UCLA Summer Undergraduate Scholars Program

Physical Activity Classification

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Introduction: The importance of health monitoring systems in daily life

Wireless Patient Monitoring

Physical inactivity is a major cause of chronic diseases such as obesity, diabetes, and depression. With their busy schedules, medical professionals have a difficult time monitoring a patient’s exercise regimen. Wireless monitoring systems enable accurate record keeping of patients both in local and remote areas.

Personal Health Monitoring

Keeping track of physical activity can be helpful when starting an exercise program. Having a record of previous activities done can allow one to challenge oneself and achieve total body fitness. Seeing real-time progress allows one to stay motivated and be more conscious of overall health.

Problem Description: Limitations on current health monitoring systems

- Unable to classify physical activities without user input
- Using one sensor limits the ability to classify activities to only walking and running
- Focused on tracking general activities
  - Active and inactive minutes
  - Floors climbed
  - Distance
  - Time duration

Apple Watch

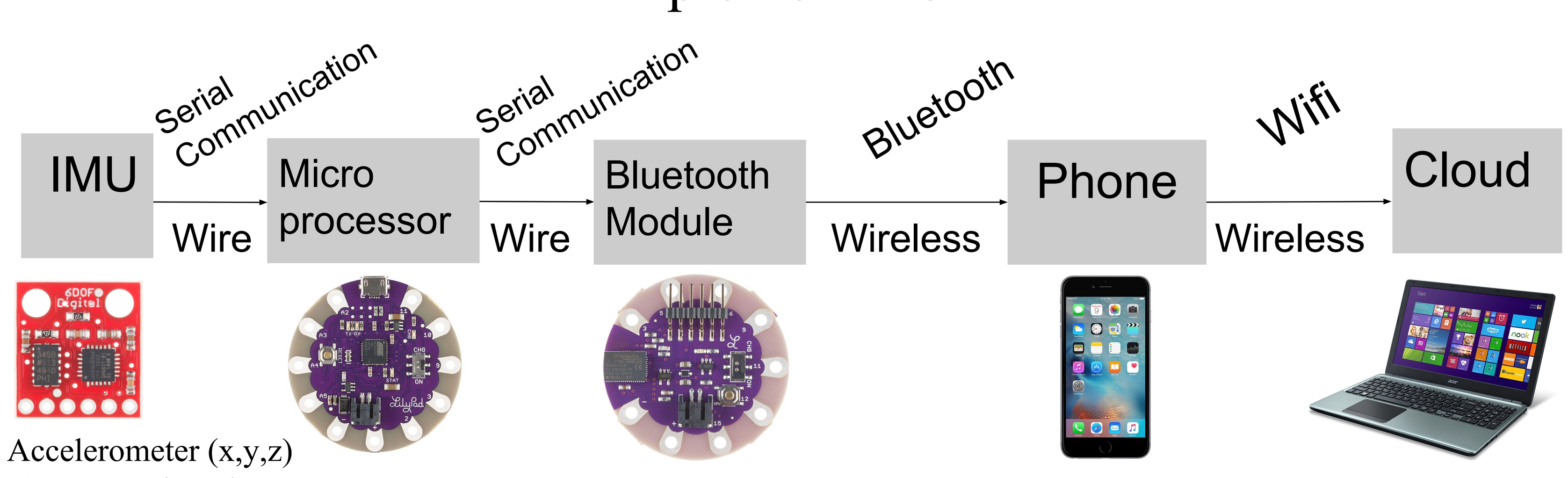
Fitbit

Proposed Solution: Wearable system that classifies and tracks user’s activity

Device Description

A bodysuit consisting of three sensors placed on the wrist, shoulder, and foot that accurately displays the physical activity performed when in use.

Implementation

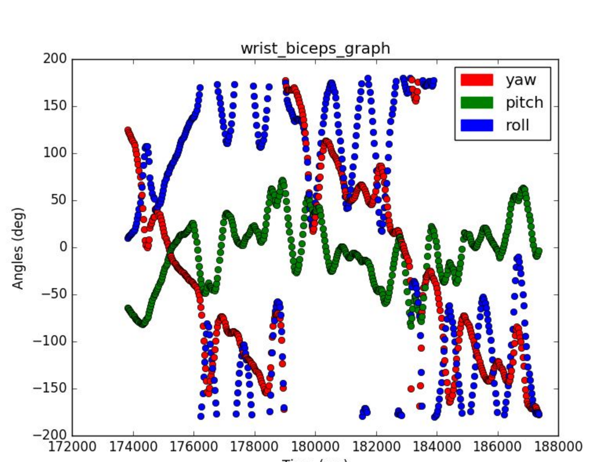


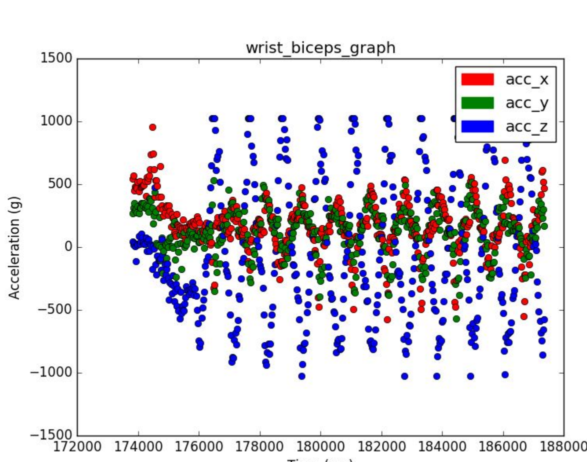
Accelerometer (x,y,z)
Gyroscope (x,y,z)
Angles (yaw, pitch, roll)

