Walking Detection Using the Gyroscope of an Unconstrained Smartphone

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Abstract. In recent years, mobile devices (e.g., smartphones, tablets and etc.) equipped with various inertial sensors have been increasingly popular in daily life, and a large number of mobile applications have been developed based on such built-in inertial sensors. In particular, many of these applications, such as healthcare, navigation, and etc., rely on the knowledge of whether a user is walking or not, so that walking detection thus has attained much attention. This paper deals with walking detection by using the gyroscope of any commercial off-the-shelf (COTS) smartphone, which can be placed at different positions of the user. Inspired by the fact that the walking activity often results in notable features in the frequency domain, we propose a novel algorithm based on fast Fourier transformation (FFT) to identify the walking activity of a user who may perform various activities and may hold the smartphone in different manners. A thorough experiment involving three testers and multiple activities is carried out and confirms that the proposed algorithm is superior to the existing well-known counterparts.

Keywords: Smartphone · Walking detection · Unconstrained · Fast Fourier transformation(FFT) · Angular velocities

1 Introduction

Nowadays, with the development of Micro-electromechanical Systems (MEMS) technologies, various low-cost inertial sensors have been integrated in almost every commercial off-the-shelf (COTS) smartphone, and are playing a vital role in a multitude of applications like gaming, navigation, augmented reality, and etc. [1–5]. Therein, gait recognition through the built-in sensors of any smartphone, involving the estimation of the step count and step length, is receiving increasing attention and has become a hot research topic. For instance, in the fields of pedestrian navigation and tracking [6–9], pedestrian dead reckoning (PDR) can be implemented on smartphones to improve positioning accuracy by providing pedestrian displacement and orientation. Evidently, successfully identifying the phase of walking during consecutive activities is prerequisite to these applications.

Therefore, many efforts have been invested on walking detection, but most of existing studies were focused on either dedicated devices, e.g. foot-mounted

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inertial sensors, or smartphones with fixed placements. As a result, it is still challenging to identify the walking activity by using unconstrained smartphones, in the sense that the smartphone's placement can be arbitrary to some extent.

In this paper, we deal with the problem of walking detection with unconstrained smartphones, and propose a robust and efficient walking detection algorithm inspired by the fact that the gyroscope data obtained by a smartphone shows notable cyclic features in most cases when its user is walking. Specifically, the optimal axis is firstly selected from the three dimensional axes in the device frame according to their respective amplitudes, the fast Fourier transformation (FFT) technique is then adopted to derive the frequency-domain gyroscope data in the optimal axis, and a sliding time window is applied to evaluate the amplitudes of multiple frequencies within the current time window, so as to judge whether the smartphone user is walking. A thorough experiment is carried out by taking into account various activities of three testers. It is shown that the overall performance of the proposed algorithm is superior to the existing best walk detection algorithms.

The remainder of this paper is organised as follows. A brief review on related works is presented in Sect. 2. Section 3 introduces the proposed algorithm in details and Sect. 4 reports the experimental results. Section 5 finally concludes this paper and sheds lights on future works.

2 Related Works

There is a wealth of studies on walk detection and step counting for smartphone users in the literature, which can be categorized into time domain approaches, frequency-domain approaches and feature clustering approaches. A thorough survey can be found in [10].

The time domain approaches include thresholding [11], autocorrelation [12], and etc. The thresholding method is simplest, but the difficulty lies in selecting optimal thresholds, especially for unconstrained smartphones. The autocorrelation method detects the period directly in the time domain through evaluating auto-correlation, and is able to obtain good performance at relatively low costs in comparison with frequency-domain approaches.

The frequency-domain approaches focus on the frequency content of successive windows of measurements based on short-term Fourier transform (STFT)[13] and continuous/discrete wavelet transforms (CWT/DWT) can generally achieve high accuracy, but suffer from either resolution issues or computational overheads.

The feature clustering approaches employ machine learning algorithms (e.g. Hidden Markov models (HMMs) [14], KMeans clustering [15], and etc.) to classify activities based on both time-domain and frequency-domain features extracted from the measurements of inertial sensors [16].

