CMPT 353: SENSORS, NOISE, AND HUMAN ACTIVITY RECOGNITION

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Introduction

Computational data science is seen as a major area to study humans and society. To be better solve real social problems with a lot of related applications, smartphones as daily tools can provide us with a lot of useful information, for example, the recorded accelerometer data. Human activity recognition is the problem of classifying sequences of accelerometer data recorded by smartphones into known well-defined movement. Here we are classifying movement activities: walk, run, go upstairs, go downstairs.

This project is based on Sensors, Noise, and Walking (https://coursys.sfu.ca/2019fa-cmpt-353-d1/pages/ProjectWalking). And here are some of the questions to be answered:

- Can we predict whether the person is walking or running or going upstairs/downstairs using pre-calculated sensor data?
- How accurate would it be? What model would be able to do it better?
- Are the results better depending on where the phone is?

Method

Data Collection

Data was collected by different individuals with the Android Application called PhysicsToolbox Suite by Vieyra Software[1]. Tied the smartphone to each subject's ankle, hand and pocket while they walked, ran, went upstairs and went downstairs for approximately 30 seconds with their regular walking-speed. Linear acceleration and angular velocity in the x-, y-, and z-directions were recorded by the smartphone application mentioned at the first.

To collect more comfortable data, random samples were chosen and we asked the subject to stand still and the start and end of the process for around 5 seconds.

Each CSV data and collected with the name format ACTIVITY-POSITION-TIME, e.g. walk-hand-2019-11-2717.02.36.csv, which will be further used to extract, transform and load.

Data ETL (extract, transform, load)

Varies Python libraries were used to process the original data including stats and pandas. There are 36 CSV files, each file has 6 columns: ax, ay, az, wx, wy, wz. The first three are linear acceleration and the last three are angular velocity in x, y, z directions. The reason why we include angular velocity is that we want to combine and use mobile phone gyroscope data to better predict the movement activity. As shown in fig1[2], the mobile phone gyroscope can also be used to conduct the direct of the movement.