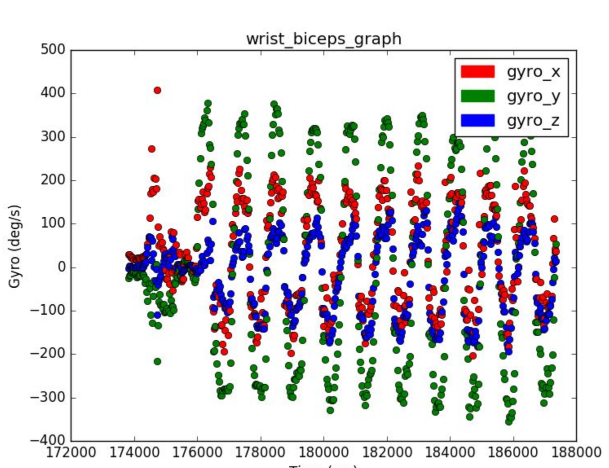
Feature Extraction

Sensor Features

- Yaw: Mean, Variance, Standard Deviation
- Pitch: Mean, Variance, Standard Deviation
- Roll: Mean, Variance, Standard Deviation
- Acc-X
- Acc-Y
- Acc-Z
- Gyro-X
- Gyro-Y
- Gyro-Z





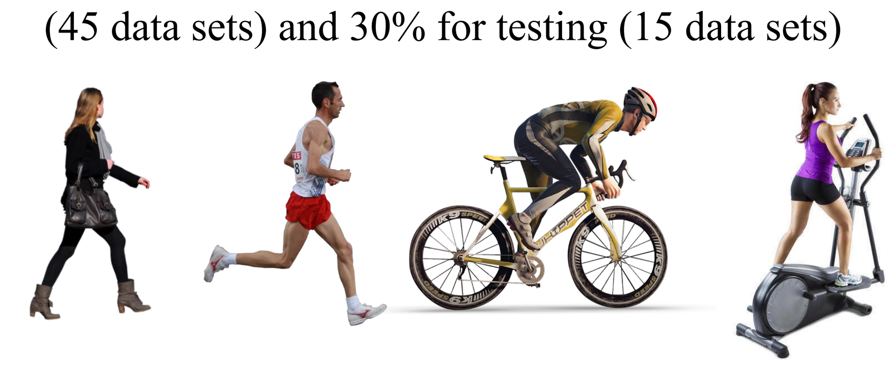


Graphs show values obtained from a sensor placed on the wrist when performing bicep curls. Features are extracted by finding mean, variance, and standard deviation of each raw IMU value, including angles (yaw, pitch, roll), acceleration (x, y, z), and gyroscope values (x, y, z).

**For a single sensor there are 27 features.
Our device with three sensors consists of 81 features in total.**

Data Collection

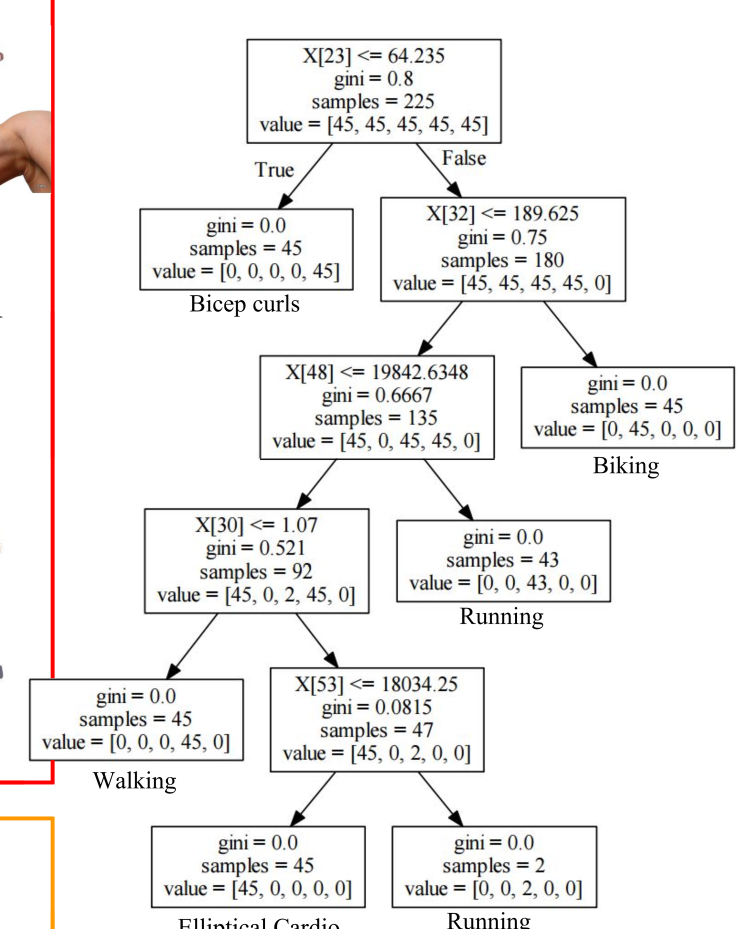
- Data was collected for 5 different physical activities: walking, running, bicep curls, elliptical cardio, and biking
- For each activity, 60 data sets were collected and each data set was taken on a 5 second interval
- Out of 60 data sets, 70% was used for training (45 data sets) and 30% for testing (15 data sets)



