An accurate step detection algorithm using unconstrained smartphones

Conference Paper · May 2015

DOI: 10.1109/CCDC.2015.7161816

Baoqi Huang
Inner Mongolia University

An Accurate Step Detection Algorithm Using Unconstrained Smartphones

Xiaokun Yang and Baoqi Huang
Inner Mongolia University, Hohhot, 010021, China
E-mail: csyangxk@126.com and cshbq@imu.edu.cn

Abstract: In recent years, mobile device (e.g., smartphone, tablet and etc.) equipped with various inertial sensors is increasingly popular in daily life, and a large number of mobile applications have been developed based on such built-in inertial sensors. In particular, detecting and counting steps is a prerequisite for many applications, such as smart healthcare, smart home, tracking and location, and etc., and thus has attained much attention. Peak detection is known to be one of the simplest and most efficient solutions in this field, but suffers from the drift in the orientation and position of the device if it is not tightly fixed on the human's body. In this paper, we present a novel method to accurately detect and count steps of a human who carries on a smartphone in an unconstrained manner. To be specific, the proposed method fuses the signals from the accelerometer, magnetometer and gyroscope of the smartphone to transform the device reference frame to the earth reference frame, and then employs the vertical acceleration to implement the peak detection algorithm. Extensive simulations are carried out and confirm that the proposed method is more robust than the existing algorithms.

Key Words: Step detection, Reference frame transformation, Inertial sensor, Smartphone

1 INTRODUCTION

With the rapid development of the mobile intelligent terminal industry, moblie devices, including smartphone, tablet and etc., are being equipped with various types of inertial sensors, such as accelerometer, magnetometer, gyroscope, light sensor, distance sensor and etc., apart from the ever-increasing CPU speed and the memory storage capacity. With these sensors, smartphone creates a new context aware application platform[1], and thus is applied in more and more aspects, including entertainment, communication, healthcare, education, business and etc.

Gait recognition, involving the estimation of the step count and step length, is increasingly receiving extensive attention and has became a hot research topic. In sports and health domain, it is used to detect the conditions of the motion and the physics of a runner[2]; in the Pedestrian Dead Reckoning(PDR) domain, it is essential for estimating user's walking distance; in the medical domain, since the main interest is to detect specific gait events (e.g., falls)[3] and to discriminate walking patterns[4], it is contributable to diagnosis of the rehabilitation of the patient's condition; in addition, it is also closely related to pedestrian tracking and individual navigation[5], in which it is used to obviously improve the accuracy of other positioning methods like GPS or the WiFi fingerprinting[6].

In regards to detecting and counting steps, the algorithms can be categorized into the time domain approaches (e.g., Peak Detection[11][12][13][14], Zero Crossing Count[7], Normalised Autocorrelation SC[8]) and the frequency domain approaches (e.g., Continuous/Discrete Wavelet Transforms[9] and Short Term Fourier Transform[10]). Peak detection is a widely used approach for step detection. Chris Nugent et al. proposed an accurate and reliable step detection method using the absolute value of Y-axis coordinate of acceleration with adaptive threshold obtained from the user's walking data[11]. Jeong Won Kim et al. also presented a method for counting the number of steps based on peak detection with the heuristic threshold[12]. Ying et al. used a foot-mounted two-axis orientation-fixed acceleration sensor to detect the step number with a rehabilitation application for neurological patients[13]. Mock reported the development of an accelerometer based step counter deployed in a java-enabled mobile phone[14]. Rui Terra et al. implemented step counting using the modulus of a worn two-axis accelerometer[15]. All the methods mentioned above required to attach the device to a specific position on the user's body, such as the front trousers pocket, the jacket pocket, the handbag. However, this is impractical especially when smartphone is used, because users may place their smartphones on any pocket and in an unconstrained manner.

