# AcTrak - Unobtrusive Activity Detection and Step Counting Using Smartphones

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**Abstract.** In this paper we introduce "AcTrak", a system that provides training-free and orientation-and-placement-independent step-counting and activity recognition on commercial mobile phones, using only 3D accelerometer. The proposed solution uses "step-frequency" as a feature to classify various activities. In order to filter out noise generated due to normal handling of the phone, while the user is otherwise physically stationary, AcTrak is armed with a novel algorithm for step validation termed as Individual Peak Analysis (IPA). IPA uses peak-height and inter-peak interval as features. AcTrak provides realtime step count. It also classifies current activity, and tags each activity with the associated steps, resulting in a detailed analysis of activity recognition. Using our model, a step-count accuracy of 98.9 % is achieved. Further, an accuracy of 95 % is achieved when classifying stationary, walking and running/jogging. When brisk-walking is added to the activity set, still a reasonable level of accuracy is achieved. Since AcTrak is largely orientation and position agnostic, and requires no prior training, this makes our approach truly ubiquitous. Classification of step-based activity is done as walking, brisk-walking and running (includes jogging). So, after a session of workout, the subject can easily self-assess his/her accomplishment.

**Keywords:** Step counting · Activity detection · Unobtrusive sensing · Mobile sensing · Mobile computing · mHealth

## 1 Introduction

The sedentary nature of urban and semi-urban lifestyle coupled with easy access to basic resources like ample food has produced a new array of physical problems [15]. Hence, a controlled diet and ample physical activity become important aspects of health and wellness. It is important for subjects to monitor and assess their daily activities with respect to the benchmark recommended by medical practitioners or health/fitness experts. The recent boom in smartphone market has made it the most pervasive and ubiquitous sensing platform available with the masses. Hence if a method were to use smartphone sensors in a power and cost effective manner to provide activity monitoring, it would be of immense use. Professional pedometers and fitness gadgets provide activity monitoring and


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step-counting features. However, there are two major issues. Firstly, there is additional cost involved in buying and "wearing" the additional sensors. Secondly, most of these devices need to be "trained" for individual users to count steps and recognize activities. AcTrak attempts to solve the above issues by using smartphone sensor, namely the 3-axis accelerometer for step counting and activity recognition, using step-frequency and a novel IPA algorithm. Though Global Positioning System (GPS) can also be used to assess user activity, but as marked by Sun et al. [14], it cannot provide refined analysis of human movements. Additionally, GPS sensor drains a lot of power, and can only be used outdoors.

## 2 Previous Work

Human activity recognition using sensors has been a widely researched area. Accelerometers have become established sensors in this respect, although some researchers have also attacked the problem using machine vision [4,16]. Research has been carried out using wearable sensors [1,10]. These solutions give fine-tuned data for recognizing even static activities like sitting, standing and even different gestures, but poses obtrusion from wearing external device(s) that the subject may not be comfortable with. After accelerometers started becoming available in mobile devices, they were taken up for activity recognition [2,3,6,14,17]. Using accelerometer in mobile and other embedded devices as a pedometer has also been explored [3,7–9,11,13]. Marschollek et al. [9] compares various open and proprietary methods of step detection using a cell phone accelerometer. Some researches pose a constraint on orientation aspect of the device [3,6,12,17]. Sun et al. [14] has relaxed this requirement and has used resultant acceleration for detecting steps. However, it still requires exhaustive training for all possible orientations and device placement options. We observe that prior approaches in this direction have performed the step detection and activity classification by including measures which employ absolute amplitude profiles of the sensor data. These profiles change from person to person, from activity to activity or placement of mobile device with respect to body and hence require a training phase. Also prior arts have not taken into account the stationary noise periods occurring during device handling, which may be of large amplitudes comparable to that of the actual activities, and can result in false positives. These are two drawbacks that AcTrak tries to eliminate.

## 3 Methodology

The methodology used in AcTrak has been outlined in Fig. 1. Different stages of the method are discussed in the following subsections.

