MCEN90032
Sensor Systems

Workshop #1 - Pedometer Design

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1 Introduction

The objective of this workshop is to design a pedometer, which is a device that records the number of steps taken. This device will utilise the accelerometer sensor in the smartphone's inertial measurement unit (IMU). Utilising the 3-axis acceleration measurements, as shown in figure 1, will require the elimination of constant biases and attenuation of noise using control measurements and frequency-space analysis to design suitable filters. For the design of the pedometer, the performance will achieve the following specifications:

1. Achieve 95% accuracy for the recorded steps and visualisation of the steps.
2. Adaptive to various cadences such as running, jogging and walking.
3. Rejection of random non-walking signals such as taking the phone out of the pocket and using the phone in hand.

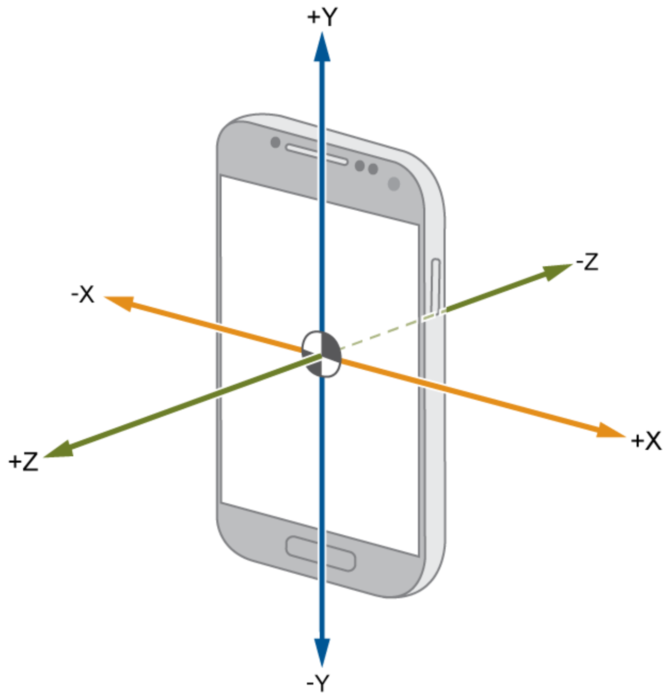


Figure 1: 3-axis accelerometer measurements on a smartphone

2 Methods

2.1 Data Acquisition

Before designing the pedometer, it is essential to determine an appropriate sampling frequency. In order to capture walking data without any distortion from aliasing effects, the sampling frequency must minimally adhere to the Nyquist frequency. Estimating that a fast walk can reach a frequency of 4Hz, the sampling frequency must be a minimum of 8Hz. For this pedometer, the sampling frequency chosen is 50Hz. The choice of this sampling frequency is to generate an accurate discretisation of the analogue acceleration without being computationally expensive—the acquired data links to the MATLAB cloud drive for further analysis.

The smartphone will be placed face down in the right pocket during data acquisition for walking based data. This orientation is the most common among the general population and will be the acquisition method for all walking-related experiments.

2.2 Sensor Calibration

To remove the accelerometer's constant bias and verify the functionality of each axis, we will take single-axis measurements of the accelerometer by orienting the phone vertically upside down on a flat surface. Note that for the y-axis measurement, removing the constant gravitational force is imperative to normalise each axis at 0 for a stationary position. For the pedometer, the algorithm utilises the magnitude of the acceleration because a single axis such as the y-axis can only accurately measure the bobbing motion of a single leg. The calibrated axes for the stationary phone is shown in figure 5 after validation of 3-axis measurements functionality.