In this paper, we propose an accurate step detection method for users who carry on a smartphone in an unconstrained manner. In the first step, a rotation matrix from the device reference frame to the earth reference frame is constructed by fusing the signals from the accelerometer, magnetometer and gyroscope of a smartphone in real time based on Kalman filter. Then, the acceleration in the device reference frame is transformed to the counterpart in the earth reference frame, and its vertical component is used to re-

This work is supported by the National Natural Science Foundation of China under Grants 61461037 and 41401519, and the Natural Science Foundation of Inner Mongolia Autonomous Region of China under Grant 2014MS0604.

alize the peak detection algorithm. To evaluate the performance of the proposed methods, two postgraduate students (one male and one female) participated the experiment by placing a smartphone on different positions of their body. The experimental result shows that the proposed algorithm can achieve the successful rate of 97.39% when smartphone is placed in the front pocket, above 92% when it is placed in the back pocket and 89% when it is totally unconstrained, which are all much better than the existing peak detection algorithm.

The remainder of this paper is organised as follows: Section 2 describes the detail of realization of reference transformation. Section 3 contains the core of the paper where we present and analyze the step detection algorithm. Section 4 presents experimental the results. The paper is concluded in Section 5.

2 REFERENCE FRAME TRANSFORMATION

Commonly, position or attitude of a smartphone changes dramatically when its holder is conducting a series of activities, such as texting, calling, playing games and etc. The device reference frame (shown in Figure 1) is affected by the pedestrian movement, a unfixed location and other factors, which reduces recognition accuracy of the existing algorithms. The signals from the built-in sensors of a smartphone involve great noises even though it is tied on the body of its holder, and thus can degrade the successful rate of step detecting and counting. Relatively, the earth reference frame (shown in Figure 2) is not affected by these unfavorable factors. Therefore, it is essential to transform the device reference frame to the earth reference frame.

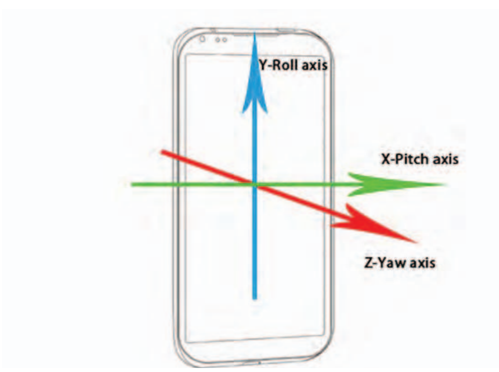


Figure 1: Device reference frame

2.1 Raw Data Preprocess

Inertial sensors not only suffer from the drift caused by own characteristics, but also are susceptible to environmental disturbances (e.g., the magnetometer is interfered by the surrounding magnetic field). Since raw signals from the inertial sensors contain large errors or irrelevant information to result in a miscounting, sliding window average filter is used to eliminate burrs and smooth signals. Determining the size of the window, denoted K, has attained much attention. On the one hand, informative features of signals are submerged by averaging if K is too big; on the other hand, burrs are not efficiently reduced if K is too small. In this work, given that the signal sampling frequency is $20Hz$, the window size K is empirically selected as 4.

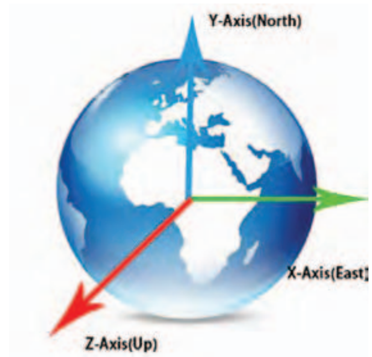


Figure 2: Earth reference frame

2.2 Smartphone's Attitude

Smartphone's attitude is composed of yaw, pitch and roll components. When a smartphone is stationary or its linear acceleration is 0, its yaw, pitch and roll can be respectively calculated by (1), (2) and (3) as follows:

$$yaw = \arctan^2\left(\frac{(a_x m_z - a_z m_x)L}{m_y(a_z^2 + a_x^2) - a_y(a_z m_z + a_x m_y)}\right), \tag{1}$$

$$pitch = -\arcsin\left(\frac{a_y}{L}\right), \tag{2}$$

$$roll = -\arctan^2\left(\frac{a_x}{a_z}\right), \tag{3}$$

where a_x, a_y and a_z are accelerations in x-, y- and z-axis respectively, m_x, m_y and m_z are magnetic field intensities in x-, y- and z-axis respectively, and L is equal to $\sqrt{a_x^2 + a_y^2 + a_z^2}$.

