MobilityAI: A Tool for Classifying Human Movements using Machine Learning

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Introduction

For doctors and nurses at Juravinski Hospital, it is important to be able to accurately assess the effectiveness of existing mobility intervention approaches and discover new strategies to improve efficacy. It is shown that early mobilization and physical therapy is a safe and effective intervention method that can have a significant impact on patient health [1]. A sensor band will be used to measure mobility data from patients. Machine Learning will then be applied to accelerometer and gyroscope sensor data to accurately determine the actions the sensor band is measuring. The nurses can then use this data to determine how mobile a patient is during their stay compared to their pre-hospitalization mobility levels.

Background

The following requirements have been developed according to discussions with the doctors from Juravinski hospital:

- Battery should last and store data for 12 hour shifts
- Easy to clean, wear and remove
- Should classify between Standing, Sitting, Lying Down and Walking
- Software should compare baseline mobility to recorded mobility
- Software should have an intuitive User Interface

Sensor Band

Patients will wear the clinical grade wristband, MetaMotionR (MMR), produced by MbientLab with several sensors including a pressure sensor, temperature sensor, and an Inertial Measurement Unit (IMU). The unit is housed in an IP40 case and is strapped on the user with a rubber wrist band.

- It contains 8MB of NOR flash memory that can be used to log data, or the device can stream data live using a Bluetooth connection.
- It also includes a 100 mAH rechargeable battery that can be easily recharged at hospitals using a micro-USB connection
- The board uses a nRF52 SOC along with Bluetooth Low Energy.

epoch (ms)	elapsed (s)	x-axis (deg/s)	y-axis (deg/s)	z-axis (deg/s)
1542836651794	0	0.976	0.549	0.183
1542836652055	0.261	0.122	0.244	-0.549

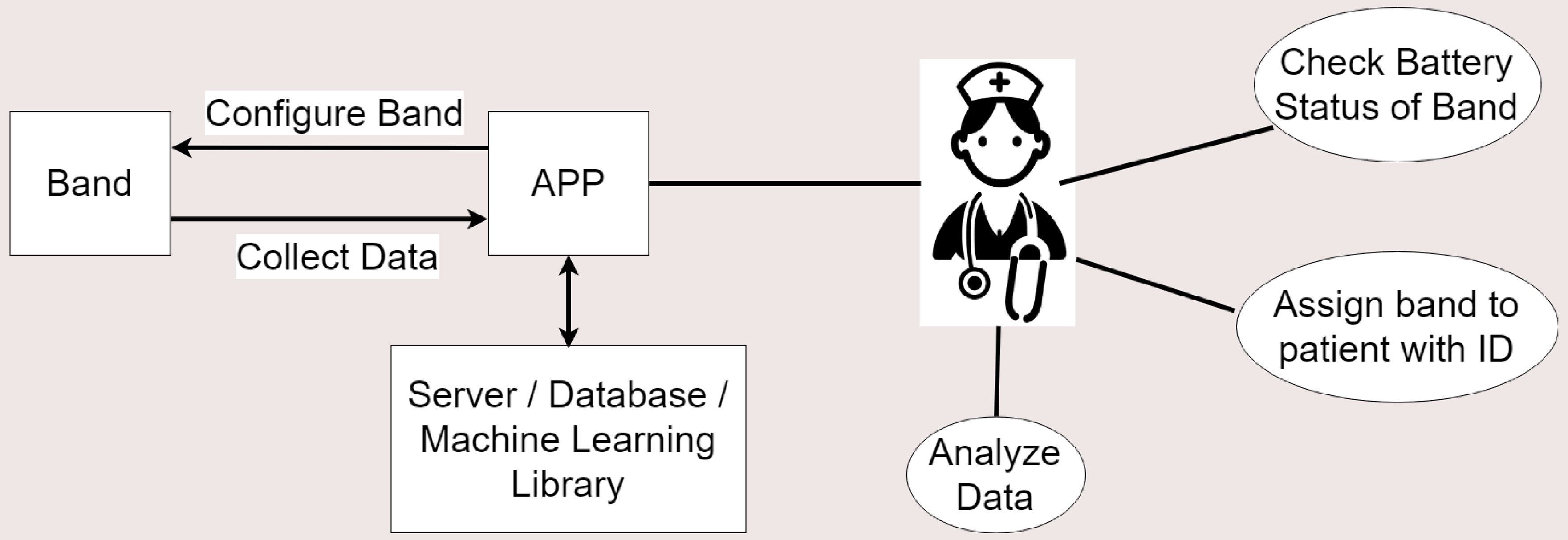
Figure 1: The accelerometer, gyroscope, and IMU will be used to log actions such as walking, sitting, or lying in bed. Each sensor will be sampled 25 times per second and saved to on-board storage. The data will be retrieved using an Android application that will connect to the device when it is nearby. Data will be stored in a CSV format until it can be written to a database.

