Design and Implementation for Measuring Walking Asymmetry using Phones

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Overview

There are many factors that affect an individual's health and walking, specifically walking can serve as an indicator to suggest whether a person might suffer from an injury or disability for both short-term as well as long-term health [1]. For this project, we came up with a question related to walking asymmetrically. If there are significant differences between the movement of the right leg and the left leg, does this suggest some sort of injury has occurred and could we detect it? For example, at the time a person might suffer from slight to severe injuries, the experiment could be conducted to observe whether the walking asymmetric at that time is different (higher) from their normal walking asymmetric result. Therefore, suggestions based on walking information could be made to detect health problems and prevent it on time.
To 'refine' the idea provided, we also wanted to see if this would be possible from just the pants pocket, instead of the phone being taped near the ankles. This would introduce more uncertainty, but after noticing that Apple could do it this way, we were motivated.

Development

Data Collection

Two phones with the app "Physics Toolbox Sensor Suite" on iOS were used to collect the data. With a phone in each of the walker's two front pockets, the Linear Accelerometer feature would track the acceleration of each phone, along with a timestamp of when it was measured. The app would then export the data into two .csv files. The csv files were read into 2 pandas DataFrames, which then needed to be cleaned.

Considering the difference in various factors, we collected the data in multiple different cases to get well-rounded results. The characteristics of the walkers are different: they have different ages, genders, heights, weights, and injuries. Some of the data was collected on a flat, straight line, but we also gathered data for walking uphill/downhill. Another set of data was collected with the participant running. We aimed for at least 1 minute of walking time so we had a large enough sample to calculate averages.

We also collected data from Apple's Health app to compare to their "Walking Asymmetry" data that they track for iPhone users. Since Apple Health includes a lot of data about their user over a long term, including waking asymmetric rate, we considered it as a source of validation and comparison between the walking asymmetric result we conduct and their normal walking asymmetric rate.

Data Cleaning

The starting and ending timestamps of both csv files would never be the same: the “start recording” and “stop recording” buttons were never pressed at the exact same time between both phones, so we needed to find the true starting and ending times.

After we found these points, we also needed to account for the time to put both phones in the walker’s pocket and start moving, as well as the time to press stop recording. We manually inputted these for each dataset because we found the time to be different for everyone, but a default value of 20 seconds from the beginning and 10 seconds from the end worked well.

The individual data points also needed to be synced together. For example, the left data might contain a record for *21:15:26.1560*, but the right dataset may only contain a datapoint for *21:15:26.1570*, so we can see a problem. This problem can also be much more severe, such as large gaps in the data where the app didn’t record for some reason. The way we decided to synchronize the data was grouping the data by 500ms and averaging the values to create an interval. Some of these intervals would be missing a record because the recording app was inconsistent, so we dropped them.

The information from Apple Health of users was exported as an XML file and parsed with Pandas. We also only want data that is relatively recent, which we decided 1 year is a good amount.

Data Analysis

Once the data was synchronized and cleared of the null values, we could begin the analysis: how different were the accelerations? To do this, each interval was compared left leg versus right leg, and these differences were computed with the following formula where acceleration (m/s^2):

$$Percentage\ of\ left\ leg\ in\ total = \frac{total\ acceleration\ in\ left\ leg}{total\ acceleration\ in\ right\ left + total\ acceleration\ in\ left\ leg}$$

$$Percentage\ of\ right\ leg\ in\ total = \frac{total\ acceleration\ in\ right\ leg}{total\ acceleration\ in\ right\ left + total\ acceleration\ in\ left\ leg}$$

$$Absolute\ percentage\ different\ in\ one\ interval\ =$$

$$|Percentage\ of\ left\ leg\ in\ total\ -\ Percentage\ of\ right\ leg\ in\ total|$$

We came up with this formula since we wanted to find the absolute difference between the left leg and the right leg in a single interval. The results of the absolute percentage difference of all intervals were then averaged to compute a final percentage. The result is the approximate difference in walking rate between the left leg and the right leg which we consider as the walking asymmetric percentage.

Comparing with Apple Health's data, they consider symmetry calculated as an overall temporal symmetry ratio. The formula is presented below:

$$SSR = \frac{swing_{time}}{stance_{time}} * 100$$

$$symmetry = \frac{max(SSR_{left}, SSR_{right})}{min(SSR_{left}, SSR_{right})}$$

where $swing_{time}$ and $stance_{time}$ are the mean swing and stance times of strides when a person walking on the flat surface condition [1].

Results

The two tables and 12 figures below are correspond with the walking asymmetric percentages of participants without injuries, with injuries and the graph of acceleration difference between their right leg and left leg.