When a smartphone is subjected to external forces, its yaw, pitch and roll calculated by above equations are far from accurate. In addition, the attitude calculated by an accelerometer and a magnetometer is not accurate either, if there exist magnetic interference in the surrounding environment. However, in this situation, gyroscope can be used to calibrate the orientation estimation by integrating the angular velocity measured by gyroscope within a short period of time. But, the drawback of gyroscope is that there exist obvious bias and calibration errors. The bias refers to the mean output from the gyroscope when it is not undergoing any rotation, and shows itself after integration as an angular drift over time. Calibration error is caused by the alignments and scale factors of the gyroscope, and leads to the accumulation of additional drift in the integrated signals; its magnitude is proportional to the duration and rate of the movements[16]. Therefore, gyroscope is not suitable to produce signals for a long time.

In conclusion, the advantage of one sensor is the disadvantage of another one. An optimal and reliable system might be expected by integrating all the built-in sensors of a smartphone. In this paper, we propose to fuse the signals from the accelerometer, magnetometer and gyroscope based on Kalman filter to evaluate a smartphone's attitude[17]. In particular, accelerometer and magnetometer are used as measurements to correct deviation of gyroscope measurements in real time.

In the filter, X is defined as the state vector of the system, which is composed of the attitude, denoted α, and the standard deviation of gyroscope, denoted β. P is defined as the corresponding covariance of X. The state prediction equation can be formulated as

$$X_{k|k-1} = AX_{k-1} + BU_k, \tag{4}$$

and covariance of $X_{k|k-1}$ can be formulated as

$$P_{k|k-1} = AP_{k-1}A^T + Q, \tag{5}$$

where k presents the k-th moment, $k|k-1$ presents the k-th moment given the measurements at moment $k-1$, $A = \begin{bmatrix} 1 & -T_s \\ 0 & 1 \end{bmatrix}$, $B = \begin{bmatrix} T_s \\ 0 \end{bmatrix}$, T_s is the sampling interval, U_k is the output of gyroscope, and Q is the covariance matrix of the system process noise.

Z is defined as a measurement vector, and the measurement equation can be formulated as

$$Z_k = CX_k^m + v_k, \tag{6}$$

where m presents measurement by accelerometer and magnetometer, C is a measurement matrix ($C = \begin{bmatrix} 1 & 0 \end{bmatrix}$, because accelerations is related to current attitude of the smartphone and not related to the deviation of gyroscope), and v_k is the measurement noise vector (i.e., acceleration measurement noise).

With integrating the prediction and the measurement, the optimal estimate equation can be formulated as

$$X_k = X_{k|k-1} + K_k(Z_k - CX_{k|k-1}), \tag{7}$$

the optimal filter gain of the system can be formulated as

$$K_k = P_{k|k-1}C^T(CP_{k|k-1}C^T + R)^{-1}, \tag{8}$$

and the estimation of the mean square error can be formulated as

$$P_k = (1 - K_kC)P_{k|k-1}, \tag{9}$$

where R is covariance matrix of errors measured.