### 3.1 Data Preprocessing

The algorithm in our approach uses resultant acceleration for processing, thereby ensuring an orientation free usage of the mobile device [7,14]. Data from the

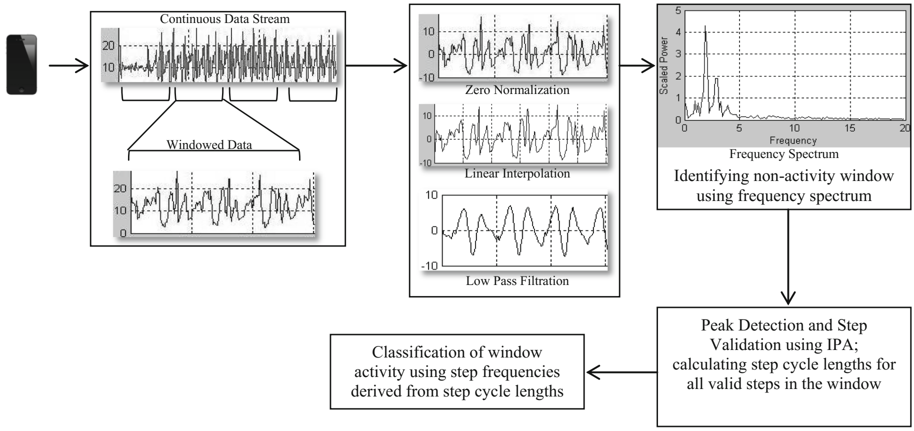



**Fig. 1.** AcTrak-Algorithm overview

3-axis accelerometer requires some pre-processing before using it for step detection in a discrete-time manner. A step-wise account of preprocessing process is described in the following sub-sections.

**Windowing.** At first, a window-based analysis is performed on the raw data stream coming from accelerometer. In this approach, a window interval of 2 s was chosen heuristically, which is short enough to provide a real time response to the user without missing a substantiate step information, and long enough in order to record inter-step temporal and frequency characteristics.

**Zero Normalization.** Next the data window is zero normalized eliminating the DC bias which is undesired in the frequency domain analysis, which is one of the subsequent steps.

**Interpolation.** Since the accelerometer data is captured at variable sampling rate due to the nature of software calls for sensor data acquisition [2], interpolation is used to make the signal in constant sampling rate, required for frequency domain analysis.

**Low Pass Filtration.** This step performs noise cancellation by filtering out the high frequency components (e.g. stray vibrations, internal sensor noises). We use an FIR low pass filter with a cutoff frequency of 4 Hz. Li et al. [7] uses a value of 3 Hz, but AcTrak uses a higher cutoff to also encompass faster step activities like running.

### 3.2 Step Detection and Activity Classification

This section describes the methodology for step detection and activity classification.

**Stationary Noise Detection.** As our solution runs dynamically on a mobile device and keeps updating the user interface in real time, an important practical problem arises of filtering out the stationary periods; the time-windows during which the user is operating the mobile device but not performing any activity of interest. This problem has been largely unsolved. [7] analyzes only manually selected periods of activity, which is not a very practical scenario, especially for a real time smartphone app. It was observed from experimental data that the stationary noise periods and the actual activity periods vary greatly in their frequency domains. Hence, we separate them using following measures from the Fast Fourier Transform (FFT) spectrum of the acceleration data window:

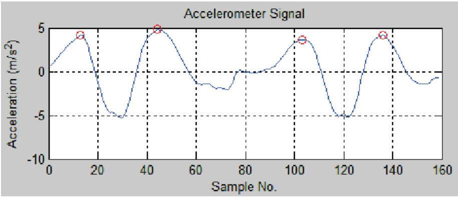
- *Dominant Amplitude* ($A_d$), the value of the largest Discrete Fourier Transform (DFT) coefficient
- *Dominant Frequency* ($f_d$), the frequency component exhibiting $A_d$
- *Peak Sharpness* ($ps$), the sum of squares of slopes for $k$ DFT coefficients on either side of the highest peak in the frequency spectrum:

$$ps = \sum_{i=-k}^{k-1} \left( \frac{A(i) - A(i+1)}{A_d} \right)^2 \tag{1}$$

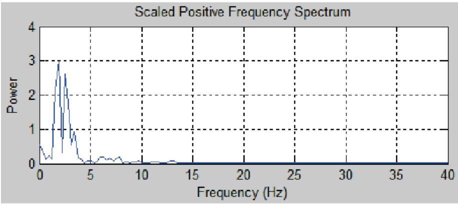
where $A(0)$ represents the largest DFT coefficient i.e. $A_d$.