Record	Age	Gender	Height (feet & inches)	Weight (kg)	Injuries	Path condition	Our walking asymmetric (%)	Apple Health (% per year)
1	22	Female	5'0"	42kg	No	Flat	4.5	2.06
2	25	Male	5'9"	80kg	No	Flat	0.11	3.15
3	23	Male	5'7"	65kg	No	Flat	1.3	1.91
4	22	Female	5'3"	58kg	No	Flat	3.5	0.79

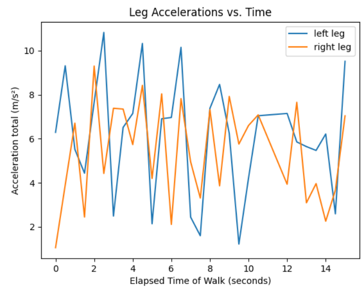
5	21	Male	5’8”	95kg	No	Flat	11	1.99
6	60	Male	5’10”	90kg	No	Flat	15.2	3.47
7	22	Female	5’0”	42kg	No	Up/down hill	0.6	2.06
8	21	Male	5’8”	95kg	No	Downhill	0.1	1.99
9	21	Male	5’8”	95kg	No	Flat (running)	2.5	1.99

Table 1: *Participant characteristics without injuries*

Record	Age	Gender	Height (feet & inches)	Weight (kg)	Injuries	Path condition	Our walking asymmetric (%)	Apple Health (% per year)
10	22	Female	5’0”	42kg	Yes (Fake)	Flat	78.52	N/A
11	21	Male	5’8”	95kg	Yes (Fake)	Flat	20.85	N/A
12	57	Female	5’2”	91kg	Minor	Flat	18.55	7.81

Table 2: *Participant characteristics with injuries*

1



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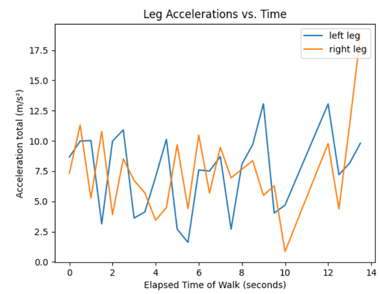

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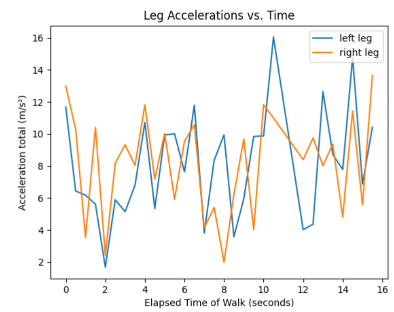

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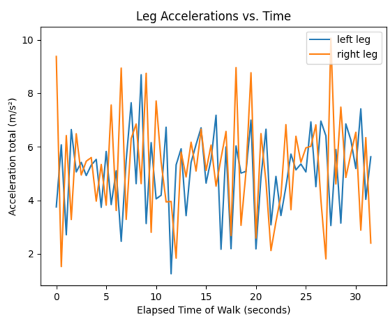

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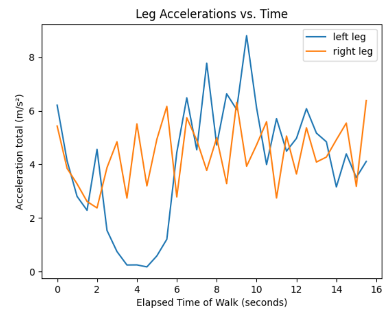

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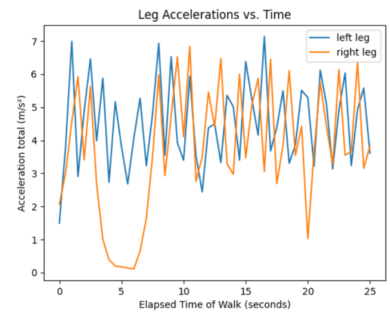

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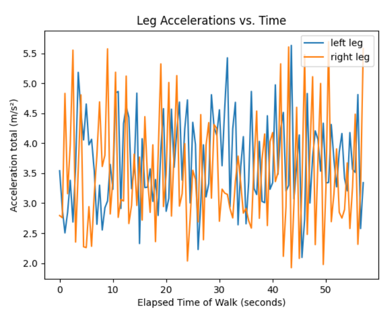

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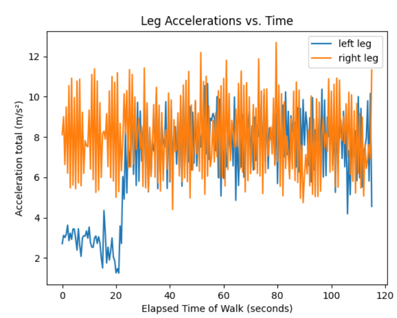

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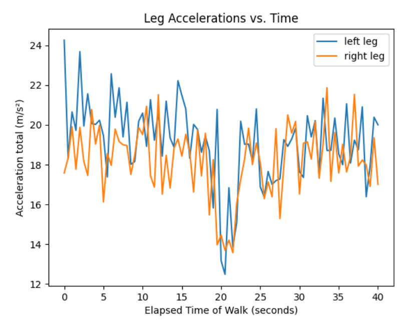

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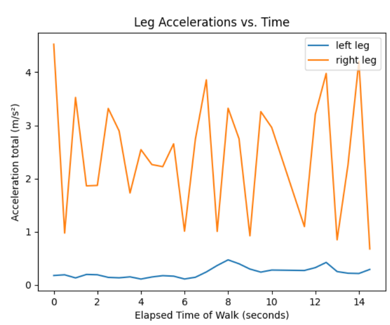

