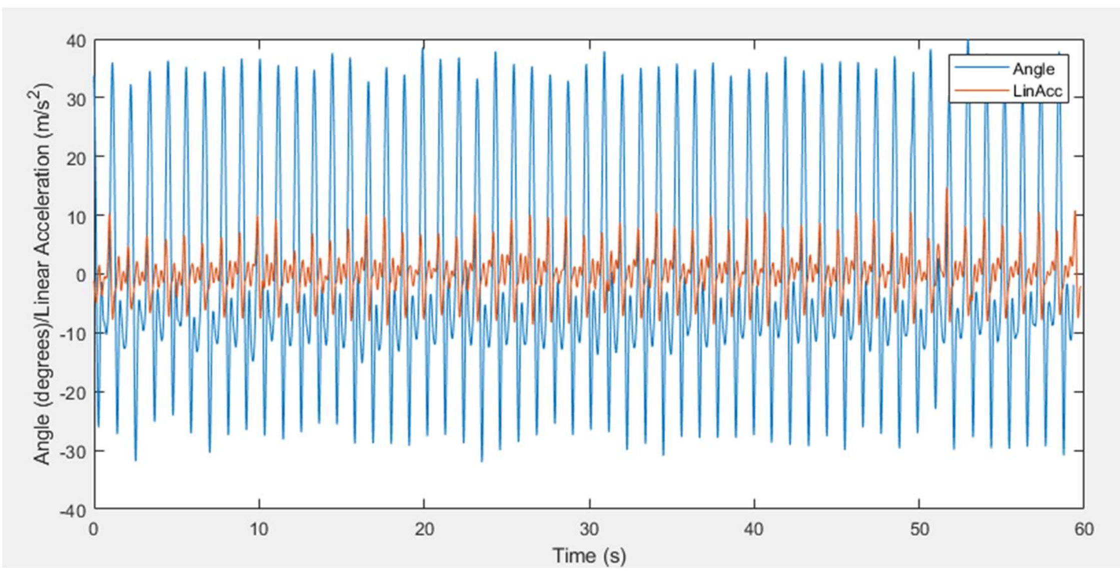


Figure 4: Filtered data of Knee angle and Linear Acceleration.

These filtered signals were then assessed and analyzed to see how they match of the with the locations of HS and TO. Based on the location of the peaks, a new signal was generated from the given signal. As noted in previous studies, the use zero-crossings worked quite well in detecting gait step-count [2]. Here, it was noted that at the zero-crossing of the filtered knee angle and at the peak of the linear acceleration matched very closely to the location of TO. Furthermore, another peak of the linear acceleration matched up with the slope increase that would occur right after HS (Figure 5).

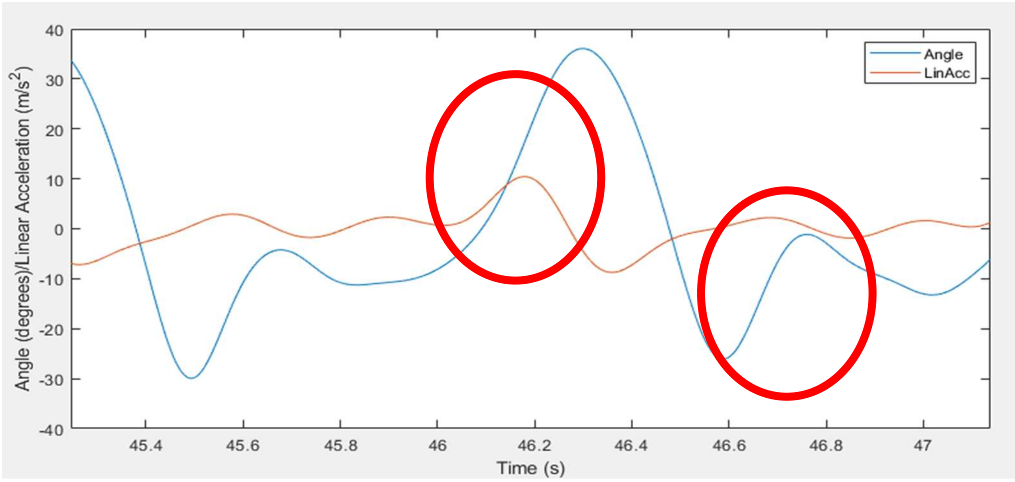


Figure 5: Zoomed in image of filtered signals. The red circles highlight the identified regions of TO and right after HS.