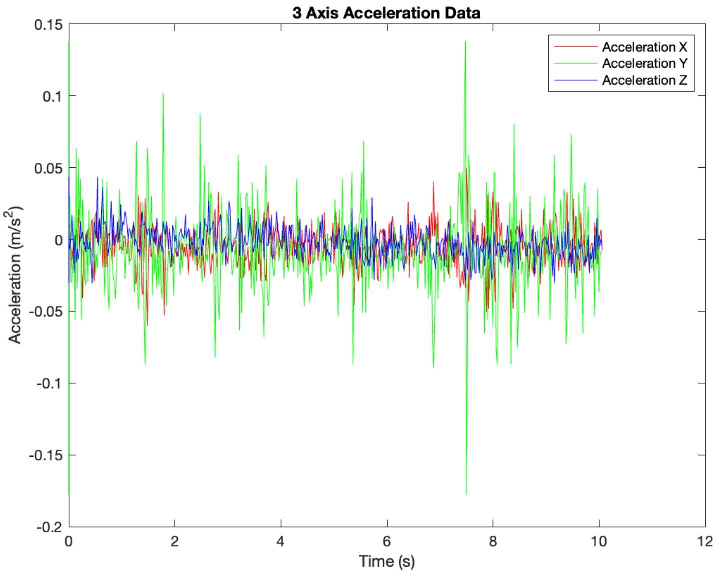
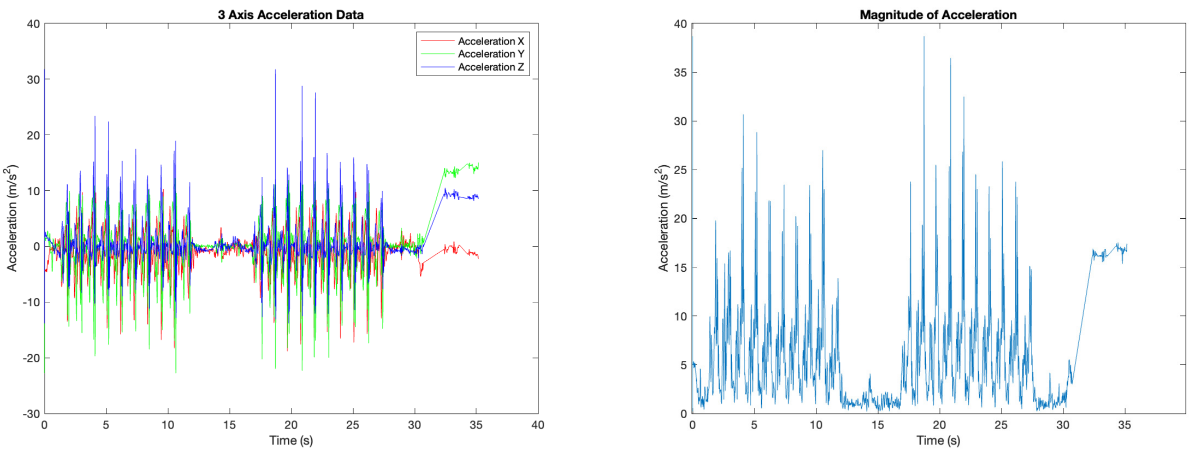


Figure 2: Calibrated x-axis accelerometer measurements

2.3 Filter Design

After acquiring discrete-time walking data, we can acquire the frequency domain representation of the signal using the Discretised Fourier Transform (DFT) of the data using MATLAB's Fast Fourier Transform command. A sample dataset as shown in figure 3 will be used as an example for the filter design.