2.3 Reference Frame Transformation

A convenient approach to formulate the transformation from the device reference frame to the earth reference frame is the rotation matrix, which can be divided into direction cosine matrix[18] and quaternion[19]. In this work, to reduce to redundancy in direction cosine matrix form, quaternion is adopted,

$$Q = \begin{bmatrix} q_0 & q_1 & q_2 & q_3 \end{bmatrix}^T, \tag{10}$$

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} = \begin{bmatrix} \cos\frac{y}{2}\cos\frac{p}{2}\cos\frac{r}{2} - \sin\frac{y}{2}\sin\frac{p}{2}\sin\frac{r}{2} \\ \cos\frac{y}{2}\sin\frac{p}{2}\cos\frac{r}{2} - \sin\frac{y}{2}\cos\frac{p}{2}\sin\frac{r}{2} \\ \cos\frac{y}{2}\cos\frac{p}{2}\sin\frac{r}{2} + \sin\frac{y}{2}\sin\frac{p}{2}\cos\frac{r}{2} \\ \cos\frac{y}{2}\sin\frac{p}{2}\sin\frac{r}{2} + \sin\frac{y}{2}\cos\frac{p}{2}\cos\frac{r}{2} \end{bmatrix}, \tag{11}$$

where y is yaw, p is pitch and r is roll.

Since angle errors may satisfy $q_0^2 + q_1^2 + q_2^2 + q_3^2 \neq 1$, the quaternion is normalized,

$$Q = \frac{q_0 + i_1q_1 + i_2q_2 + i_3q_3}{\sqrt{q_0^2 + q_1^2 + q_2^2 + q_3^2}}, \tag{12}$$

where i_1, i_2 and i_3 are unit vectors in the earth reference frame.

Therefore, the rotation matrix, denoted T, can be formulated as

$$\begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1q_2-q_0q_3) & 2(q_1q_3+q_0q_2) \\ 2(q_1q_2+q_0q_3) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(q_2q_3-q_0q_1) \\ 2(q_1q_3-q_0q_2) & 2(q_2q_3+q_0q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix},$$

Finally, the transformation of an acceleration vector from the device reference frame to the earth reference frame can be realized as follows:

$$\begin{bmatrix} x_e \\ y_e \\ z_e \end{bmatrix} = T \times \begin{bmatrix} x_p \\ y_p \\ z_p \end{bmatrix}. \tag{13}$$

3 STEP DETECTION

A cycle of human's walk is composed of the swing phase and the heel-touch-down phase[12] as shown in Figure 3.

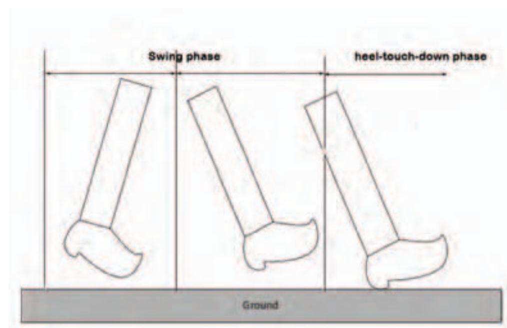


Figure 3: A walking cycle

By combining the swing phase and heel-touch-down phase, the periodic pattern in the cyclic nature of human's walk can be found obviously, which can be seen from the Figure 4. In addition, typical walking frequencies are around $1-2Hz$, a range that few activities other than walking exhibit.