Using this information, the following equation was created:

$$New\ Signal = 10 * \frac{d}{dt}(FKA) * (-1 * \min(FLA) + FLA))$$

$$FKA = Filtered\ Knee\ Angle, FLA = Filtered\ Linear\ Acceleration$$

This signal was then passed through a wavelet transformation. As noted by Rahul Soangra, et. al., the Daubechies family of wavelets was useful for them in identifying states of the gait cycle. Here, the Daubechies family of wavelets was also used to highlight the desired states from our new signal. Specifically, DB10 was used after trial and error. Various levels of Discrete Wavelet Transforms were tested, and the 8th level seemed to produce the best results (Figure 6).

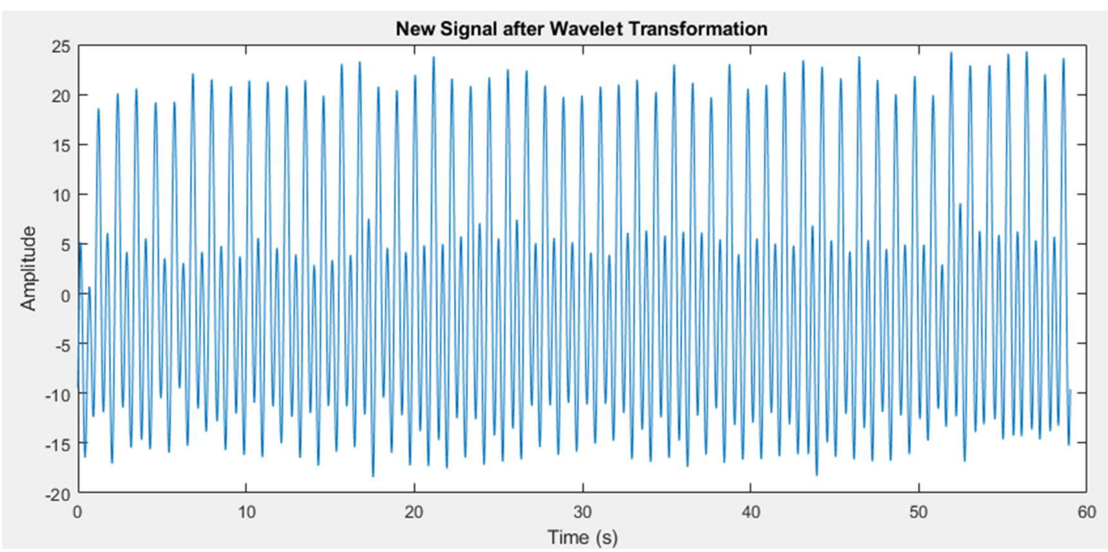
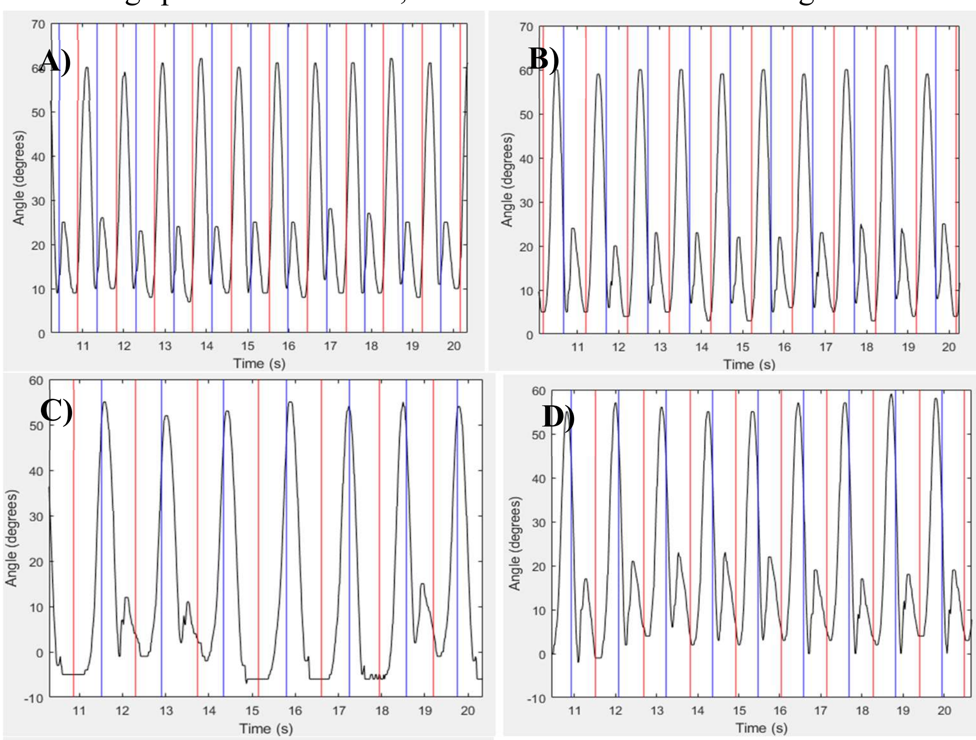