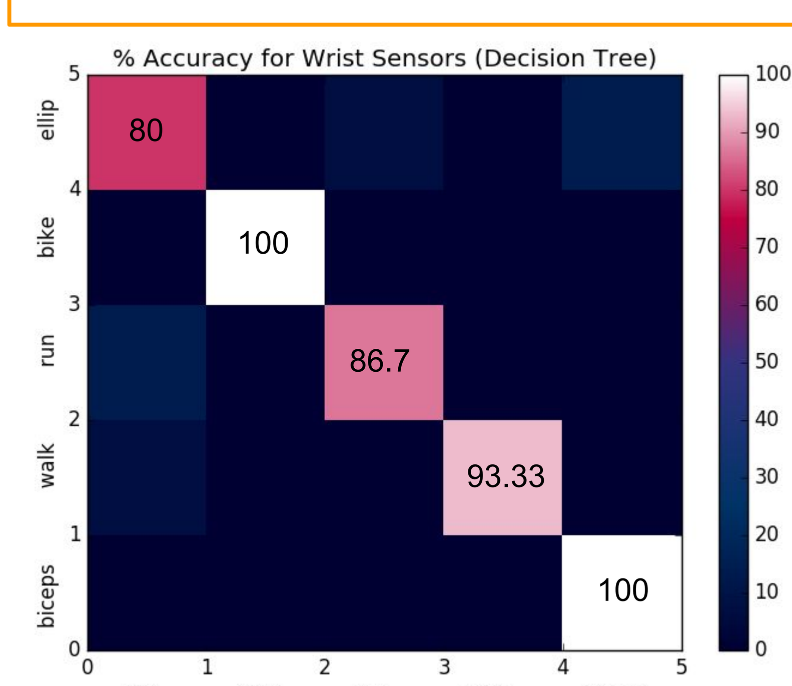
Classification

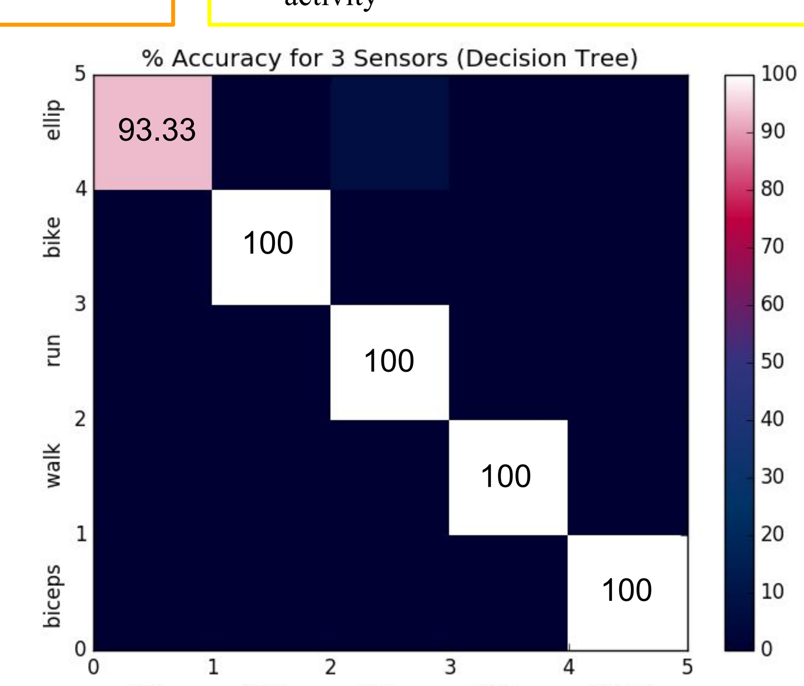
- Machine Learning Algorithms: Decision Tree, Random Forest, Linear Support Vector Machine (SVM), and Polynomial SVM
- Most accurate classifiers were Decision Tree and Random Forest

Decision Tree



- X[index]: feature
- Gini Index: finds the most “useful” feature when classifying
- Samples: number of data sets
- Value: shows the data set for specific activity





Results

The heat maps above compare the percent accuracy of classifying physical activity between one sensor (left map) versus three (right map). The map on the right has higher accuracy shown by the white color along the diagonal as opposed to the left map. In conclusion, for activity classification, our device using three sensors is more accurate than a one sensor device.

Fast Track to Success
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Wireless Health UCLA

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