Visual Reconstruction of Human Activities from data generated using Inertial Motion sensors

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Motivation

For **Human Activity Recognition** (HAR) research, **generating a comprehensive dataset** with diverse activities & subject demographics is often a **laborious process** needing a huge amount of time, money, & effort.

To fix this problem, **generative models** can be used to **synthetically produce data**, but there is **no method to visually reconstruct** sensor data **& validate its consistency** with activity labels. This visual reconstruction can aid in **recognition of bad training data** for generative networks & provide a metric to **assess the reliability of the synthetically generated data**.

Objective

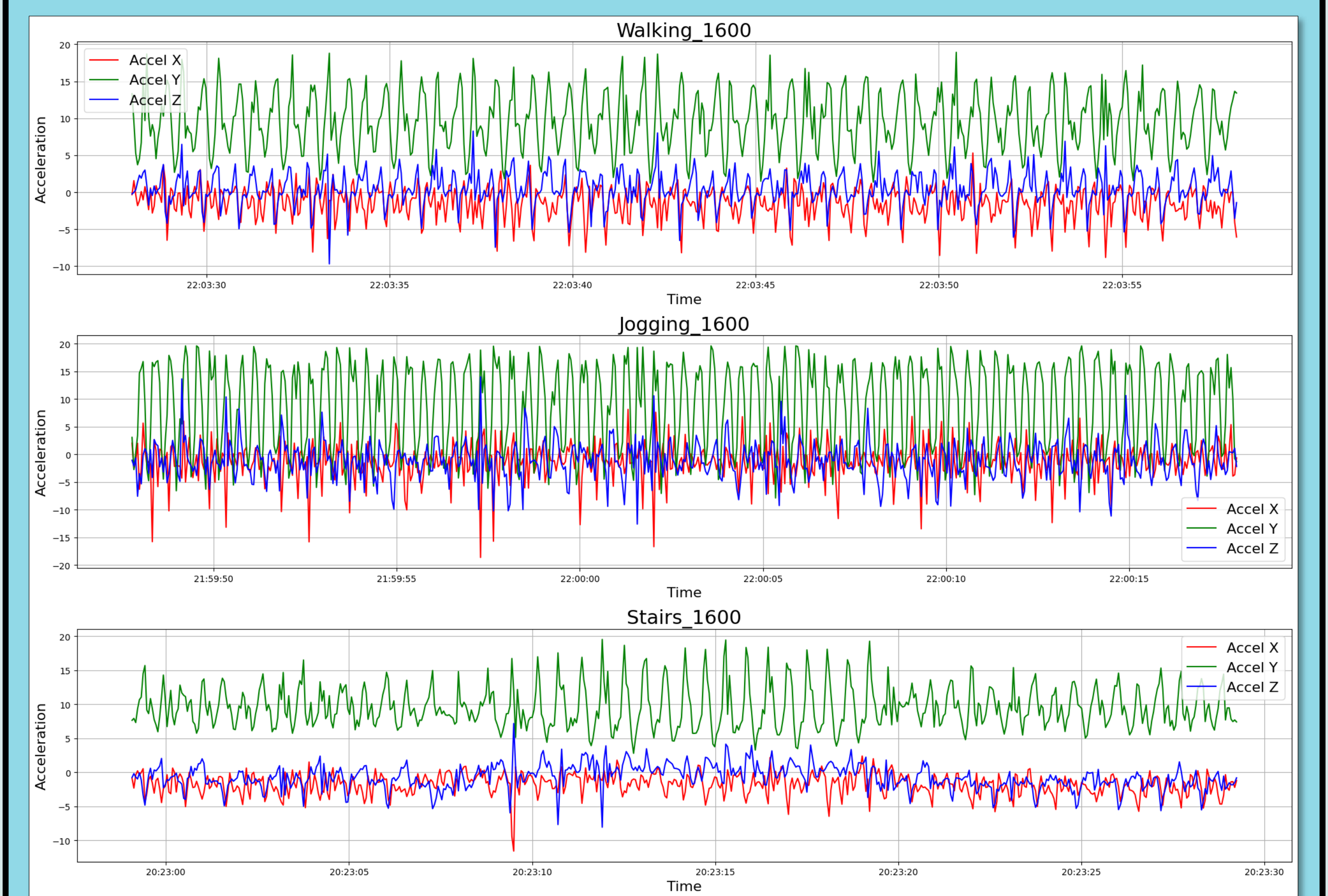
- This project aims to use motion tracking data to **visually reconstruct human movement** in 3 dimensions with **6 degrees of freedom**, with the intention of manually classifying human activities & validating them against a set of ground truth labels.

Dataset & Framework

- **WISDM dataset [1]** was chosen
  - as it offers **ample training data** for generative networks.
  - Its **raw data format** allows for customized preprocessing, correction of inconsistencies & real-world data scale for visual reconstruction.
  - It includes recordings from **both accelerometer** & **gyroscope sensors** of smartphones.