Figure 6: New Signal Generated after the given formula and wavelet transformation.

As can be seen in this signal, there are two sets of distinct peaks that alternate between a higher state and lower state. These peaks correspond to the states we set out to identify, heel strike and toe off, respectively. Furthermore, these distinct peak differences make it easy to separate distinct steps which could be useful for further processing of individual windows for other gait events [4]. Unfortunately, this didn't work too well with more abnormal and nonperiodic or time variant data and therefore, was not done.

Results

For all walking speeds, this classification technique did well, especially in the middle of the signal. A few spots towards the beginning and end of the signal were either misclassified or not labeled at all due to distortion at the edges (Figure 7). Fastest walking speed did the best and as walking speed slowed down, the classification seemed to lag more.



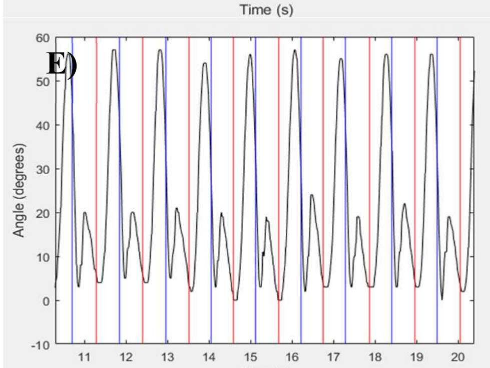


Figure 7: Classification Results for each walking speed. A) Fast, B) Fast/Medium, C) Medium, D) Slow/Medium, E) Slow. Red is Toe Off, Blue is Heel Strike.

As mentioned above, two additional abnormal gait cycles were analyzed (Figure 8). In the first abnormal gait cycle, the subject stood still during the recording period. In the second abnormal gait cycle, the subject progressively straightened their leg during the gait cycle as seen with the lower swing phase peaks. Both had significant lag and some level of misclassification.

