# Task 8.3D - SIT225

Truong Khang Thinh Nguyen

September 23, 2024

## 1 Data Collection Protocol and Annotation Mechanisms

I've set up a system where accelerometer data from a smartphone is streamed via Arduino IoT Cloud to a Jupyter notebook script on my computer. The data, which includes readings from the x, y, and z-axis, is captured every 10 seconds to ensure there are enough samples for each activity segment. Using Plotly Dash, I've created a real-time dashboard that updates graphs of accelerometer data whenever new data is received (every 10 seconds). Simultaneously, a laptop webcam captures images, saving them with filenames that include timestamps for synchronization with the accelerometer data. Each 10-second interval of accelerometer data is saved into CSV files, paired with an image depicting the concurrent activity.
After data collection, activities are manually labeled using the captured images. An annotation CSV file links each data/image pair to an activity label (1 for waving the phone, 2 for rotating the phone, and 3 for holding the phone still on a surface). In terms of efficacy, this protocol enables real-time visualization of accelerometer data and simultaneous image capture, making it easy to observe activities immediately. Timestamps ensure accurate pairing of accelerometer data with images, which is crucial for later analysis. While manual labeling based on images can introduce some subjectivity, it allows for detailed analysis of specific activities. Regarding limitations, relying solely on images to determine activity types can be prone to subjectivity and errors. The absence of video data limits the ability to capture continuous activity transitions, possibly overlooking subtle changes. Additionally, handling large volumes of CSV files and images over extended periods can become cumbersome and time-consuming.

## 2 Data Analysis

After recording the accelerometer data into CSV files, the preprocessing stage involves combining the different CSV files from each interval and merging them with the corresponding activity labels into a single CSV file. This process also includes formatting the datetime objects to ensure proper synchronization and organization of the data. We then attempted to plot line graphs showing the trends of all accelerometer readings to observe any distinct patterns or trends associated with each specific activity.