3 Method

Commonly, positions and attitudes of a smartphone often experience continuous and dramatic changes when its user is conducting a series of activities, such as walking, texting, calling, playing games and etc. Since different activities result in different inertial measurements, activity recognition can be realized to some extent by extracting unique features of different activities from such measurements.

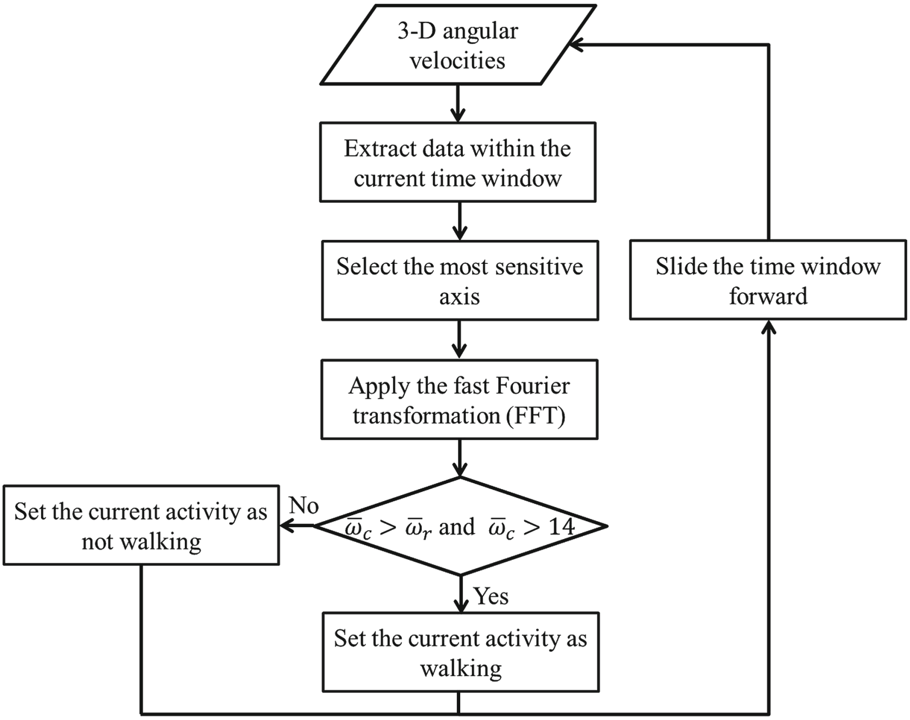

Fig. 1. The flow diagram of the walk detection

Considering the fact that gyroscope is more sensitive and accurate than accelerometer, and for cyclic activities like walking, the angular velocities sensed by gyroscope often swing around zero, though most existing studies on walk detection were carried out based on accelerations as mentioned previously, gyroscope is adopted in the proposed algorithm, the flow diagram of which is illustrated in Fig. 1.

As can be seen, the algorithm mainly involves three components, namely a sliding time window, sensitive axis selection and a spectrum analysis, which will be described in detail in what follows.

3.1 Sliding Time Window

In order to continuously detect walking activities, the algorithm is designed based on a sliding time window. As suggested in [17], the typical walking frequency of human ranges between 0.6 Hz and 2 Hz; that is to say, the duration of the walking activity approximately ranges between 0.5 s and 1.6 s. Therefore, the time window should contain a sequence of data longer than 1.6 s and the sliding step is around the duration of one stride.

Moreover, according to the Shannon sampling theorem, it is sufficient that the sampling frequency is more than two times of the walking frequency. As such, by trading off the energy consumption and minimal sampling frequency, the sampling frequency of the sensors in the smartphone is set to be 20 Hz.

On these grounds, since the base-2 FFT algorithm will be adopted, let the sizes of the time window and sliding step be 64 and 25, respectively, which are equivalently 3.2 s and 1.25 s in the terminology of time.

