MHAM Task 3

Group 7

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1 Introduction

Using different signals recorded with smartwatch and phone while traversing the five predefined paths in Zurich, the task is to develop algorithms to detect (i)activity, (ii)smartwatch location, (iii)path and (iv)step count.

2 Method

The accelerometer signal $acc_{xyz} = acc_x^2 + acc_y^2 + acc_z^2$, where acc_x^2, acc_y^2 and acc_z^2 are signals in different directions is used in both methods. The two described methods reinforce and complement each other to obtain the desired result.

2.1 Traditional Approach with Thresholding

The goal of this approach was to implement in code what could be discerned visually by looking at the various plots, mainly accelerometer energy in the time and frequency domains.

2.1.1 Frequency Domain

The most evident feature here is the presence of peaks in certain intervals. A peak in the 1.4Hz-2.3Hz interval usually indicated the presence of walking, and a peak in the 2.4Hz-3.5Hz interval often indicated running. The walking peak was especially reliable, (though the dataset was unbalanced as most traces contained walking) while the running peak had much greater variability.

Another recurring feature was the presence of peaks in the 0.7Hz-1.2Hz and 1.1Hz-1.6Hz intervals. These intervals are at about half the frequency of the aforementioned ones, and were usually absent when the band was located on the belt, while present otherwise, especially if on the ankle. This might be due to the acceleration difference between a left and right step from the perspective of only one ankle/hand. A left step will twist the right ankle, but the acceleration effect will be smaller there than a right step. This asymmetry causes a neutralizing effect on every two steps and thus with half frequency (e.g.: sin(2x)-0.5sin(x)). It would be absent in the symmetrical case, i.e. the belt. We used these two peaks to help decide the band location.

We implement peak detection partly by taking the highest peak in the given interval, but mostly by computing the energy of the whole interval and comparing it to the total energy. Looking at interval energy rather than peak height was justified by the possibly irregular gait of the user, which often flattened the peak over a certain frequency range. Maximum peak height was still used when very noticeable. We thresholded these values but generally didn't make immediate decisions, using them to corroborate the clues found in the time domain.

2.1.2 Time Domain

This domain displayed clear amplitude differences between the activities (except cycling). We exploited this by splitting the data in various sub-ranges such that each would have a consistent energy mean over its span. These sub-ranges are catalogued in categories depending on energy means. Looking at these values we tried to infer the presence of a certain activity and helped ourselves in distinguishing between wrist and ankle location (ankle usually resulted in larger amplitudes due to greater movement). This was done on high-pass filtered data, with a much quicker second pass on unfiltered data. We also noticed that, of all the activities, cycling had (unsurprisingly) the most irregular magnitudes. We thus thresholded the standard deviation computed over the energy peaks.

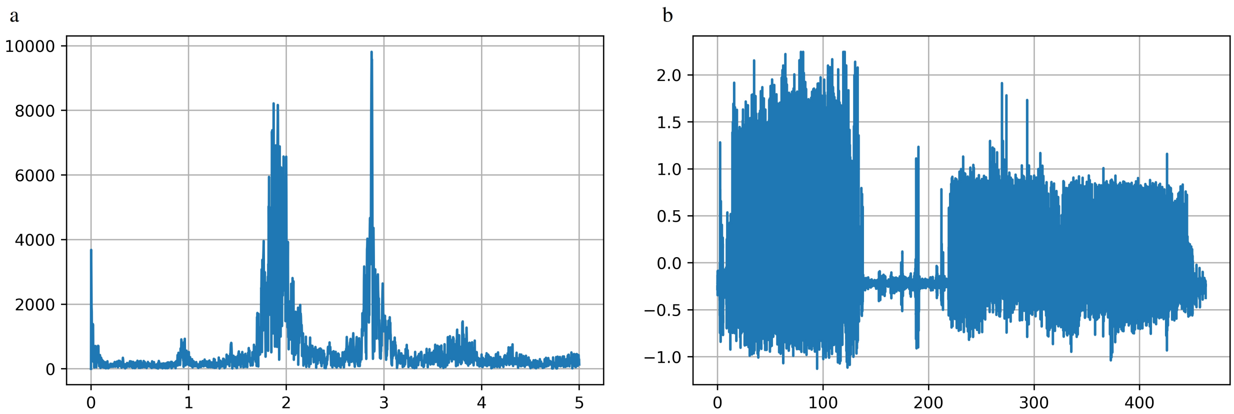

Figure 1: a) Accelerometer in frequency domain: peaks indicate walking, running and belt location; b) Accelerometer in time domain: three distinct subranges indicate standing, walking and running;

2.2 Machine Learning Method

For activity and location recognition we use acc_{xyz} while for the path detection we utilize phone signals such as 'altitude' and 'phone_pressure'.