The last measure differentiates distinct long and narrow peaks with substantial periodicity in the sensor data with otherwise short and wide peaks, which mostly represent noisy windows. Such wide peak spectrum have been observed when the mobile device experiences a jerk, e.g. while freely allowing the device to fall into the pocket. It was observed that except when the mobile device is hand-held, the order of the peak amplitudes of acceleration values pertaining to steps is well greater than $1.0\,\mathrm{m/s^2}$. This is evident because whenever the user places the device in the upper half of his body, the intensity of net acceleration is less than as compared to when the device is placed anywhere in the lower body, such as trouser pockets, where an additional component of the leg movement and free movement of the device in sometimes very loose pockets (like those in casual trousers) add up to give a higher resultant acceleration. Next, it was also found that in almost all of scenarios where the mobile device was placed with the lower body, the acceleration signals posed a different frequency spectrum, which contained, no more than, two major peaks, with an additional note that the amplitude of the second peak was no shorter that $\approx 80\,\%$ of the amplitude of the greater peak, as shown in Fig. 2(b).

In order to ensure the validity of the peaks we place limits on $A_d$ followed by thresholds on $ps$ and no. of peaks, $P_n$. This flow is shown in Fig. 3. $A_l$ is a lower




(a) Accelerometer Signal




(b) Scaled Positive Frequency Spectrum

**Fig. 2.** Filtered acceleration signal and the related frequency spectrum

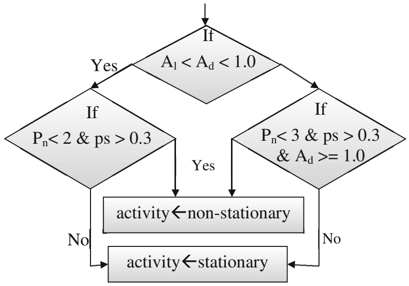



**Fig. 3.** Flow for deciding a stationary window

threshold limit on $A_d$ and $P_n$ is the number of peaks present with height at least 75 % of $A_d$. After a stationary window, activity and step update is given after processing two consecutive windows. Thereafter, updates are provided after each window.

**Step Detection.** The process of robust step-detection is important as the accuracy of both step count as well as activity classification depends largely on it. After a data window has been verified, as discussed above, to be non-stationary, the step detection algorithm is applied to that window. For identifying steps, we use a peak detection algorithm, with a constraint of minimum number of samples between two peaks. After identifying peaks, each peak is validated if it represents an actual step. Li et al. [7] uses Dynamic Time Warping (DTW) technique with some heuristics in order to validate the detected peaks as steps. As in Fig. 2(a), number of samples between consecutive steps are not uniform. Instead the number of samples for the whole step cycle shows the required periodicity. Naqvi et al. [11] tried to bring out a relationship between step frequency and threshold for the peak heights using the vertical axis signal from accelerometer. However their work poses an orientation constraint on the device.