Out of 17 available activities, we chose the below **3 activities**

Activity Classes	Walking	Jogging	Stairs
Observations	32.60%	33.01%	34.39%

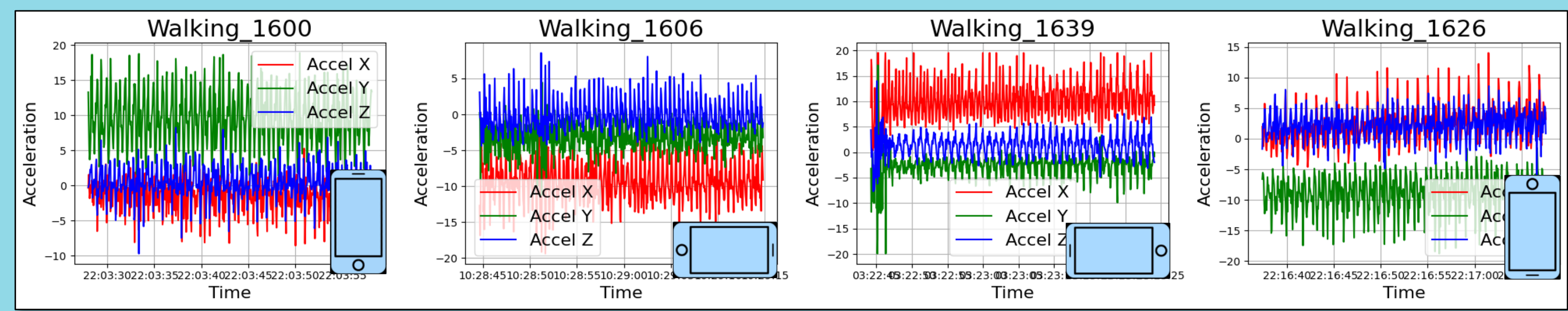


- After exploring multiple frameworks, assessing their limitations & fit with respect to our requirements, we chose the **Unity [2]** game engine for visual reconstruction of human activity data. It provided us with a platform to use both displacement & orientation data to reconstruct the motion data.

Methodology

Data Issues fixed

- **Phone Orientation issues**



We fixed this by shifting the signals, i.e., adding two times the absolute average of the amplitude and exchange X and Y axes if the average amplitude of the X-axis was more significant than the average amplitude of the Y-axis [3].

- **Sampling issues**

Data collected on different smartphones resulted in different sampling frequencies. For example, No. of sample points: ~**3600 points** for subjects 1600, 1602, 1604, ~**4500 points** for subjects 1601, 1647, ~**14280 points** for subject 1629, etc. We fixed this by resampling the frequency to 20 Hz [3].

- **Bad data removal**

For some activities, in case of some subjects, there is not enough data. For e.g., in case of Jogging, subjects 1614, 1641, 1642, 1644, 1645, 1646., have **less than 300 data points**. We removed them.

Visual Reconstruction process

- **VS Code (Python) – Preparing the csv files:**

Merging Accelerometer & Gyroscope data files per subject → Calculating orientation using Sensor fusion techniques [4] → Separating activities per subject & selecting required activities → Applying the data issue fixes → Calculating Displacement from Accelerometer data [5] → Generate & save csv files

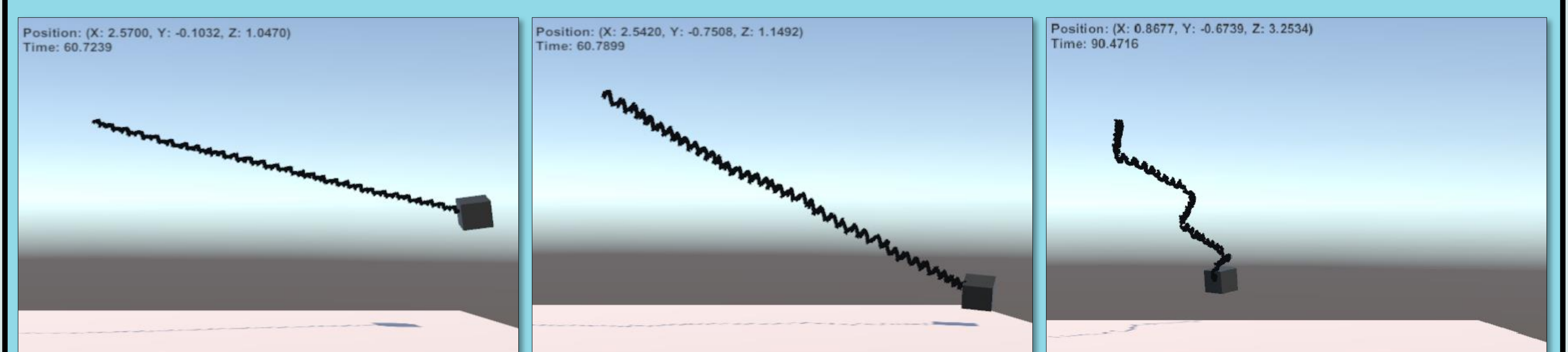
- **Unity (C# Script) – Processing the csv files:**