3.2 Sensitive Axis Selection

Imagining that a smartphone user is required to perform an identical activity repeatedly, it is true that the three axes of inertial measurements derived by the gyroscope of the smartphone in the device reference frame demonstrate different characteristics according to the position and attitude of the smartphone, and thus play different roles in successfully identifying the user's activity. Therefore, it is of great importance to select the most sensitive axis in the sense that the corresponding data is closely correlated with the activity, so as to improve the performance of the recognition algorithms. Currently, an alternative approach is to use the magnitude of the corresponding 3-dimensional (3D) inertial measurements instead of the sensitive axis, but inevitably suffers from information loss.

On the one hand, the measurements of the gyroscope incur constant bias, thermo-mechanical white noise, flicker noise or bias stability, temperature effects, and calibration errors (e.g. scale factors, alignments and output linearities). In general, the measurement noises appear to be quite obvious when the measurements are relatively small, and on the contrary, can be ignored when the measurements are huge. Therefore, it is advisable to select the axis whose data has the maximum magnitude. On the other hand, regarding the walking activity, no matter where the smartphone is placed, certain cyclic features are involved in all the three axes of measurements; that is to say.

Inspired by the above analysis, we come up with the following simple method based on the absolute values of the 3-D angular velocities to select the sensitive axis for the proposed walking detection

$$\text{The most sensitive axis } = \max_{a=x,y,z} \sum_{i=1}^{n} |\omega_a(i)| \,, \tag{1}$$

where $\omega_a(i)$ denotes the angular velocity of the axis a with $a = x, y, z$ at time i within the current time window, and n is the size of the time window.

3.3 Walking Detection

Based on the above step, the most sensitive axis is determined and the corresponding measurements are fed into the process in this step.

In the first step, FFT is applied to transform the time-domain angular velocities in the most sensitive axis into the following frequency-domain data

$$X(k) = \sum_{n=0}^{N-1} \omega(n)(e^{-j\frac{2\pi}{N}})^{nk}, \tag{2}$$

where $k = 0, 1, \ldots, N-1$, $\omega(\cdot)$ is the angular velocity in the most sensitive axis, N denotes the number of the sampling points and equals to 64 in this case. The frequencies can be calculated as follows

$$F_n = (n-1) * \frac{F_s}{N} \ , \tag{3}$$

where F_n represents the frequency of the n-th point, and F_s is the sampling frequency and equals to 20 Hz in our case.

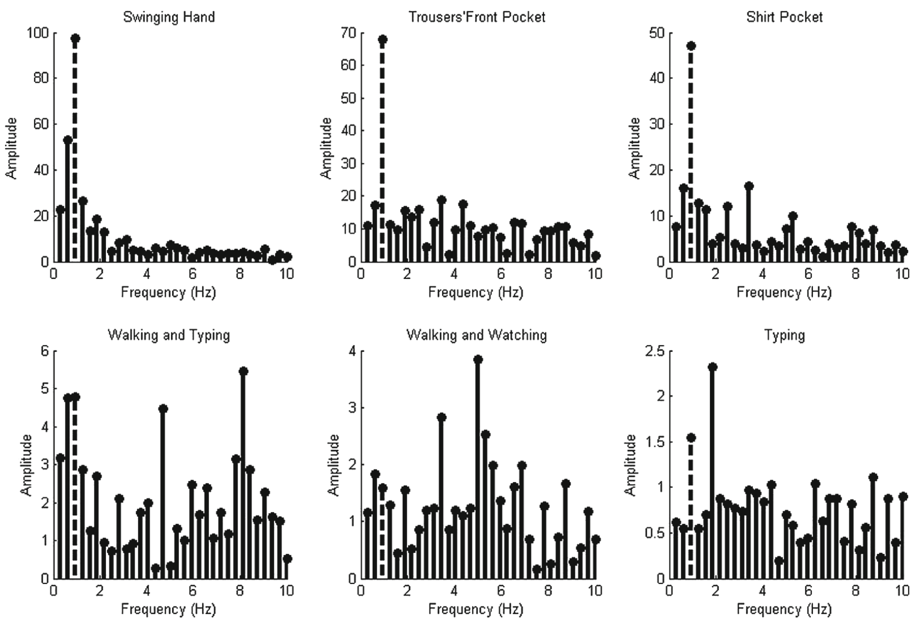

Fig. 2. Frequency-domain data obtained by FFT with respect to various daily activities. The dashed line denotes the amplitude at the frequency 0.9375 Hz.