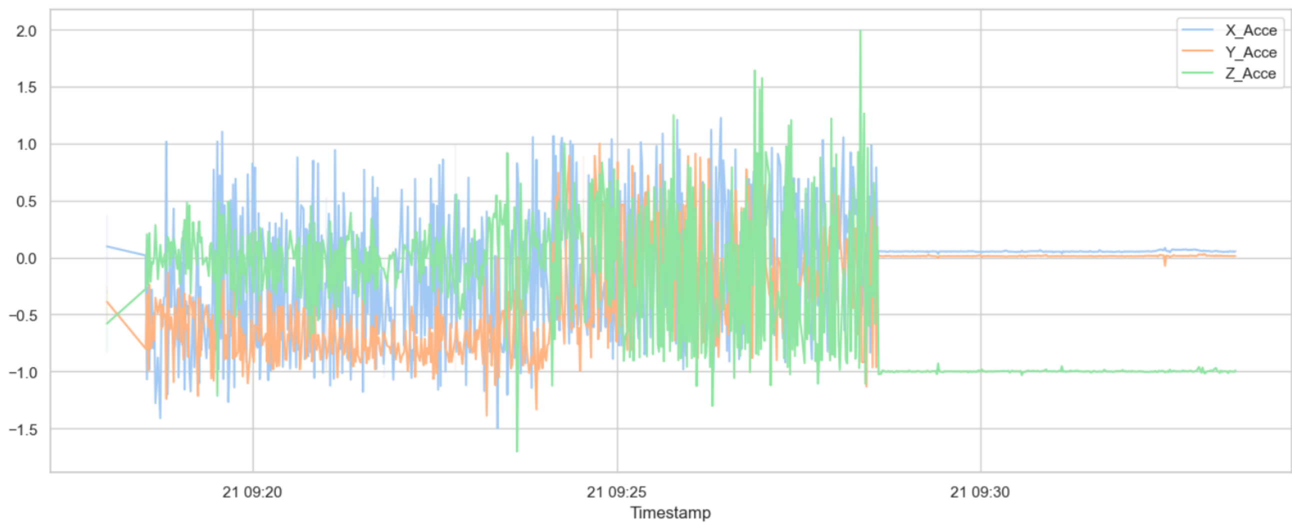


Figure 1: Accelerometer Data Trends over time

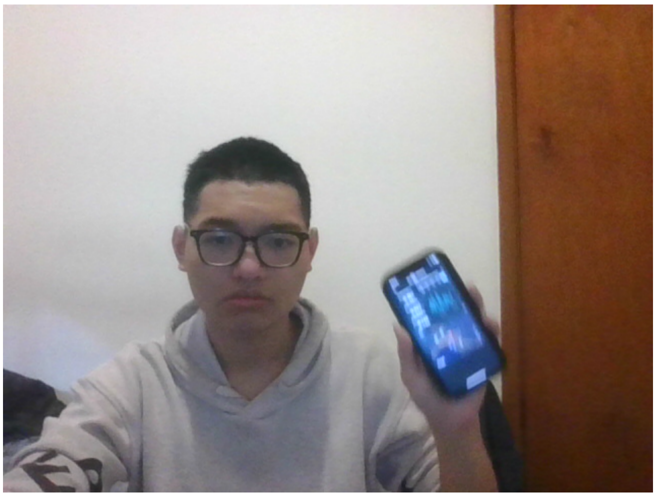

Figure 2: Image captured from the Camera of the Activity 1

Looking at the accelerometer readings for the first activity 1, waving the phone, the X-axis (X_Acce) showed the most fluctuation, ranging from $-1.5$ to 1.0, indicating significant lateral movement. The Y-axis (Y_Acce) fluctuated but remained lower, between 0.0 and $-1.4$, showing less motion. The Z-axis (Z_Acce) fluctuated moderately, with values between 0.6 and $-0.5$, reflecting some vertical movement. These patterns highlight the dominant side-to-side motion during the waving activity, with less vertical and forward/backward movement, as indicated in figure 2.

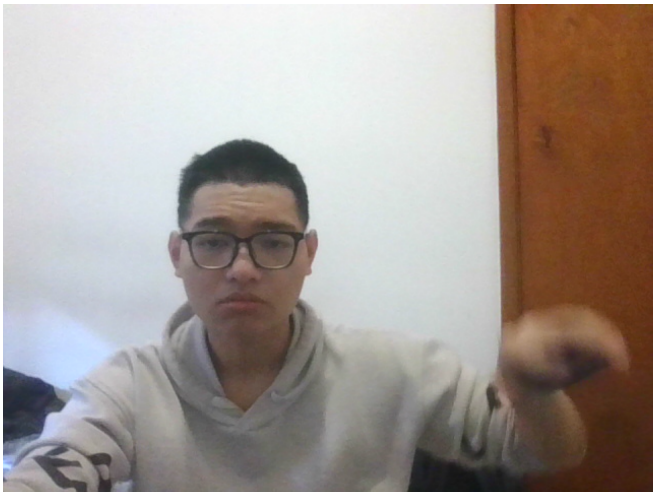

Figure 3: Image captured from the Camera of the Activity 2

For the second activity, rotating the phone, the accelerometer trends shift noticeably. The X-axis (X_Acce) still fluctuates, but its range narrows slightly, between 1.0 and $-1.0$. The Y-axis (Y_Acce) undergoes the most significant change compared to the first activity, fluctuating between 1.0 and $-1.0$, a marked difference from its behavior during the waving motion. The Z-axis (Z_Acce) is the most prominent, showing a wider range of fluctuation, from $-1.5$ to 1.5, indicating more pronounced movement along the vertical axis during rotation. These patterns reflect the distinct motion dynamics of rotating the phone, with more balanced fluctuations across all axes, as shown in figure 3.

Figure 4: Image captured from the Camera of the Activity 3

For the third activity, holding the phone still on the surface, there's not much to discuss as expected—the accelerometer readings remain stable throughout. Interestingly, both the X-axis (X_Acce) and Y-axis (Y_Acce) stay at 0.0, while the Z-axis (Z_Acce) consistently holds at $-1.0$, reflecting the phone's stationary position on a flat surface.

# 3 Annotation File and Activity Identification Challenges

For the annotation step, to easily keep track of the images captured alongside the corresponding CSV files and labeled activities, I combine the filenames of both the images and CSV files in the format {sequence_number}_{timestamp}.csv (or .png for images). This ensures that each image

and its corresponding CSV file are consistently linked for reference.
One of the main challenges in this project arose when trying to differentiate between activity 1 (waving the phone) and activity 2 (rotating the phone), particularly during the transition from one activity to the other.

1. Overlap in Motion Between Waving and Rotating
   Both waving and rotating the phone involve significant movement of the device, often causing similar fluctuations in the accelerometer data, particularly in the transition period

   - During the transition, the hand position and movement trajectory captured by the webcam often looked similar for both activities. For instance, in many cases, the images showed the phone mid-motion, with no clear indication whether the person was still waving or beginning to rotate the phone.
   - For example, in the image filename: 29_20240921-092355.png

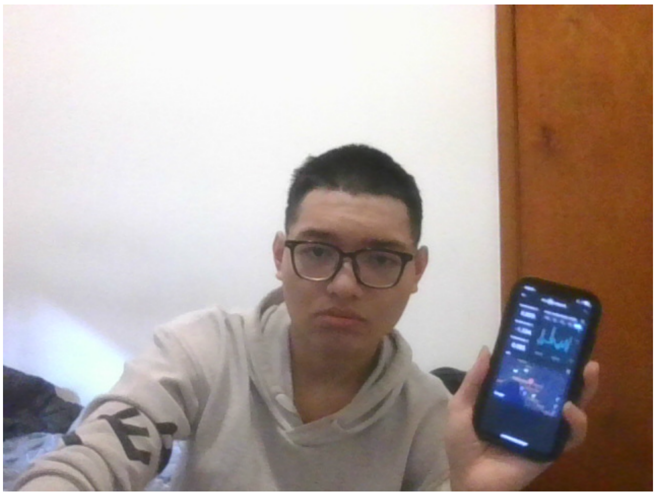

Figure 5: Similarity in motion of waving and rotating the phone

   The image captured during the transition from waving to rotating showed the hand holding the phone in a position that could be interpreted as either mid-rotation or still continuing the waving motion, making it difficult to determine the activity based solely on the visual.