We introduce IPA (Individual Peak Analysis), a novel and a robust method, in order to perform peak validation. Using information from the frequency spectrum of the data window, we get an estimate of the properties of valid peaks. For all the peaks, we observe two features, viz. peak height, i.e. the difference between peak crest ($pkHt$) and the least value until the previous valid peak ($ppm$), and the inter-peak intervals ($pDiff$). It was observed that the product of these two parameters in a window is a consistent measure for all the peaks representing valid steps. This is also evident from Fig. 4 where the peak height for peak 2 ($pkHt_2 + |ppm_{1,2}|$) and peak 3 ($pkHt_3 + |ppm_{2,3}|$) varies, but is countered with their corresponding peak differences ($pDiff_{1,2}$ and $pDiff_{1,2}$ respectively). Hence we derive that this new feature, which we call $peakProduct$, is a good measure for classifying accelerometer signal into step and non-step clusters using the frequency domain analysis. We define $peakProduct$, $P_k$ as follows:

$$P_k = (pkHt_k - ppm_{k-1,k}) \times \frac{pDiff_{k-1,k}}{f_s} \tag{2}$$

where $P_k$ denotes the product for $k^{th}$ peak in the window and $f_s$ is the sampling frequency. For $k = 1$, i.e., first peak of the window, last valid peak of previous window is taken into consideration. Parameters of Eq. 2 are depicted in Fig. 4.

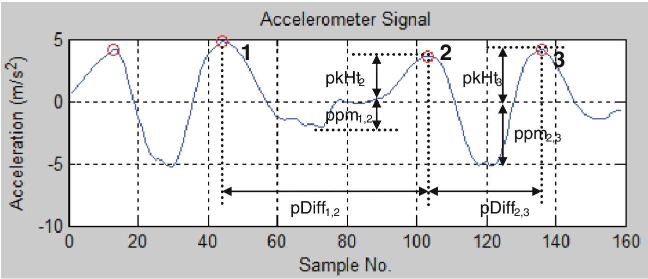


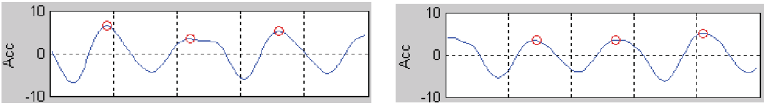

**Fig. 4.** Parameters for $P_k$

Since the values $A_d$ and $f_d$ represent the periodicity of steps, the cycles in the acceleration signal pertaining to valid steps are expected to exhibit similar values. The measure corresponding to $P_k$ generated from the frequency spectrum of the window is $F_p = \frac{A_d}{f_d}$. After analyzing various windows of steps ($\approx 5000$) with the device placed at different positions, it was observed that for almost all the valid peaks, the product $F_p$ behaved proportionally to the product $P_k$, as expected. Hence, the following criterion was selected for a peak to represent a valid step:

$$P_k \geq (\tau \times F_p) \tag{3}$$

Using regression we determined that a value of 1.3 for $\tau$ gave best validation results. We call the above peak validation method as IPA. This stage outputs a step cycle length vector, $SCL$, where $SCL_i$ is the sample difference between $i^{th}$ valid peak and $(i-2)^{th}$ valid peak.

*Case of Edge Peaks:* As with all windowed analysis, there are peaks which are flat enough to make their presence at the edge of two consecutive windows (see Fig. 5). Such peaks would typically pass undetected by the peak detection algorithm used, producing a glitch in the overall step cycle length vector of the window. For solving this problem, AcTrak employs a smart technique whereby we mark the first sample of every window as a peak (if *amplitude* $> 0$), which is then further validated using IPA.




(a) Data Window $k$ (b) Data Window $k + 1$

**Fig. 5.** Two consecutive data windows with a flat undetected edge peak

**Classification.** As mentioned in Sect. 2, substantial research has been done in the field of activity classification using trained classifiers, which use various signal features as classification parameters, both amplitude and temporal. Classification results are fairly accurate [1,6,14] with these measures, but the success of the trained classifier depends on the similarity of situations of training phase and testing phase, which is not completely feasible practically especially in case of mobile devices which pose wide possibilities of placement options. In this paper, we have attempted to classify activities without using any training phase. Towards this end, we use only temporal measures of the activities, which take care of wide possibilities of amplitude characteristics of the sensor signals owing to different user positions and even different pocket profiles (jeans vs. casual trousers). We have chosen a subset of activities from existing classification researches, viz., walking, brisk walking and jogging/running, which can be differentiated on their temporal profiles alone, as a step towards a complete orientation and placement free unobtrusive method. We classify the mentioned activities using a windowed-analysis whereby we determine threshold step frequencies for the mentioned activities as $f_{bw}$ and $f_r$.

