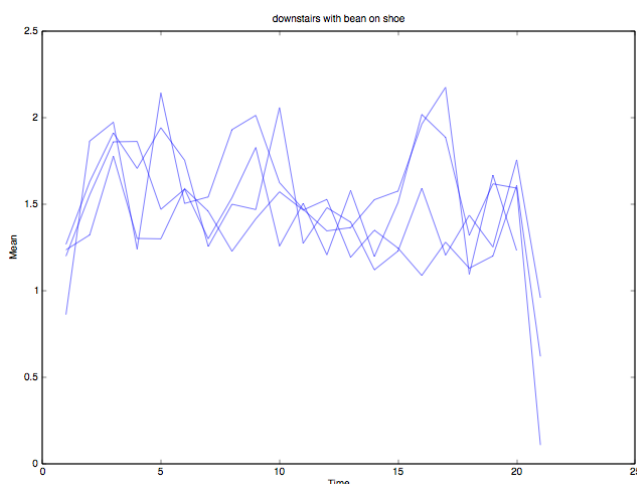


Intuitive Classification for Motion-tracking using an Arduino Bean Microcontroller

It is of great interest to us to be able to determine and label primitive motions such as those demonstrated in this project (running, walking, standing). It is evident through the data shown throughout this project that some motions have signatures and patterns that we can easily take advantage of through the usage of machine learning. Our goal is simple: we want to classify the user's motions dynamically. Having collected data with different bean positions and multiple samples per combination, we are ready to set up shop for classification.

Figure 1: Downstairs on Shoe Signature



In a similar vein to how we collected bean sensor data in a thread, we will create a separate thread to handle classification and setting the UI appropriately to the calculations. The thread will call a method to handle this responsibility until the switch for `classifying` is switched off. Prior to this, we assume all our training data resources exists on the external memory of the smartphone. We can take an extra step and write a script to pull the overall acceleration data from all our collected data into respective one-dimensional vectors for ease of use.

On the startup of the application, we can

train the data even before we connect to bean since we already have all of our needed data on phone storage. We can accomplish this using the `java-ml` library and add instances of each separate text file of interest with the appropriate labels. From this, we can build a simple k-nearest neighbors classifier with $k = 10$, and we are now ready to predict incoming data to be read through bean.

As the thread handles the classification, we will maintain a list `currentData` to hold our data to be classified. Bean will intermittently push values to it until it reaches a capacity of interest (we may want to classify every 2 seconds, in which case we will set this capacity to 10 values if we are reading every 200 ms). Once it reaches capacity, we will pass it into an instance and classify it and pass this result to the UI. `currentData` will then be reset and the process continues until the user chooses to "Stop Classifying."

This is a naive approach however that takes each time series and uses each acceleration point read as feature. Thus we are performing multi-class classification with 10 features, which can be computationally expensive. This also ignores the fact that our data is a time series and should be treated as such. A revised methodology would compare time series obtained from training data and live time series to be used as a heuristic when computing classification - effectively a similarity index - some examples include euclidean distance and dynamic time warping.

The topic of classification of time series is a very important one - an implementation of a Hidden Markov Model would have perhaps been the most elegant solution as it closely relates to continuous time series. In terms of classification accuracy, our simple approach yielded decent results in classifying whether the user is currently standing, sitting, walking, running, going upstairs, or going downstairs. When it comes to precise motion, voice, and signal processing, we may want to opt for a sturdier model like those prescribed earlier.

Appendix