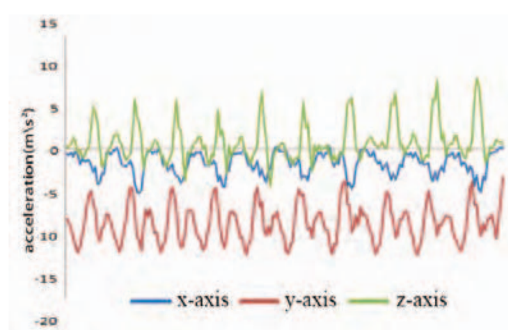


Figure 4: Accelerations during a period of walking

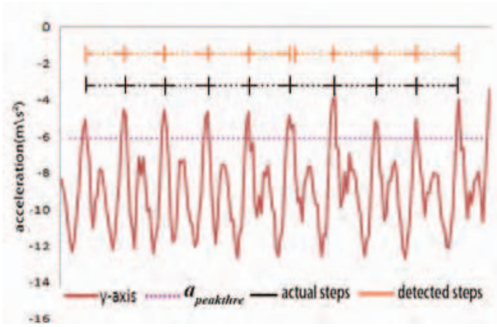


Figure 5: Step detection using the acceleration in y-axis

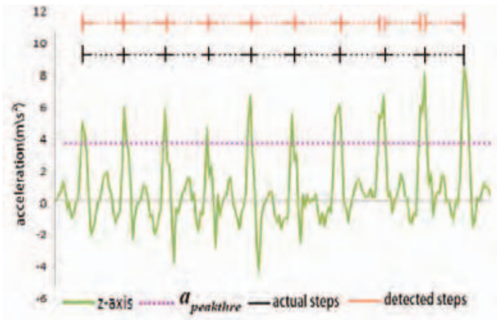


Figure 6: Step detection using the acceleration in z-axis

In this work, peak detection is employed to detect steps. When a peak, denoted a_{peak}, or a trough, denoted a_{trough}, is detected, one step will be counted if $a_{peak} > a_{peakthre}$ or $a_{trough} < a_{troughthre}$, where $a_{peakthre}$ and $a_{troughthre}$ are "safety" thresholds which make the step counting more insensitive to minor bumps or other undesired movements of the smartphone.

In essence, we can utilize any one component of accelerations in the device reference frame to detect and count steps. However, the successful rate may be extremely low if employing an arbitrary component of accelerations to detect steps. For instance, when a smartphone is fixed in the front trousers pocket with a vertical posture, the x-axis captures horizontal motions, the y-axis the upward and downward motions and the z-axis the forward motions of the leg. Therein, we can accurately detect steps by employing accelerations in y- (as shown in Figure 5) or z-axis (as shown in Figure 6), but cannot obtain a good accuracy by employing acceleration in x-axis (as shown in Figure 7). Moreover, the situations can be totally different if positions or postures of the smartphone are changed because one cannot always automatically choose an optimal axis to run the peak detection algorithm. Particularly, since the vertical component of accelerations in the earth reference frame is not affected by these unfavorable factors, it is indispensable to transform the device reference frame to the earth reference frame for step detecting and counting.

4 EXPERIMENTAL VALIDATION

In the experiment, a Samsung GALAXY-I9108 is used, and two postgraduate students (one is male, 24 years old, about $168cm$ high with weight of $64kg$, and the other one is female, 22 years old, about $156cm$ high with weight of $46kg$) participate and perform walking actions. To better evaluate the performance of the proposed method, we carry out simulations with respect to different aspects.

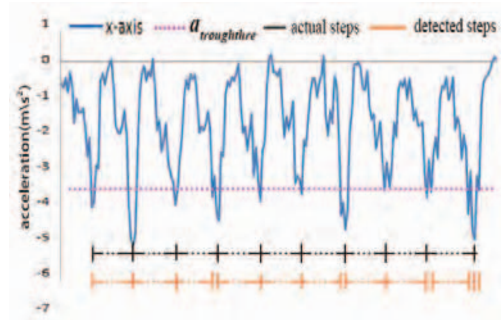
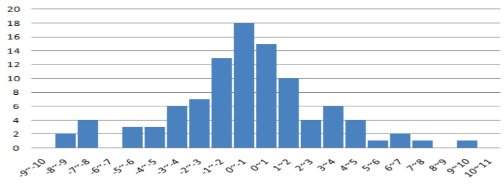