In the second step, the frequency-domain data obtained through (2) is plotted with respect to various activities performed by Tester1 (see Table. 1) in Fig. 2.

As can be seen, the amplitudes at the frequencies in the vicinity of 0.9375 Hz are obviously greater than the counterparts at the other frequencies provided that the tester is walking with the smartphone placed at different positions (e.g. hand, shirt pocket, and etc.), except that the smartphone is being operated regardless of walking or not. Inspired by the observation, we propose to identify the walking activity by comparing the amplitudes of different frequencies. To be specific, the average amplitude within the typical walking frequencies (i.e. between 0.6 Hz and 2 Hz), denoted by ω_c, and that at the frequencies which fall outside of the typical frequencies, denoted by ω_r, are evaluated respectively, and then, walking is identified if the following condition is satisfied

$$\bar{\omega}_c > \bar{\omega}_r. \tag{4}$$

As illustrated in Fig. 2, when the holder is operating the smartphone (e.g. walking and typing, walking and watching, and typing), the resulting amplitudes are relatively small, reflecting that the smartphone is experiencing some mild motions which might involve walking or not; however, in this situation, it always happens that the condition in (4) is satisfied such that incorrect detection results are returned. Therefore, another condition is imposed by thresholding the average amplitude as follows

$$\bar{\omega}_c > 14, \tag{5}$$

where the lower bound 14 is experimentally determined and does not change.

To sum up, if and only if the conditions (4) and (5) are simultaneously satisfied, the current activity of the smartphone holder is identified to be walking. It is noticeable, the proposed algorithm cannot detect the walking activity when the smartphone is being operated by its holder due to the aforementioned analysis.

4 Experimental Results

In this section, an thorough experiment is reported to confirm the effectiveness of the proposed walk detection algorithm.

4.1 Setup

In the experiment, a smartphone (RedMi Note 2) running Android 5.0.2 LRX22G was adopted to collect measurements of gyroscope at the frequency of 20 Hz, and three testers with different heights, step lengths and genders were invited to continuously perform a predefined sequence of different daily activities including the walking activity along a corridor. The detailed information of the three testers is shown in Table 1. Specifically, the daily activities included in the experiment are shown in Table 2. In order to better distinguish all these activities during each trial, a video camera is used to record the whole procedure.

In order to verify the performance of the proposed algorithm (denoted by FFT), another two walking detection algorithms are performed in the experiment. The first one, denoted by STD_TH, belongs to the time-domain

Table 1. Subjects and their characters in the experiment

	Gender	Height(cm)	Step length(cm)
Tester1	Male	176	130
Tester2	Male	184	151
Tester3	Female	159	88

Table 2. The symbols and the corresponding daily activities

Symbol	Daily activities
A	Standing with the smartphone in the trousers' front pocket
B	Picking up the smartphone
C	Standing with the smartphone in the palm
D	Walking with the smartphone in the swinging hand
E	Standing and typing
F	Walking with the smartphone in the trousers' front pocket
G	Walking with the smartphone in the shirt pocket
H	Standing with the smartphone in the shirt pocket

approaches, and is implemented by thresholding the standard deviation of accelerations [11]. The other one, denoted by STFT, belongs to the frequency-domain approaches, and relies on STFT and accelerations [13]. Both of the algorithms were validated to be best among many existing algorithm for detecting the walking activity with an unconstrained smartphone [10].

The parameter values of all the three algorithms for comparison are listed in Table 3. As can be seen, f represents the length of FFT, w is the length of the apodization window (Hanning), dft_{win} and std_{win} are the size of the sliding step, dft_{th} is the threshold of spectral energy and std_{th} is the threshold of the standard deviation for the acceleration magnitudes.