2. To address the previous issue, in instances where the image was inconclusive, a thorough review of the accelerometer data was performed. If the data indicated a gradual transition from dominant fluctuations on the x-axis (waving) to increased fluctuations on the z-axis, along with a significant rise in the range of the y-axis, it suggested that the phone rotation had begun.

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | | index | Timestamp | X_Acce | Y_Acce | Z_Acce |
| 2 | 0 | 1 | 21/09/2024 9:23 | -0.69408 | -0.62048 | 0.166595 |
| 3 | 1 | 2 | 21/09/2024 9:23 | 0.413513 | -0.98404 | -0.00301 |
| 4 | 2 | 3 | 21/09/2024 9:23 | -0.2563 | -0.80391 | -0.09592 |
| 5 | 3 | 4 | 21/09/2024 9:23 | 0.119751 | -0.97284 | -0.0524 |
| 6 | 4 | 5 | 21/09/2024 9:24 | -0.85811 | -0.57887 | 0.237183 |
| 7 | 5 | 6 | 21/09/2024 9:24 | 0.39061 | -0.8743 | -0.11436 |
| 8 | 6 | 7 | 21/09/2024 9:24 | -0.1308 | -0.90616 | 0.12677 |
| 9 | 7 | 8 | 21/09/2024 9:24 | -0.26106 | -0.77231 | 0.14801 |
| 10 | 8 | 9 | 21/09/2024 9:24 | -0.52167 | -0.75648 | 0.341583 |
| 11 | 9 | 10 | 21/09/2024 9:24 | -0.57843 | -0.632 | 0.191437 |
| 12 | | | | | | |

Figure 6: CSV file corresponds with the previouly captured image

Based on our analysis from the previous section, the data readings clearly align with the trends observed in activity 2. Therefore, we can confidently label the corresponding image as activity 2.

## 4 Checking Clustering Distinct Activities Using K-means++

To verify the reliability of the recorded data readings for identifying activities without depending on the images, we need to apply clustering algorithms, specifically K-means++, using the manually labeled data as the ground truth.
After conducting K-means++, we compared the results with the ground truth labels and obtained the following metrics:

- Adjusted Rand Index (ARI): 0.4735
- Adjusted Mutual Information (AMI): 0.4364
- Homogeneity: 0.4127
- Completeness: 0.4661
- V-Measure: 0.4378

While the data readings show some promise in identifying distinct activities, their reliability is limited based on the clustering metrics. The results indicate that the activities are somewhat distinguishable but not with high confidence.

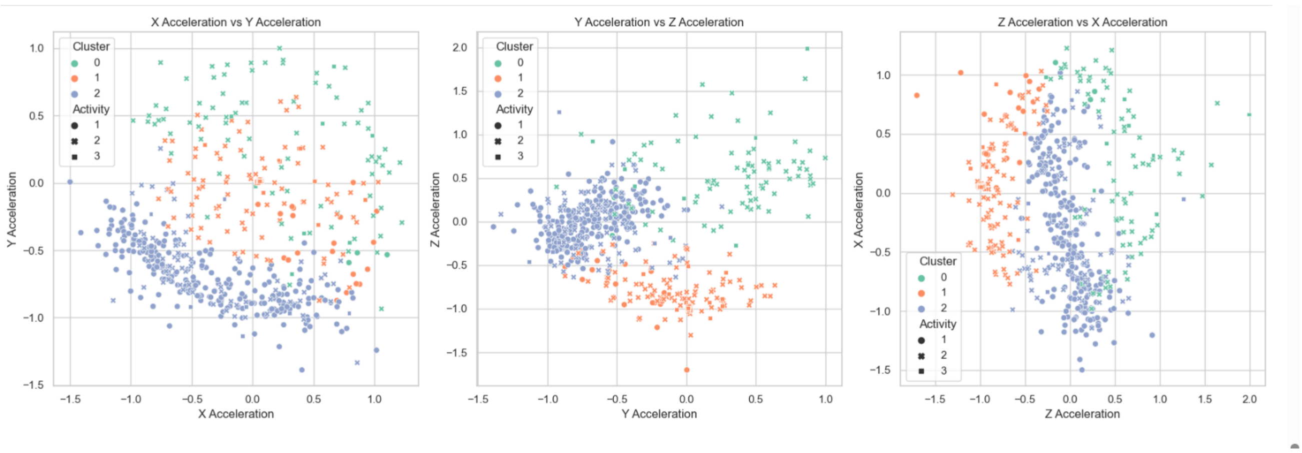


Figure 7: Clusters of three accelerometer variables

We observe some mixing and overlap of activities within the clusters, indicating that the current data may not be sufficient. To distinguish distinct activities more effectively, it would be beneficial to record data over a longer duration with a refined sampling rate.