To estimate these thresholds, we gathered data from five subjects of varied demographics (different from the test subjects used for gauging the classification performance in Sect. 4) and determined the mean step frequency for each activity as $MSF_w, MSF_{bw}$ and $MSF_r$ (Table 1). Thereafter we determined the boundary thresholds, $f_{bw}$ as $\frac{MSF_w + MSF_{bw}}{2}$ (= 1.85) and $f_r$ as $\frac{MSF_{bw} + MSF_r}{2}$ (= 2.4). Using $SCL_i$ from step detection stage, we define four weight measures: w1, w2, w3 and w4 as shown in Fig. 6. The data window is then assigned as representing a particular activity as shown in Fig. 7. The four weights classify the activities on the basis of above calculated boundary thresholds, which can be defined with fair accuracy for a wide demography of persons. The key advantage of using only temporal features for classification is that it works seamlessly with any option of device placement.

**Table 1.** Step frequencies from test subjects

| | Sub 1 | Sub 2 | Sub 3 | Sub 4 | Sub 5 | Mean |
|---|---|---|---|---|---|---|
| Walking | 1.78 | 1.72 | 1.81 | 1.7 | 1.755 | 1.753 ($MSF_w$) |
| Brisk walking | 1.9 | 2.03 | 2.033 | 1.86 | 1.92 | 1.9486 ($MSF_{bw}$) |
| Running | 2.77 | 2.86 | 2.97 | 2.89 | 2.82 | 2.862 ($MSF_r$) |

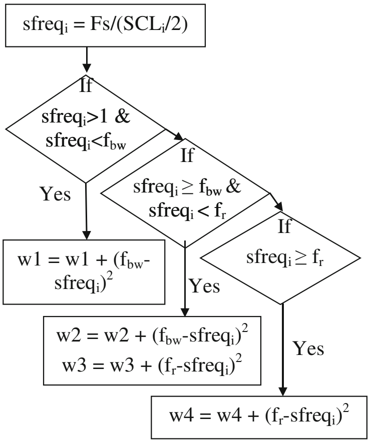



**Fig. 6.** Flow for assignment of activity weights

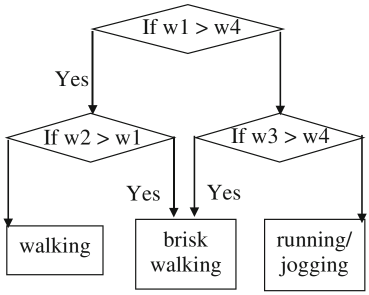



**Fig. 7.** Classification of activities on the basis of calculated activity weights

## 4 Experiments and Results

We produce results in a threefold manner, whereby first we show the effectiveness of the step-counting method and compare it with the established methods. Then we show the robustness of AcTrak in cancelling out stationary noise caused by normal operation of the mobile device and in the last phase, we illustrate the activity detection performance of AcTrak. The application was built on an iPhone with a sampling frequency of accelerometer as 80 Hz. For analyzing step count accuracy, four subjects were allowed to walk freely inside a typical office space, by keeping the phone in different orientations attached to different parts of the body as shown in Table 2. To compare with the step detection algorithm by Li et al. [7], five sets of accelerometer data was logged with an iPhone placed in the subject's trouser pocket. Results of AcTrak were obtained in real-time while the algorithm by Li et al. [7] (Peak Detector+Heuristics+DTW) was run offline. The results are shown in Table 3, where IPA outperforms the DTW in step validation. DTW was observed to deem invalid steps as valid in some very noisy situations in spite of applying proper heuristics, where IPA correctly eliminated invalid peaks.

AcTrak's error, as in Table 3, is also lower when compared to those of the open algorithms as analyzed by Marschollek et al. [9], where Wolf method yields least step detection error of 8.4 %, and also when compared to the energy algorithm by Schindhelm et al. [13], where the least error yielded is 3.6 %.