(a) 3 axis acceleration

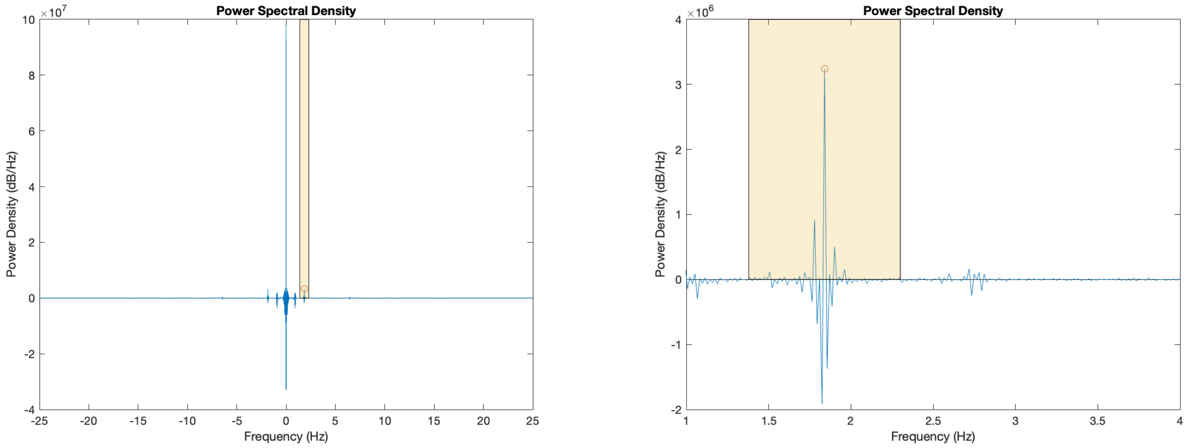
(b) Magnitude of acceleration

Figure 3: Accelerometer data for 40 steps walking dataset in intervals of 20.

Shifting this frequency representation such that the zero-frequency component is at the centre of the spectrum will allow us to visualise the relative amplitude for each frequency component of the measured signal. Instead of using this relative amplitude-frequency domain representation, we can calculate the autocorrelation sequence of the discrete-time data since the walking signal is a random stationary process using equation 1. Using the Wiener–Khinchin theorem, we can compute the DFT of this auto-correlation sequence and calculate the power density at each frequency using equation 2.

$$r_{xx}[k] = \mathrm{E}\left[x[n]^* x[n-k]\right] \tag{1}$$

$$S(f) = \sum_{k=-\infty}^{\infty} r_{xx}[k] e^{-i(2\pi f)k} 2 \tag{2}$$



(a) Power Spectral Density

(b) Power Spectral Density from 1Hz to 4Hz

Figure 4: Power Spectral Density of walking data with frequency range for bandpass filter

From this PSD plot, we can identify the maximum peak between the walking frequency bounds of 1Hz to 4Hz to find the frequency of the walking cadence in the dataset. We can generate a frequency range as the cutoff frequencies for a sixth-order Butterworth bandpass filter which will have an s^{12} term in the denominator and an approximated magnitude gradient of $-240\frac{dB}{Dec}$.

$$F_{upper} = F_{cadence} + 0.25 * F_{cadence}, \quad F_{cadence} \leq 4Hz \tag{3}$$

$$F_{lower} = F_{cadence} - 0.25 * F_{cadence}, \quad F_{cadence} \geq 1Hz \tag{4}$$

Note that the frequency range for the bandpass filter is bounded between the defined minimum and maximum walking frequency, which is 1Hz and 4Hz respectively.