Figure 7: Step detection using the acceleration in x-axis

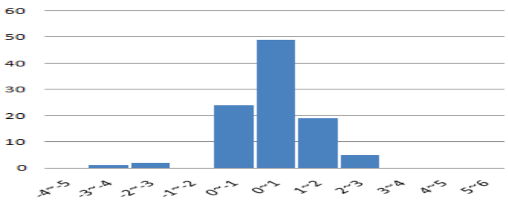
Figure 8: A horizontal turntable

Figure 9: A vertical metal bar

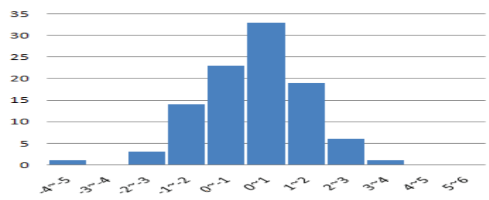
Firstly, we evaluate the performance of the reference frame transformation method (i.e. the Kalman filter) introduced in Section 2. Because of the difficulty in measuring the ground truth of the smartphone's attitude, the filter was tested by rotating the smartphone around a fixed axis, To do so, a horizontal turntable and a vertical metal bar (as shown in Figure 8 and 9) are utilized as holders to conveniently have the smartphone revolve. For instance, when the smartphone is placed on the turntable, it respectively revolvs 360 degrees and an arbitrary degree (which is far greater than 360 degrees) by 100 times at arbitrary but different angular speeds. The errors (i.e. the differences between the attitudes measured based on the holders and predicted by the



(a) Yaw error

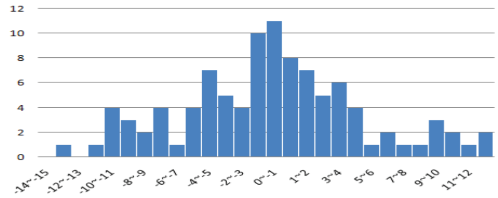


(b) Pitch error

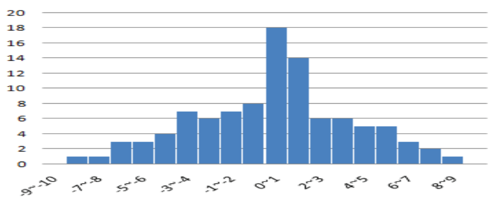


(c) Roll error

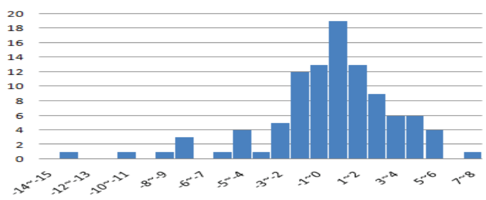
Figure 10: Errors when revolving 360 degrees



(a) Yaw error



(b) Pitch error



(c) Roll error

Figure 11: Errors when revolving an arbitrary degree

filter) are plotted in Figure 10 and Figure 11, in which the horizontal axis denotes the range of attitude errors and the vertical axis denotes its occurrence count.

As can be seen from Figure 10 and Figure 11, the error distributions are approximately normal with nearly zero means and relatively small standard deviations (less than 2.9), implying that the reference frame transformation method is effective. Obviously, yaw's error is much bigger than pitch's and roll's in both cases, because it is essential to calculate yaw with magnetometer that is susceptible to the unpredictable disturbances from surrounding magnetic sources when users are walking. In addition, errors when revolving 360 degrees are smaller than those when revolving an arbitrary degree, which is because the error is accumulated with the degree revolved.

Secondly, the step detection algorithm is tested by using the multitude threshold approach[14] and taking into account two scenarios. In the first scenario, the two postgraduate students respectively placed the smartphone in their front trousers pockets and the back trousers pockets and kept it in a vertical posture, and the smartphone did not incur any movement relative to the human bodies during the walking period. The experiment was carried out with respect to different durations from 20 seconds to 60 seconds, and 5 tests were conducted by each student for every duration. Then, the vertical acceleration in the earth reference frame is used in the peak detection algorithm, and to make a comparison, the x-, y-, z-axis accelerations and its modulus in the device reference frame are respectively considered as well. The experimental results are listed in Table 1 and Table 2, where x_{device}, y_{device} and z_{device} are x-, y- and z- accelerations in the device reference frame respectively, m_{device} is the modulus, and z_{earth} is the vertical component of accelerations in the earth reference frame. Therein, the successful rate in each test is calculated as follows:

$$Accuracy = 1 - \frac{|S_d - S_a|}{S_a} \times 100\% \qquad (14)$$

where S_d is the number of steps calculated, and S_a is the actual number of steps. The final successful rates are averaged over two students and 5 tests.