Setting up the game scene by adding cube, plane, cameras & assigning suitable materials → Loading the csv files → Reading the csv files by iterating through each line → Storing elapsed time, displacements, accelerations & rotation angles in class object → Applying position & rotation values on the cube to move it by looping it over time → Applying a line renderer object to the cube to trace its movement

Visual Reconstruction outputs

- For Jogging, the cube portraying the phone kept in the subject's hip pocket showed more frequent ups & downs as compared to Walking & Stairs.
- The reconstruction for Walking displayed less error by maintaining a straight line of action in most cases which might be due to the smartphone being kept relatively movement-free in the pocket.
- The Stairs movement showed a change in pace & orientation in fixed intervals resulting from the landing area after a flight of stairs.

Walking | Jogging | Stairs



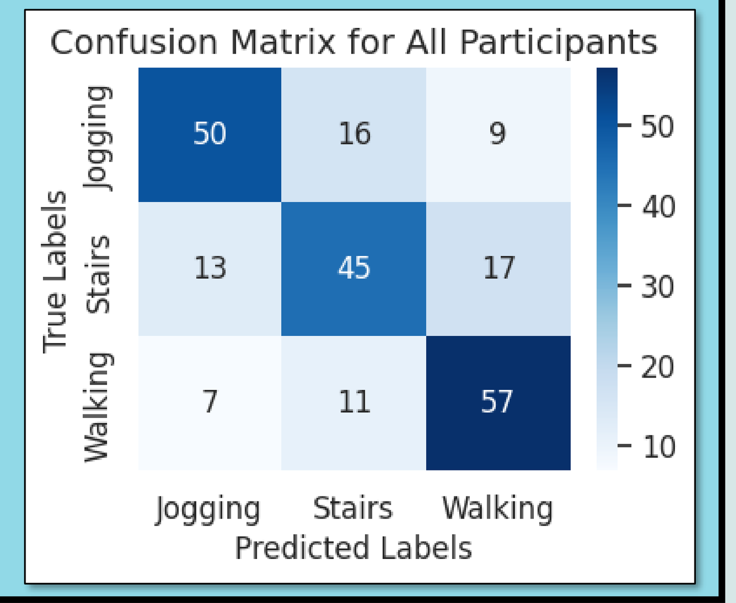
Results

- **Result Collection**
  - 15 test cases were created – 5 sets for 3 activities.
  - A form was sent out with unnamed labels for surveyors to fill out.
- **Metrics**
- **Percentage of Activities Predicted Correctly:**

Walking – 76%	Jogging – 66.67%	Stairs – 60%

- **Classification Report & Confusion Matrix:**

	Precision	Recall	F1-score
Walking	0.69	0.76	0.72
Jogging	0.71	0.67	0.69
Stairs	0.63	0.60	0.61
Overall Accuracy	0.68		



Discussion

- **Evaluation**
- The current setup used to reconstruct human activities visually showed that humans can identify the outputs with some accuracy.
- It's easier to compare reconstructed visuals and label them than look at an isolated visual when viewing it without prior context.
- It was easier to identify Walking activity compared to the other two, since Stairs and Walking were almost similar in the case of some reconstructions, and some Jogging reconstructions showed deviation away from a straight line of motion.

- **Limitations**
- The reconstructions showed a sinking effect in the Y-axis, which might be due to accumulation of errors while the sensor fusion process or while converting acceleration to displacement.
- The current setup is not useful in the case of multi-sensor data obtained from sensors placed in multiple body locations of a human subject.

- **Future Work**

As the extension to this project, we want to visually reconstruct synthetically generated data using our setup. We further look to address the limitations discussed above by exploring filtering techniques and better sensor fusion algorithms. The multi-sensor approach can be looked at using a humanoid model in Unity and applying forces in different joints. While this can be a starting point for future work, it needs rigorous experimentation to make a multi-sensor visual reconstruction model work due to error accumulation and calibration issues.

References

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- [2] A. Juliani et al. Unity: A General Platform for Intelligent Agents. 2020. arXiv: https://arxiv.org/abs/1809.02627
- [3] M. Heydarian and T. E. Doyle. "rWISDM: Repaired WISDM, a Public Dataset for Human Activity Recognition". In: arXiv preprint arXiv:2305.10222 (2023).
- [4] Reference listTechnologies, x-io (2024). xioTechnologies/Fusion. [online] GitHub. Available at: https://github.com/xioTechnologies/Fusion?tab=readme-ov-file [Accessed 31 Jul. 2024].
- [5] A. Blake, G. Winstanley, and W. Wilkinson. "Deriving Displacement from 3-Axis Accelerometers". In: Computer Games, Multimedia & Allied Technology. 2009.

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