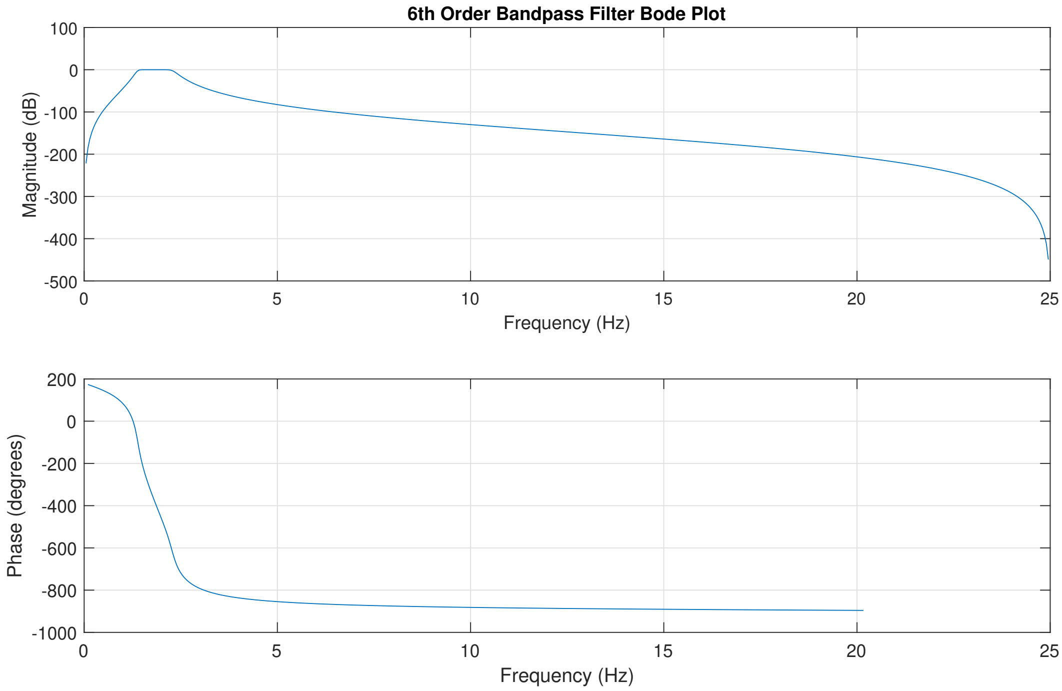


Figure 5: Bode plot of the sixth order Butterworth bandpass filter

Examining the bode plot of this bandpass filter, signals outside of the defined frequency range is strongly attenuated, which allows us to reject high-frequency measurement noises, low-frequency drift and the constant gravitational signal at 0Hz. Rejection of the gravitational signal around 0Hz is important due to the high power density at this frequency as seen from the PSD in figure 4a. An important note is that this sixth-order bandpass filter introduces a considerable phase shift to the signal. However, this does not affect the performance of the pedometer since the algorithm assumes that there is a roughly constant cadence frequency in the dataset, which means the filtered signal will have a consistent phase shift applied that does not affect the amplitude. This assumption will be further detailed in the discussion.

2.4 Steps Counter

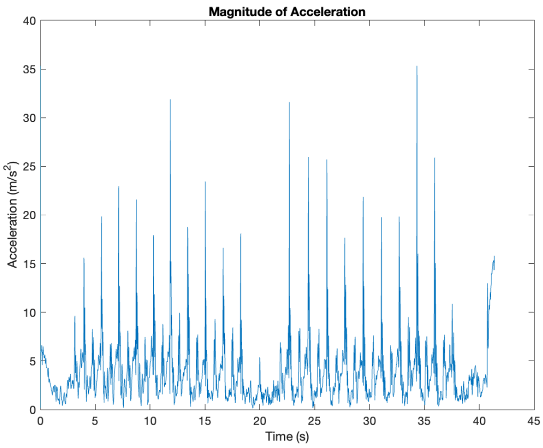
Application of this bandpass filter to the original discrete-time signal produces a filtered acceleration magnitude for the taken steps. The local peaks represent the point between an acceleration forward when the leg strides forward, followed by a deceleration when the leg contacts the ground and stops. Therefore, the number of local peaks in the filtered acceleration magnitude graph provides a rough estimation of the number of steps. The issue arises from other sources of low-amplitude peaks from moving the phone in and out of the pocket and low-grade movements when standing still or turning around. To reject these peaks, we implement a minimum amplitude using the average of the upper quartile:

$$step_{min} = \mu_{Q3} * 0.45 \tag{5}$$

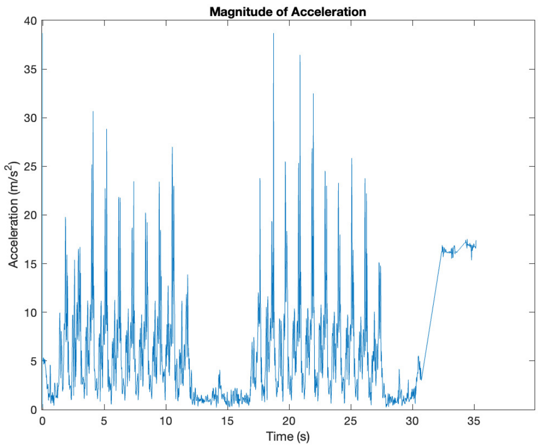
Where only local peaks greater than this value is considered as a valid step. The constant multiplier 0.45 is found using a trial and error method for a variety of datasets.