Table 1: The successful rate with the smartphone in the front trousers pocket

Input	x_{device}	y_{device}	z_{device}	m_{device}	z_{earth}
$20s$	62.92%	94.87%	93.20%	94.88%	96.89%
$30s$	37.35%	94.56%	94.42%	95.34%	96.62%
$40s$	58.58%	93.51%	94.11%	96.13%	97.45%
$50s$	56.50%	95.20%	94.93%	96.12%	97.61%
$60s$	60.37%	95.06%	95.99%	96.16%	97.81%

Table 2: The successful rate with the smartphone in the back trousers pocket

Input	x_{device}	y_{device}	z_{device}	m_{device}	z_{earth}
$20s$	62.20%	74.73%	81.99%	94.73%	89.47%
$30s$	72.41%	74.39%	84.00%	84.00%	92.74%
$40s$	59.45%	73.68%	83.68%	86.84%	92.11%
$50s$	42.62%	80.06%	84.39%	89.47%	93.10%
$60s$	66.67%	81.99%	84.73%	89.65%	93.98%

Table 1 and Table 2 show that different successful rates can be obtained by using different inputs. In general, using the accelerations of any single axis in the device reference frame result the worst accuracies, while the z-axis acceleration in the earth reference frame results in the best accuracies, which are all nearly above 90% and can be even as high as 97.81% if the duration is 60 seconds and the smartphone is in the front trousers pocket; this confirms that the proposed method is efficient to detect and count steps using smartphones in a constrained manner. Particularly, the successful rate is proportional to the duration, because the beginning and ending steps during a walking period tend to be irregular and are hard to detect, so that a long walking duration will dilute such a negative impact. In addition, since the low frequency and irregular motion of the hip to some extent damages the periodic patter of walking, the successful rate is not desirable when the smartphone is placed in the back trousers pocket.

In the second scenario, two postgraduate students carried on the smartphone in an unconstrained manner, which is positions of the smartphone relative to the human bodies can be arbitrarily changed in the front trousers pocket, the bank trousers pocket or hands and the other setup is the same as in the first scenario. The experimental results are listed in Table 3.

Table 3: The successful rate with the smartphone held in an unconstrained manner

Input	x_{device}	y_{device}	z_{device}	m_{device}	z_{earth}
$20s$	15%	77.5%	70%	80%	85%
$30s$	90.24%	73.17%	53.66%	70.73%	85.12%
$40s$	12.82%	74.62%	61.54%	82.31%	91.44%
$50s$	47.5%	62.5%	70%	80%	90%
$60s$	28.95%	71.05%	78.95%	87.37%	91.37%

In general, the successful rates listed in Table 3 are much lower than their counterparts in Table 1 and Table 2, indicating the negative influence of holding the smartphone in an unconstrained manner. However, the proposed method can still attain the best successful rates, which are significantly better than other approaches and can be as high as 91.44%. In addition, the successful rates do not increase with the duration because with tests of different durations the sequences of the smartphone's positions are different.

5 CONCLUSION

In this paper, we proposed a novel algorithm to accurately detect and count steps of users who carry on a smartphone in an unconstrained manner. To begin with, signals from the accelerometer, magnetometer and gyroscope of the smartphone based on Kalman filter are fused to evaluate its attitude, and then transform accelerations in the device reference frame to the counterpart in the earth reference frame by formulating a rotation matrix. Finally, the vertical component of accelerations in the earth reference frame is employed to detect and count steps. Extensive experiments were carried out and confirmed the effectiveness of the proposed method especially when the smartphone is carried in an unconstrained manner. In the future, we plan to continue studying on improving the accuracy of the reference frame transformation, wisely determining the threshold for the peak detection algorithm, and accurately estimating the step length.