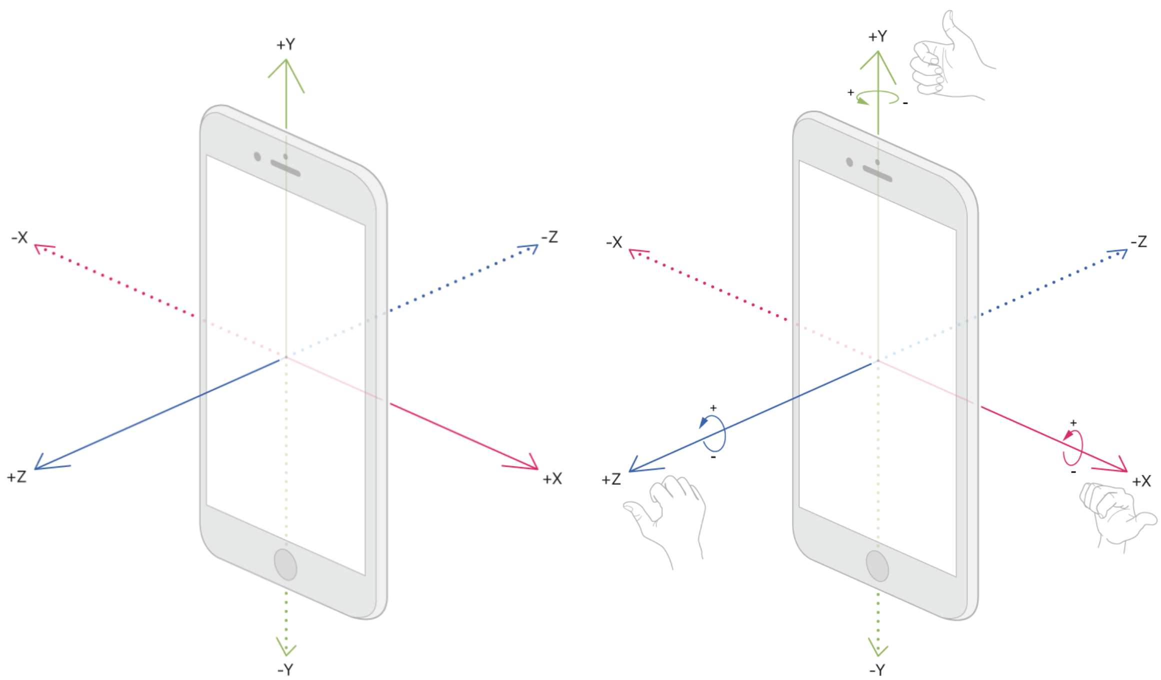

Fig 1

The next step is to join the same category data by their filename. There are 3 files collected under the same category (e.g. walk-hand-timestamp) and consider the 5 seconds dummy data in the beginning and the end, data were joint with delete those 5 seconds dummy data. The data was then further transformed by filtering with a low pass Butterworth filter to eliminate high-frequency noise present from the sensor readings. This was accomplished through the use of SciPy's signal.butter() method, with an order of 3 and a cut off frequency of 0.05 half-cycles per sample. Column added for those filtered data, e.g. ax_filtered. Dramatically improvements made after applied the filter.

After processing the data, to be better evaluate we plotted the following distribution figure2:

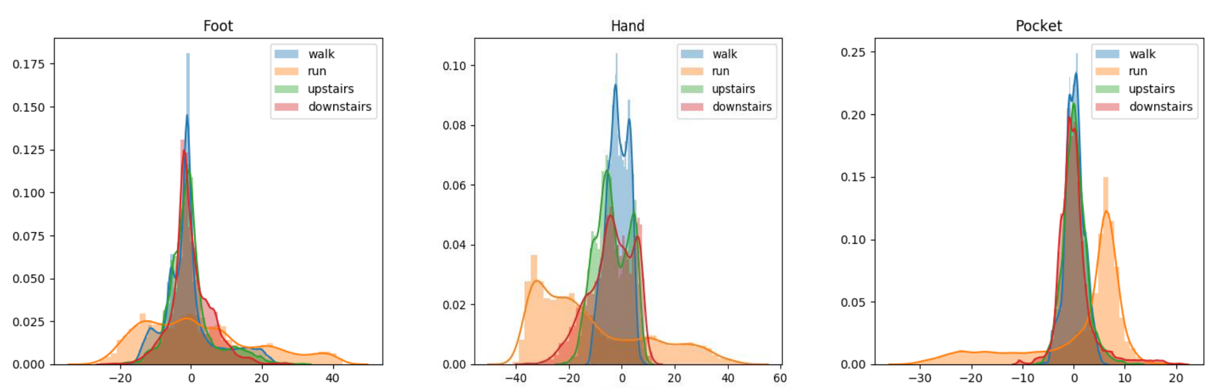

Fig 2

Figures show a single factor ax for different activities and different positions we tie to the subjects. As shown from the graphs, use a single factor e.g. ax to distinguished different types of movement activities is not realistic. Most of the data are concentrated around 0.
In the following steps, all the factors will be used to model human activities.

Results and Analysis

Velocity Analysis

The initial thought after getting linear acceleration data is that whether we would be able to calculate velocity and whether we could conclude a useful conclusion based on the calculated velocity. In theory, velocity could be calculated $v(t) = \int a(t)dt + C$, where C is a constant of integration. Besides, based on directions in Fig 1 and how data is collected, acceleration on z-axis shouldn't have affected velocity in forward direction, we decided to use the linear acceleration data on x, y axis and $a_{total} = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2}$ respectively to see how velocity changes over time. Below is the velocity graph calculated using data collected from ankle