3 Results

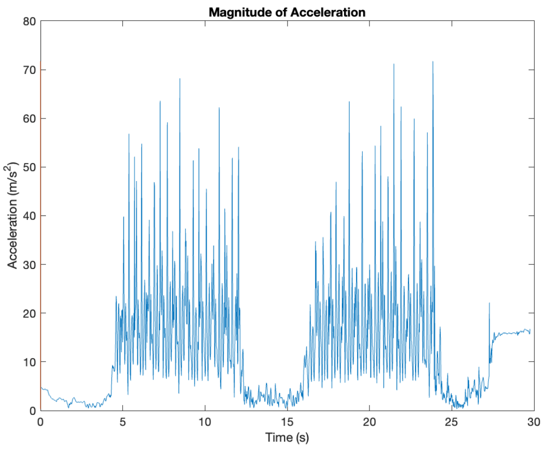
Four different sets of data is taken at different cadences; slow walking, walking, jogging and running.



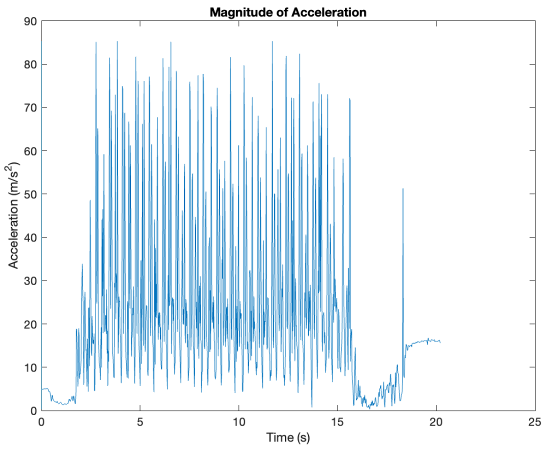
(a) Slow walking



(b) Walking



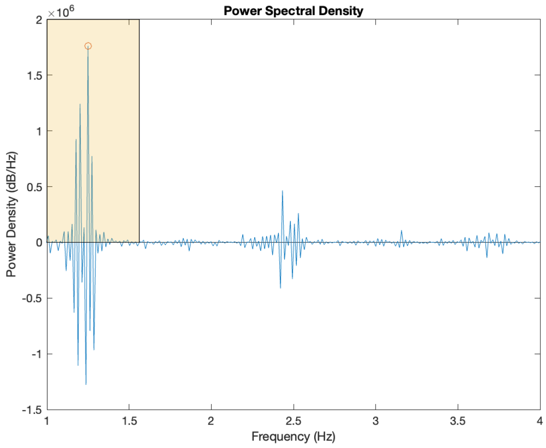
(c) Jogging



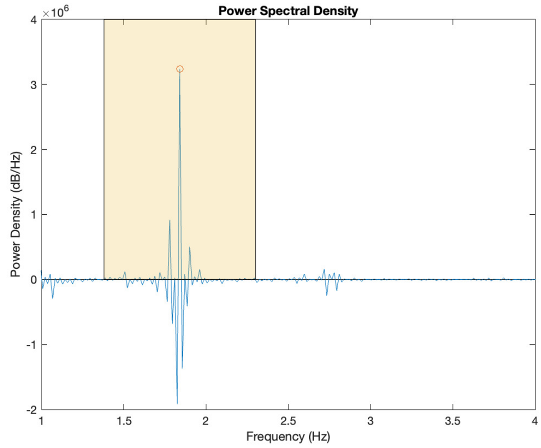
(d) Running

Figure 6: Raw magnitude of acceleration for the different activities.