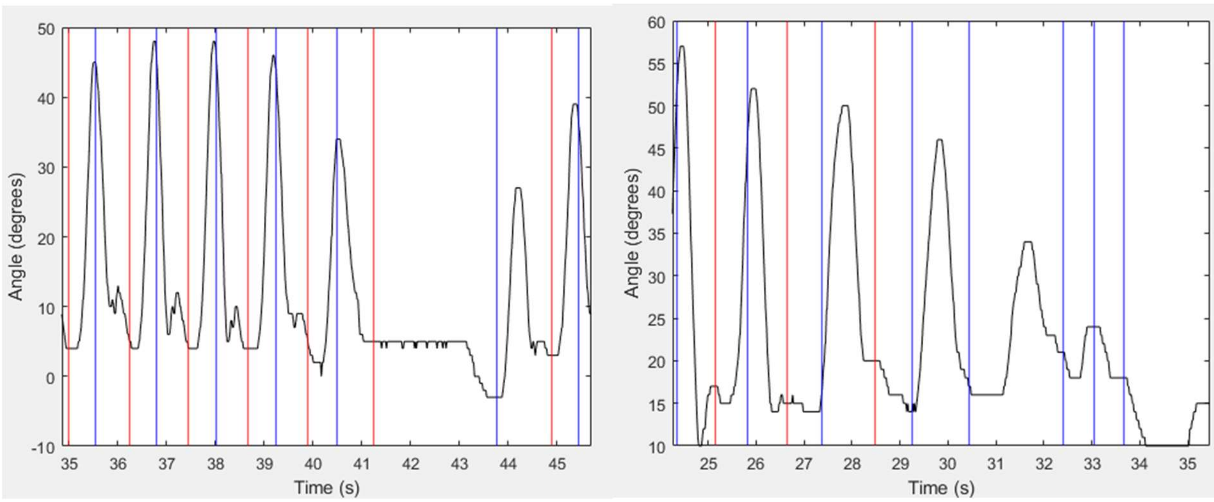


Figure 8: Results for abnormal gait cycles. In the left panel, the subject stood still. In the right panel, the subject progressively kept their knee more straight during the swing phase.

Discussion

Overall, there is much improvement to be done in with this method of classification for these two gait cycle states. Results the cleaner more periodic signals had no misclassification and only suffered from lag at slower speeds. This is obviously still a problem that could be addressed through additional signal information such as gravitation acceleration data, or angular acceleration data. When looking at the abnormal gait cycles, this classification method did alright for the subject where they stood still but suffered much more when the subject changed their walking style—like straightening their leg. The misclassification or lack of classification towards the edges was expected as there was some level of distortion of the signal either from preprocessing filtering or from the wavelet transform.

Several locations in this process were identified as problematic. First, the data acquisition is problematic. Sensors aren't perfect and some sensors, especially IMU's suffer from drift. Second, the preprocessing filtering. Because this data came from multiple subjects who walk slightly differently and at varying speeds, it is possible that the cutoff frequencies may need to be adjusted to prevent cutting out important frequencies. Third, the new signal. Other sensor data should be evaluated and various forms of the formula for this new signal should be investigated. Or, other signals should be used to cross-check and validate the classification—or prevent misclassification. Fourth, the choice of the wavelet. Here, the DB10 wavelet was chosen from the Daubechies Family of wavelets because it produced the best result and was recommended. However, there are many other families of wavelets with multiple forms that should be investigated, as they may more closely match the time inverted signal. The level of the wavelet should also be looked at for each chosen wavelet.

Another approach to this problem would be to segment it, as mentioned before. First, steps would be identified, and windows would be split up for individual analysis. This would help prevent misclassification. However, this presents some challenges too. Especially with abnormal gait cycles, detecting steps may be more difficult depending on the subject's movements and change in movements.

References

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[2] G. Flores, "UC Santa Cruz UC Santa Cruz Previously Published Works Title WeAllWalk: An Annotated Data Set of Inertial Sensor Time Series from Blind Walkers Publication Date WeAllWalk: An Annotated Data Set of Inertial Sensor Time Series from Blind Walkers," 2017. Accessed: Apr. 02, 2021. [Online]. Available: https://escholarship.org/content/qt64v6c4vz/qt64v6c4vz.pdf?t=p06vi4.

[3] Rahul Songra, Thurmon Lockhart, and N. Van, "An Approach for Identifying Gait Events Using Wavelet Denoising Technique and Single Wireless IMU," *ResearchGate*, Sep. 2011. https://www.researchgate.net/publication/271716122_An_Approach_for_Identifying_Gait_Events_Using_Wavelet_Denoising_Technique_and_Single_Wireless_IMU (accessed May 11, 2021).

[4] A. Anwary, H. Yu, and M. Vassallo, "An Automatic Gait Feature Extraction Method for Identifying Gait Asymmetry Using Wearable Sensors," *Sensors*, vol. 18, no. 3, p. 676, Feb. 2018, doi: 10.3390/s18020676.