Table 3. Parameter values

Algorithm	Frequency/time	Window size (s)	Step size (s)	Threshold
FFT	Frequency	3.2	1.25	14
STFT	Frequency	3	0.7	20
STD_TH	Time	1.25	1.25	0.74

4.2 Performance Evaluation

In the first place, the results of the three walking detection algorithms associated with the three testers are illustrated in Figs. 3, 4 and 5, respectively, where

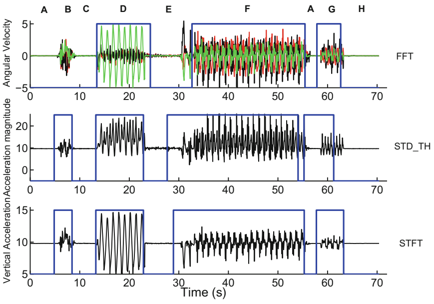

Fig. 3. The results of walking detection associated with tester1

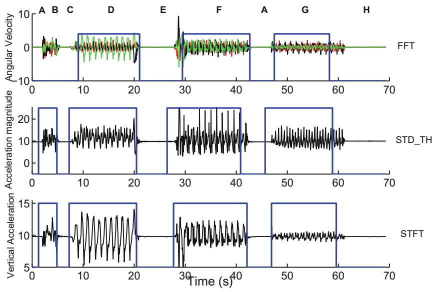

Fig. 4. The results of walking detection associated with tester2

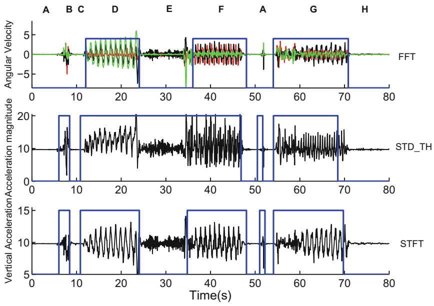

Fig. 5. The results of walking detection associated with tester3

symbols A-H define the corresponding activities listed in Table 2, the blue solid lines reflect the detection results and the other curves denote the measurements adopted by the corresponding algorithms. Specifically, if one tester is identified to be walking during a period of time, the corresponding blue solid line will be drawn in the upper side; otherwise, it is drawn in the lower side.

As can be seen, unlike the algorithms of STD_TH and STFT, the propose algorithm (i.e. FFT) seldom identify other activities into the walking activity, revealing that the proposed algorithm is more robust than the other two algorithms.

In the second place, in order to have a more clear knowledge about the performance of the proposed algorithm, precision (P) and recall (R) are calculated as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \times 100\% \tag{6}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \times 100\% \tag{7}$$

where TP is the true positive duration of walking, FP is the false positive duration of walking and FN is the false negative duration of walking. The precision

Table 4. Experimental results for different testers

Tester	FFT		STD_TH		STFT	
	P(%)	R(%)	P(%)	R(%)	P(%)	R(%)
User1	94.79	92.15	75.99	87.72	84.04	95.94
User2	89.44	90.7	73.31	91.69	77.56	95.92
User3	95.83	99.11	68.06	93.16	85.23	98.73
Total	93.49	94.1	72.19	90.83	82.33	96.90

and recall are listed in Table 4. As can be seen, the proposed algorithm outperforms STD_TH in both precision and recall, and is slightly worse than STFT in precision but is significantly better in recall. To sum up, the proposed algorithm is able to achieve superior overall performance in comparison with the other two algorithms which were shown to be best.

5 Conclusion

In this paper, we proposed an efficient and robust walking detection algorithm for users with unconstrained smartphones. Unlike most existing solutions relying on accelerometer, gyroscope is adopted for walking detection. The algorithm was developed based on the sliding time window. At any time window, one most sensitive axis among the 3-D measurements are selected according to their absolute values, the corresponding measurements are then quickly transformed into frequency domain through FFT, and a spectrum analysis is conducted to judge whether the user is walking within the time window. Finally, a thorough experiment was carried out and confirmed the superiority of the proposed algorithm in comparison with the other two algorithms which had been verified to be best.

Regarding future works, we would like to take into account the following problems. First, we plan to continue studying on improving the accuracy of the walking detection algorithm. Second, besides walking detection, we would like to work on movement detection which is contributable to localization and navigation via smartphones.

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