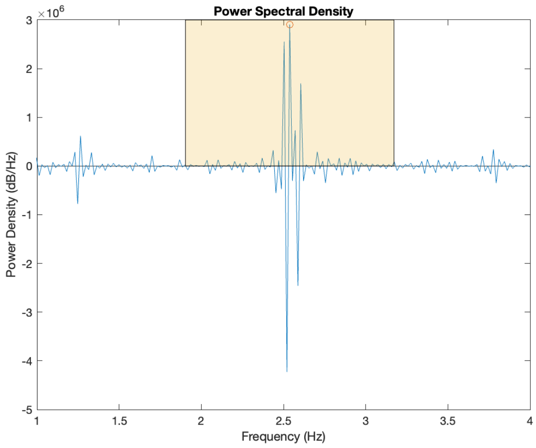
The raw unfiltered acceleration magnitudes have very large spikes throughout the graphs. This is mainly caused by the influence of gravity because during calibration of the accelerometer, the influence of gravitational acceleration is purely removed for the y-axis. However, the orientation of the phone is not purely vertical during walking, with the changing angle leading to the other axes measuring this gravitational acceleration.



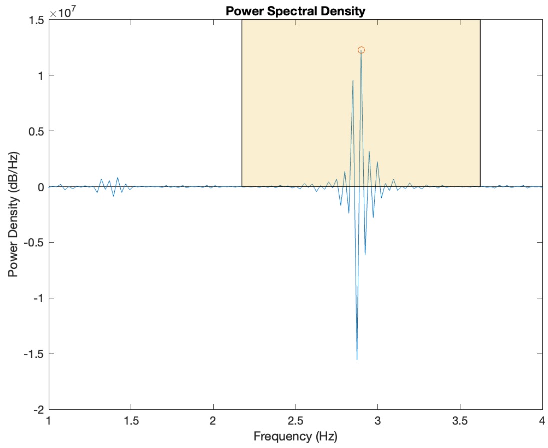
(a) Slow walking



(b) Walking



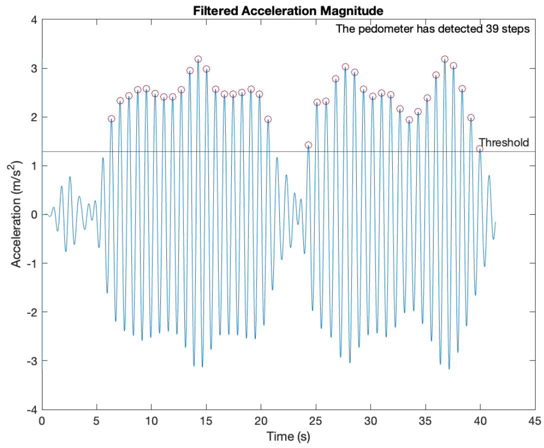
(c) Jogging



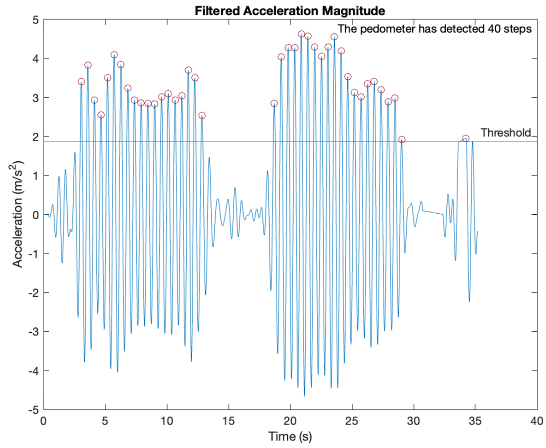
(d) Running

Figure 7: Power Spectral Density and bandpass range for the different activities from 1Hz-4Hz.