REFERENCES

[1] P. Zhang, A. Purohit, The Cloud Meets the Crowd: Framework for Distributed Cloud Sensing, UbiCom, 9-10, 2005.

[2] S. Das, L. Green, B. Perez, M. Murphy, Detecting User Activities Using the Accelerometer on Android Smartphones, http://www.truststc.org/reul1OlReports/DasGreenPerezMurphy_Paper.pdf, Accessed: May 10, 2012.

[3] S. J. Preece, J. Y. Goulermas, L. P. J. Kenney, D. Howard, K. Meijer, R. Crompton, Activity Identification Using Body-mounted Sensors - A Review of Classification Techniques, Physiological Measurement, Vol.30, No.4, 1-33, 2009.

[4] J. J. Kavanagh, H. B. Menz, Accelerometry: A Technique for Quantifying Movement Patterns During Walking, Gait and Posture, Vol.28, No.1, 1-15, 2008.

[5] E. Foxlin, Pedestrian Tracking with Shoe-mounted Inertialsensors, IEEE Computer Graphics and Applications, Vol.25, No.6, 38-46, 2005.

[6] P. Bahl, V. N. Padmanabhan, RADAR: An In-Building RF-based User Location and Tracking System, IEEE INFOCOM, 1-10, 2000.

[7] J. Kappi, J. Syrjarinne, J. Saarinen, MEMS-IMU Based Pedestrian Navigator for Handheld Devices, Proc. of ION G-PS, 1369-1373, 2001.

[8] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, R. Sen, Zee Zero-effort Crowdsourcing for Indoor Localization, Mobicom, 293-304, 2012.

[9] S. Mallat. A Wavelet Tour of Signal Processing, Third Edition: The Sparse Way, Academic Press, 1999.

[10] M. Vetterli, J. Kovacevic, Wavelets and Subband Coding, PrenticeHall PTR, 2005

[11] Y. Huang, H. Zheng, C. Nugent, P. McCullagh, S. M. McDonough, M. A. Tully, S. O. Connor, Activity Monitoring Using an Intelligent Mobile Phone - A Validation Study, Conference PETRA, 1, 2010.

[12] J. W. Kim, H. J. Jang, D.H. Hwang, C. Park, A Step, Stride and Heading Determination for the Pedestrian Navigation System, Journalof Global Positioning Systems, Vol.3, No.1-2, 273-279, 2004.

[13] H. Ying, C. Silex, A. Schnitzer, S. Leonhardt, M.Schiek, Automatic Step Detection in the Accelerometer Signal, 4th International Workshop on Wearable and Implantable Body Sensor Networks, 80-85, 2007.

[14] M. Mladenov, M. Mock, A Step Counter Service for Java-enabled Devices Using a Built-in Accelerometer, Proceedings of the 1 st International Workshop on ContextAware Middleware and Services, 1-5, 2009.

[15] R. Terra, L. Figueiredo, R. Barbosa, R. Anacleto, Step Count Algorithm Adapted to Indoor Localization, Conference C3S2E, 128-129, 2013.

[16] D. Gafurov, E. Snekkenes, Towards Understanding the Uniqueness of Gait Biometric, In FG08, 1-8, 2008.

[17] J. Zhang, Dynamic Tilt Sensor Based on MEMS Gyro and Accelerometer, Machinery Design & Manufacture, No.9, 141-143, 2013.

[18] S. Ayub, A. Bahraminisaab, B. Honary, A Sensor Fusion Method for Smart phone Orientation Estimation, 13th Annual Post Graduate Symposium on the Convergence of Telecommunications, Networking and Broadcasting, 1-6, 2012.

[19] L. Zhao, Q. Wang, Design of an Attitude and Heading Reference System Based on Distributed Filtering for Small UAV, Mathematical Problems in Engineering, 1-9, 2013.

[20] A. Brajdic, R. Harle, Walk Detection and Step Counting on Unconstrained Smartphones, UbiCom, 225-234, 2013.