Next, the robustness of AcTrak in eliminating the random stationary noise is demonstrated. Two spells were performed whereby two different users operated on the mobile phone (games, texting etc.), randomly giving some jerks (placing on table, allowing the device to freely fall in the pocket etc.) The results were compared with the algorithm by Li et al. [7]. Results for the two spells, S1 and S2, are tabulated in Table 4. It can be seen that AcTrak efficiently avoids any wrong detection of steps in case of stationary noise and random operation of device, which is important from a practical perspective as already discussed in Sect. 3.2.

**Table 2.** AcTrak: step detection performance with various device placements

| | Sub 1 | | Sub 2 | | Sub 3 | | Sub 4 | | |
|---|---|---|---|---|---|---|---|---|---|
| | A[a] | D[b] | A | D | A | D | A | D | Avg. Error % |
| Hand | 90 | 76 | 84 | 83 | 96 | 91 | 85 | 70 | 9.9 |
| Shirt's pocket | 90 | 90 | 86 | 86 | 93 | 85 | 88 | 88 | 2.1 |
| Trouser's front pocket | 90 | 84 | 85 | 90 | 95 | 96 | 89 | 92 | 4.24 |
| Trouser's rear pocket | 92 | 90 | 85 | 83 | 95 | 91 | 90 | 81 | 4.68 |
| Waist clip | 89 | 96 | 85 | 84 | 94 | 91 | 87 | 83 | 4.2 |
| Avg. error % | 6.4 | | 2.12 | | 4.45 | | 7.1 | | 5.02 |

[a]Actual steps

[b]Detected steps

**Table 3.** AcTrak: step detection performance comparison

| A | D: [7] | D: AcTrak | Error%: [7] | Error%: AcTrak |
|---|---|---|---|---|
| 130 | 133 | 132 | 2.3 | 1.5 |
| 64 | 72 | 63 | 12.5 | 1.5 |
| 54 | 58 | 54 | 7.4 | 0.0 |
| 40 | 42 | 41 | 5.0 | 2.5 |
| 37 | 41 | 37 | 10.8 | 0.0 |
| Avg. error % | | | 7.6 | 1.1 |

**Table 4.** AcTrak: comparison of false detections in stationary noises

| | Time | FD[c]: [7] | FD:AcTrak |
|---|---|---|---|
| S1 | 50 s | 18 | 2 |
| S2 | 40 s | 16 | 0 |

[c]False step detections

Finally the results for activity detection are presented. Here, we used the HASC corpus 2011 data set [5] with individuals of varied demographics and using different devices for data logging. We performed classification for the activities stay, walk and jog, as available in the data set. We selected a set of 100 persons randomly to perform the classification and the resulting confusion matrix is presented in Table 5, where each entry represents the percentage of time classified under the head of a particular activity by AcTrak. Also the classification of [5] was preceded by a training phase including up to 80 individuals, where AcTrak doesn't use any training. Comparing with the classification accuracy as in [5], we achieve a better accuracy as shown in Table 5, even after aggregating the classification accuracy of Jog and Skip [5] to only Jog/Run(AcTrak) and Walk, Stairs Up and Stairs Down [5] to only Walk(AcTrak) in order to attempt a sensible and a fair comparison.

**Table 5.** AcTrak: comparison of activity classification accuracy with HASC corpus dataset [5] (all in % accuracy)

| | Stay | Walk | Jog/Run | Accuracy [5] |
|---|---|---|---|---|
| Stay | **99.8** | 0 | 0.2 | **86.7** |
| Walk | 2.1 | **96.7** | 1.2 | **97.0** |
| Jog/Run | 1.2 | 2.8 | **96.2** | **82.3** |