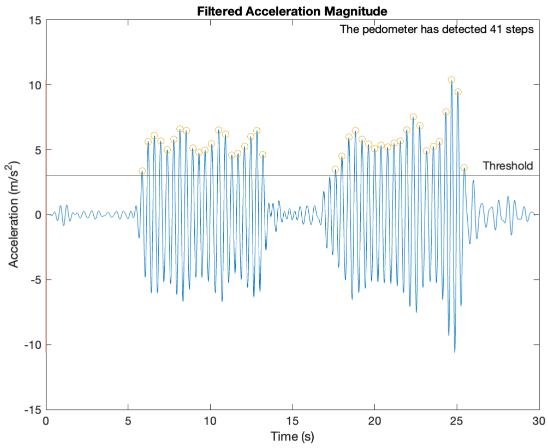
According to expectations, the frequency with the highest power spectral density gradually increases for the different activities, from slow walking to running. A cluster of peaks is present close to this dominant frequency from minor fluctuations of the cadence during experiments. Furthermore, smaller local peaks from measurement noises and phone movements in and out of the pocket are present.



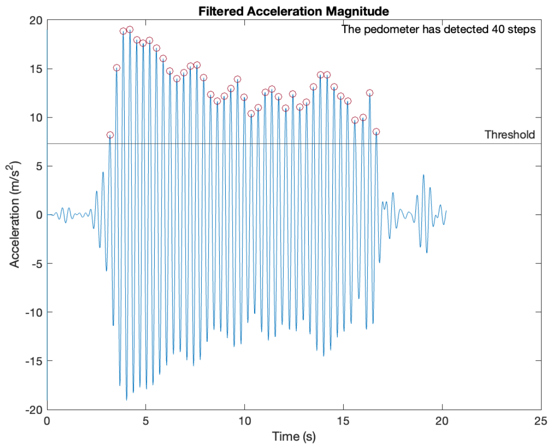
(a) Slow walking



(b) Walking



(c) Jogging



(d) Running

Figure 8: Pedometer performance for the different activities.

The adaptive bandpass filter with cutoff frequencies described in equation 3 and 4, along with an amplitude threshold described in equation 5 leads to a $\pm$ 1 step error during testing. This threshold allows the pedometer to ignore any local peaks caused by handling the phone or turning around. This result corresponds to an accuracy of 97.5%. There is a gradual increase in magnitude for the different activities, from slow walking to running. Overall, the designed pedometer satisfies the three specifications:

1. Achieve 95% accuracy for the recorded steps and visualisation of the steps.
2. Adaptive to various cadences such as running, jogging and walking.
3. Rejection of random non-walking signals such as taking the phone out of the pocket and using the phone in hand.

4 Discussion

The designed pedometer satisfies the outlined criteria with excellent accuracy of 97.5% accuracy; however, this is only valid when the dataset contains one consistent walking pace. When an individual displays two drastically different cadences (e.g. walking then slow walking), the pedometer will only be able to detect one portion of the steps—the one with the most significant power density since the other portion will be filtered out.

Additionally, a dataset with a similar cadence with different magnitudes (e.g. fast walking followed by sprinting) will generate a threshold that invalidates local acceleration peaks from jogging. We can ease this limitation by subsampling the data into 30 seconds intervals, where there is enough walking data for the cadence frequency to be the largest power density and small enough such that it is likely to have a single cadence. However, this assumption is not always valid and can lead to unsatisfactory performance when the subsample does not have a single cadence and magnitude. Lastly, the pedometer will not detect walking frequencies below 1Hz or above 7Hz; however, this is a robust assumption for most use cases.

One method to combat the limitation of multiple cadences in a dataset is using two high-order bandpass filters with no overlapping frequency bands when two walking cadences are identified, then summing the detected number of steps after separately filtering the raw data. For the instance where there are two different acceleration magnitudes in a dataset, an experimentally determined constant threshold that rejects noise can be used instead of an adaptive solution based on the observed peaks. Note that this solution might lead to less accurate results as it is not as robust to noise sources such as stationary handling of the phone.