2.2.1 Data Cleaning and Preprocessing

We observed that the GPS altitude signal is unstable and therefore we filter all input traces to the ones where GPS altitude sample rate has at least 50 unique values per minute on average and where gap between any two consecutive samples of the GPS altitude trace is not more than 10 seconds. Furthermore, the traces which don't contain the optional 'phone_pressure' signal were removed.

2.2.2 Feature Extraction

The acc_{xyz} signal is transformed to frequency domain where all the frequencies whose energy is below 95% quantile were removed. The features are extracted in the range of $[0 - 5HZ]$, as a mean of values in each of the 25 consecutive windows of size $\sim 0.2Hz$. From altitude and phone pressure signals we extract slope features on 20 consecutive windows of the same size as an average of differences of signal values on consecutive time steps. Furthermore, a feature corresponding to the difference of signal values on first and last time step was added.

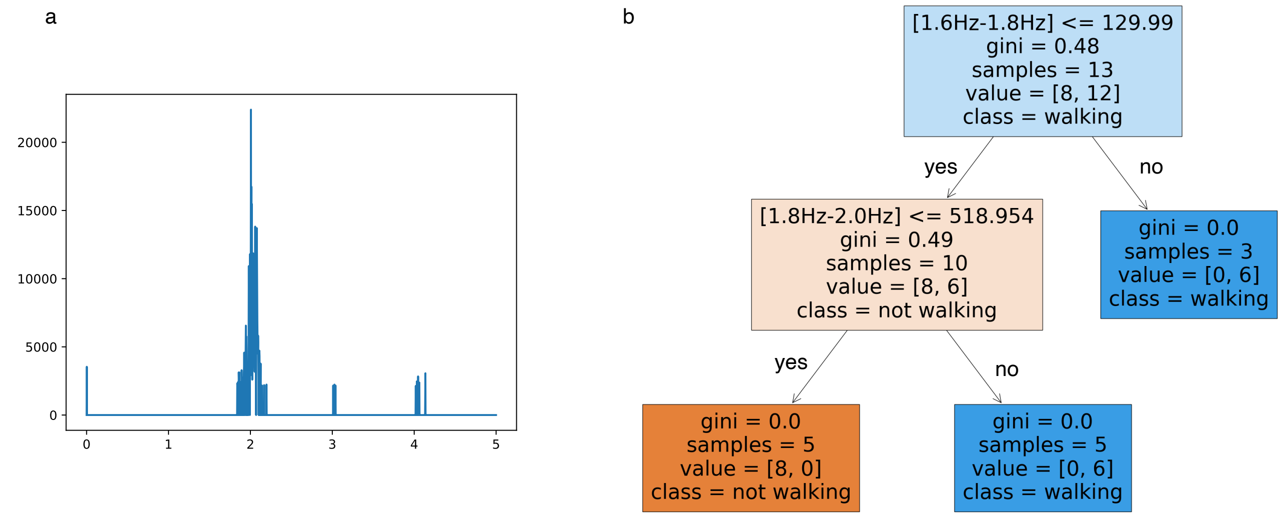

Figure 2: a) Accelerometer data in frequency domain used for feature extraction in ML method; b) An example of a decision tree from the random forest model trained to predict walking activity;

2.2.3 Model Training and Evaluation

For all three tasks at hand we train a random forest model. The models were evaluated with 5-folds cross-validation. For activity and location recognition we train models with binary labels. To counter the problem of unbalanced datasets (e.g. cycling happens in only few traces), the models were trained on a balanced subsample of the training data. For two downhill paths we train one model with only 'phone_pressure' data and one model with 'altitude' data and similarly for uphill paths we train to predict one of three paths either with phone pressure or altitude data. Based on the difference of the signal value in first and last time step and the existence of phone pressure field, one of the four models is called.

3 Discussion

For the two tasks where the movement of the person is crucial we choose to use the accelerometer data while for the path detection we rely on GPS altitude and pressure sensors. For machine learning method we pick an ensemble model which counters overfitting issues, while more complex models were avoided due to lack of data and hardware and time constraints. Step counting was left unchanged from task 1, except the "pruning" phase which was made more lenient in the presence of large amplitude differences.