**Table 6.** Activity classification results (all in % error accumulated)

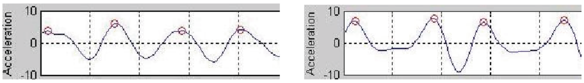
| | Walk | Brisk walk | Run |
|---|---|---|---|
| Sub 1 | 0.00 | 0.00 | 0.00 |
| Sub 2 | 17.19 | 19.57 | 0.00 |
| Sub 3 | 3.33 | 4.55 | 15.00 |
| Sub 4 | 7.02 | 17.95 | 0.00 |
| Sub 5 | 0.00 | 25.71 | 8.33 |

In order to explore the accuracy of brisk walking using AcTrak, which was not possible in the previous comparison with [5] due to data availability limitation, we carried out an independent experiment using 5 volunteers. As like the previous case, since unsupervised and training free activity detection was performed it was very important to validate the algorithm against a variety of people spanning across demographics. As shown in Fig. 8, the same step-based activity may produce significantly different accelerometer signal for different subjects. In order to validate that the algorithm works well for most individuals, a set of five individuals were selected with varying demographies as illustrated in Table 7, and the volunteers were asked to perform the activities of interest, viz., walking, brisk-walking and running. Results collected over these subjects are depicted in Table 6, along with the percentage error accumulated for each activity.

The error was calculated against ground-truth data of step count annotated by the subjects themselves. Error percentage is given as:

$$Error\ Percentage = \frac{|Total\ Steps\ Detected - Steps\ Detected\ for\ Activity|}{Total\ Steps\ Detected} \times 100$$

As is clear from Table 6, the percentage error between walking and brisk walking is higher than between walking and running based activities. Also for a few subjects, brisk-walking and running came as overlapped activities. To point the above issue, individual step frequency during each activity for each subject were also recorded as presented in Table 8 where it can be seen that the step frequency for walking and brisk-walking for some individuals like subjects 3 and 4, are almost similar. Also for subject 2, brisk-walking and running step-frequencies are almost equal. Hence, the difference in frequency between walking and brisk walking is a fuzzy boundary that is open to human interpretation, whereas the activities of running/jogging can be easily differentiated from others. So, from Table 6 it is clear that an unconscious mix-up of activities had taken place during the experiment, leading to a marginally higher error. However, the purpose of AcTrak is served well, as it is built to correct similar errors often committed by people during workout sessions.



(a) Profile 1 (b) Profile 2

**Fig. 8.** Different acceleration signal profiles for brisk walking for two different subjects

**Table 7.** Demographics of different subjects

| | Age | Height | Gender | Body | Weight |
|---|---|---|---|---|---|
| Sub 1 | 25–30 | Short | Male | Slim | Light |
| Sub 2 | 25–30 | Tall | Female | Fat | Heavy |
| Sub 3 | 35–40 | Short | Male | Stout | Medium |
| Sub 4 | 25–30 | Tall | Male | Stout | Heavy |
| Sub 5 | 40–45 | Tall | Male | Slim | Medium |

**Table 8.** Average step frequencies

| | Walk (1.2–1.85) | Brisk walk (1.85–2.4) | Run (>2.4) |
|---|---|---|---|
| Sub 1 | 1.63 | 1.89 | 2.8 |
| Sub 2 | 1.23 | 2.44 | 2.75 |
| Sub 3 | 1.69 | 1.86 | 2.84 |
| Sub 4 | 1.75 | 1.82 | 2.6 |
| Sub 5 | 1.66 | 1.8 | 2.77 |

## 5 Conclusion and Future Work

In this work we have depicted AcTrak for unsupervised classification of common step-based activities on commercially available mobile devices. The method uses only temporal features, and hence is able to tolerate large variations in signal due to human imperfections, varied placement options and different activities. While competitive methods require extensive training, AcTrak requires none. For step detection, we use IPA to validate steps for multiple activities. Also we address the problem of false positives due to normal handling of the device.

As a future endeavor, we plan to include options for positioning the device at places like arm-bands, which is typical for workout sessions. This is a challenging problem, since multiple components from the arm movements needs to be captured in addition to vertical acceleration component of the overall body.

Also we plan to include detection of ascending and descending stairs. Though already addressed in existing literature, we aim at a completely unsupervised training-free method. Preliminary observations have shown that such classification is possible.

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