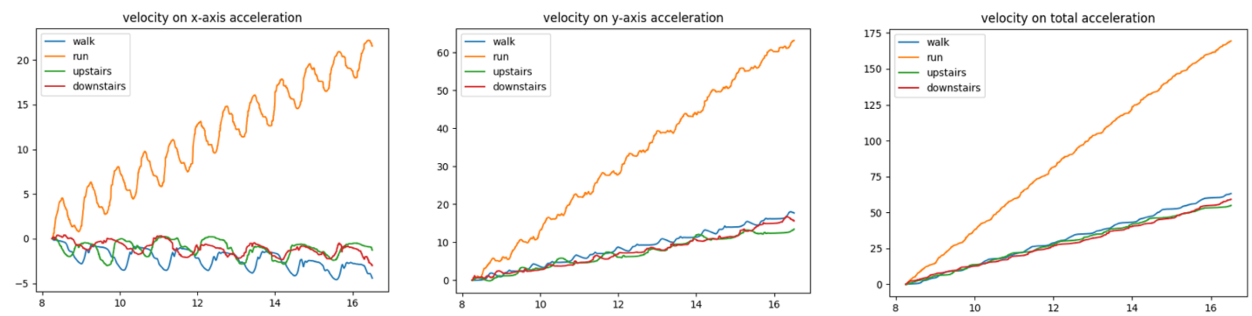

Fig 3

As can be seen from Fig 3, the velocity does show different patterns especially when the activity is running. However, the calculation of velocity is not very accurate. First of all, there must be some noises during data collection, a calibration routine would be beneficial, but the step of integration will likely introduce more error. Second, since human walking/running is more like a pendulum movement, so calculating velocity without considering the directions and angles is not very accurate. Third, if we use the total acceleration based on the function above, it actually cancels out the positive and negative patterns which is essential for activity detection. So based on the graph it's possible to identify running activity based on velocity, however for the other three activities we need further analysis.

Classification Analysis

Since phone rotation on each direction happens all the time during human activities and stride cycle should also be considered during calculation, using velocity to determine human activity seems too much work, so in the end we decided to see if we can train the model just using the filtered data from accelerometer and gyroscope without doing other calculations.

We included all columns ax, ay, az, wx, wy, wz and grouped them based on its collecting position, then trained models to see how accurate they can be:

	Foot	Pocket	Hand
Bayesian classifier	0.481	0.526	0.713
kNN classifier	0.960	0.969	0.998
Rand forest classifier	0.789	0.812	0.871

From the above tables, the k-nearest neighbors classifier performed the best when identifying different activities with Random Forest classifiers producing second best results, while the Bayesian classifier's score is the worst and has trouble distinguish different activities. Besides, depending on where the phone is the results can be quite different. We could argue that k-nearest neighbors classifier performs the best because of the nature of the data as they are all wave-shaped signal. And hand performs better because in both foot and pocket there could be lots of unexpected drifting thus introducing noises.

Conclusion from Analysis

Based on all the analysis we have done, we could conclude that for similar subjects kNN classifier would be able to identify human activities using accelerometer and gyroscope data, and the position of where the phone is does have some impact on how accurate the model can be, as in hand position it has the least drifting errors. However, there are some restrictions and limitations that prevent us from jumping to conclusions.

Limitation

One limitation is that the subjects are of similar height, weights, and ages, therefore it might not be accurate to describe the relationship between accelerometer data and movement activities as people can have quite different moving frequencies/speed, etc.

The second limitation is that the data collected was not entirely accurate, especially when it's located on one's ankle and in the pocket. The sensor on the cellphone is not accurate in the first place, and then during collection, the phone might be bouncing around, so it may not capture the pattern for each person very accurately, and filtering doesn't cancel out the errors.

Project Experience Summaries

Jing Wen

- Data collection, extraction, transformation, and load
- Collected 36 sample data in total
- Applied the knowledge about Pandas learned from the class, read CSV files, eliminate noise and Join the same category data
- Worked with regex and pandas to extract certain categories and movement activity names from the file path and also add a specific label to each column
- Researched data filters and use Butterworth filter which showed a good result
- Prepared the data to be used to model, to analysis in a more deeper way

Wenshuai Lu

- Worked with a group member to determine appropriate data collection method and analysis needed for the problems
- Researched different velocity calculation method with phone sensor data
- Calculated velocity using linear acceleration data and performed related analysis
- Applied Bayesian Classifier, KNeighborsClassifier, and Random Forest Classifier to predict human activities with filtered phone sensor data

Reference

[1] Sensor & Generator Info: vieyra-software. (n.d.). Retrieved December 1, 2019, from https://www.vieyrasoftware.net/sensors-sensor-modes.

[2] Malyi, V. (2017, November 14). Run or Walk (Part 2): Collecting Device Motion Data the Right Way. Retrieved December 1, 2019, from https://towardsdatascience.com/run-or-walk-part-2-collecting-device-motion-data-the-right-way-58a277ff2087.