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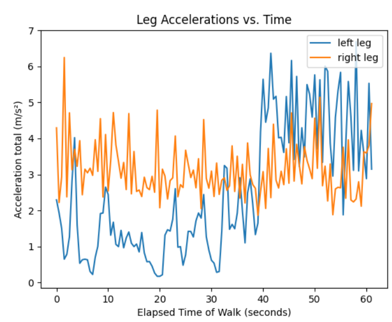

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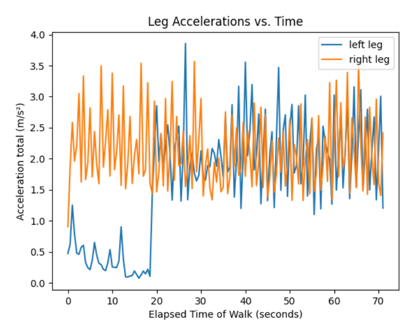

***Figure 1**. The graphs 1-9 are corresponding to the characteristics of record 1-9 in Table 1 (no injury). The graphs 10-11 are corresponding to the characteristics of record 10-11 in Table 2 (on-purpose fake data). The graph 12 is corresponding to the characteristics of record 12 in Table 2 (real data with a minor injury).*

The graphs are aligned with the health conditions of the instance experiment. While the graphs 1-9 fluctuated, the shape between their left legs and right legs are considered as having a similar pattern shape, the graph 10 suggest an severe asymmetric thus an injury might occur since the acceleration values between left foot and right foot are significantly different. The graph 11 and 12 could be considered mild walking asymmetry..

Discussion

According to a study in the journal *Medicine & Science in Sports & Exercise* [2],
the average walking asymmetric percentage for healthy adults falls between 5 and 15 percent. Our datasets and predictions are aligned with that assumption, record 1-9 is recorded from different datasets with no injuries condition. There are 2 records with pretend injuries (Record 10 and 11), both produce expected results (78.51 % and 20.85%). While Record 12 is a real person who experiences slight pain in her foot and who's doctor says they may have "plantar fasciitis" which causes heel pain in their first few steps of walking [3].

Findings

Throughout the many experiments we conducted, we encountered some records that were especially high. The results before cleaning and after cleaning data is significant, since data can be lost in the csv file. For example, one time the phone screen was locked in the middle of the walk, and in another instance, the duration of the recordings was too short.

Limitations

The development and validation of the metrics can be limited in several ways. First, the limitations of the diversity of the dataset. Although the datasets vary from gender, height, weight, and health conditions, the number of instances experienced are still limited, for example all individuals were 5'10" and below. Second, while the walking situations include walking on a flat surface, running, combination of walking uphill and downhill, more path conditions are necessary. Third, the study population didn't span and was restricted to individuals in Canada only.

Conclusion

The metrics outlined here can give a good result for tracking normal walking across a lifespan, but further validation for different walk characteristics such as athletic capabilities, ethnicity, and environmental conditions (snow, mud, sand) are needed.

Future works

Since the experiment is conducted using the assumption that the person needs to use two sensors (phone usually), it is not very easy for people to conduct. Further work could consider conducting the experiment using only one phone and a method to distinguish which pocket the phone is in. Also, collecting data from different ethnicities and pathways are needed to avoid bias and increase accuracy.

References

[1] “Measuring Walking Quality Through iPhone Mobility Metrics,” p. 15, May 2021. https://www.apple.com/ca/healthcare/docs/site/Measuring_Walking_Quality_Through_iPhone_Mobility_Metrics.pdf

[2] D. P. Laroche, S. B. Cook, and K. Mackala, “Strength Asymmetry Increases Gait Asymmetry and Variability in Older Women,” *Med. Sci. Sports Exerc.*, vol. 44, no. 11, pp. 2172–2181, Nov. 2012, doi: 10.1249/MSS.0b013e31825e1d31. https://journals.lww.com/acsm-msse/Fulltext/2012/11000/Strength_Asymmetry_Increases_Gait_Asymmetry_and.17.aspx

[3] “Plantar fasciitis - Symptoms and causes,” *Mayo Clinic*, Jan. 20, 2022. https://www.mayoclinic.org/diseases-conditions/plantar-fasciitis/symptoms-causes/syc-20354846 (accessed Dec. 07, 2022).

Project Experience Summary

Adam:

- Analyzed phone sensor data using Python to calculate a walking asymmetry percentage for discovering injuries
- Organized data in Python dataframe to sync timestamps, filter different values, and group records
- Presented results in a detailed report with visualizations and conclusions of the study

Clare:

- Utilized and analyzed Apple Health data information to extract user health information
- Converted raw data from phone sensor tool into actionable insight by analyzing walking outcome
- Developed and calculated walking asymmetry percentage using Python by analyzing participants walking pattern
- Prepared report that interpret user walking behavior results and make suggestions to prevent further injuries may occur