References

- Joseph Adler and Daniel Malone. "Early mobilization in the intensive care unit: a systematic review". In: *Cardiopulmonary physical therapy journal* 23.1 (2012), p. 5.
- Andrea Mannini and Angelo Maria Sabatini. "Machine Learning Methods for Classifying Human Physical Activity from On-Body Accelerometers". In: *Sensors* 10.2 (2010), pp. 1154–1175. ISSN: 1424-8220. DOI: 10.3390/s100201154. URL: http://www.mdpi.com/1424-8220/10/2/1154.
- F. Pedregosa et al. "Scikit-learn: Machine Learning in Python". In: *Journal of Machine Learning Research* 12 (2011), pp. 2825–2830.

Server and Database Architecture

The server stores two data sets, accelerometer and gyroscope. It determines when and how the subject is moving. The data sets are collected through the bands that patients will be wearing. The Android application will upload this data after it is collected. The app can request data to display it to the user.



API Name	API Description
Add Data	Accepts CSV file Writes to database
GetRangeAccelerometer GetRangeGyroscope	Retrieves data based on time range

Machine Learning

This is a Human Activity Recognition (HAR) problem, and our activity set is defined as follows:

- Sitting
- Standing
- Lying in bed
- Walking

The data collection process involves 3 subjects performing each activity for a 2 minute trial, the sampling rate of sensor is 25Hz. The collected dataset is broken down into data frames using a 2.5 second sliding window, starting a new window every 0.5 seconds, allowing for more accurate classification of actions [2]. Each data frame calculated key statistical information such as min, max, average, and variance of x, y, z acceleration and angular velocity.

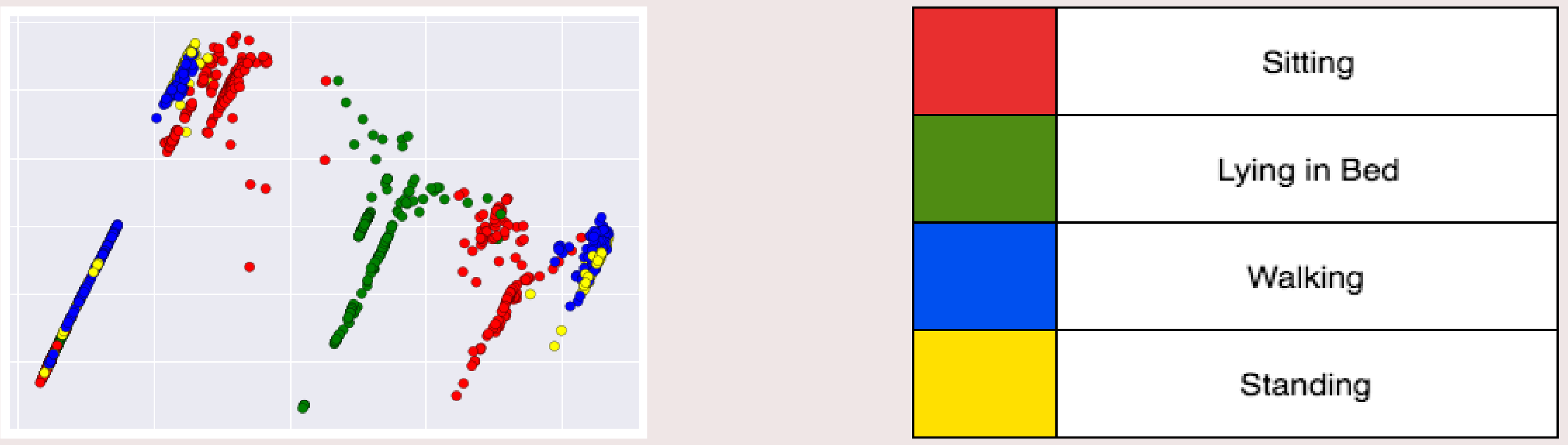


Figure 2: Using Principle Component Analysis (PCA), the dataset is reduced from 24 features to 3[3]. The 3 features that were selected are those with the greatest proportion of variance, however, due to the nature of PCA, it is unclear which of the original 24 features were chosen. The result of PCA is projected in 2 dimensions in the image above. Each point represents a window. Clusters of like coloured windows can be used to classify future data. There is a strong correlation between the X-Axis values and the action being performed, while the Y-Axis has a smaller effect.

Future Work

Moving forward with this project, we would like to support new actions such as counting steps and unanticipated actions. Furthermore we would also like to implement live streaming and classification of data from the band.