Improved Step Detection and Step Length Estimation Based on Pedestrian Dead Reckoning

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***Abstract*—In the indoor environment, the Global Positioning System (GPS) cannot provide accurate location information due to the complexity of the internal structure of buildings and the interference of indoor equipments. Pedestrian Dead Reckoning (PDR) is an indoor positioning method that relies on smartphone carrying sensors (such as accelerometer, gyroscope, and magnetometer) without requiring additional equipments. The intense electromagnetic interferences caused by indoor electronic equipments have serious influences on the accuracies of indoor location. This paper presents an improved step detection and counting method based on PDR. There is continuity in the walking process. In order to make full use of this feature, this paper firstly filters and differential processes the acceleration data obtained from the smartphone, then uses the improved peak detection algorithm to detect and count the steps. This paper compares two algorithms of step length estimation, and presents an improved step length estimation algorithm based on differential acceleration data. As a result, this paper improves the accuracies of both step number detection and step length estimation.**

Keywords*—*indoor positioning, PDR, difference calculus, step detection, step length estimation

I. INTRODUCTION

Typical indoor location methods such as WIFI [1], Bluetooth [2], RFID [3], UWB [4], and so on require the deployments of specialized equipments. With the popularity of smartphones, the uses of sensors in smartphones for indoor positioning have gradually become a research hot spot, and PDR [5] comes into being. The accelerometer built into a smartphone is used to record acceleration data, while step detection and counting can be done by extracting acceleration features. Direction estimation depends on the magnetometer and gyroscope. How to improve the positioning accuracy has been widely studied due to the low accuracies of the sensors embedded in smartphones, the body shaking of pedestrians, and the interferences of electromagnetic signals inside buildings.

There is a great deal of studies on step detection and counting based on PDR. There are three main methods of step detection: time-domain approach, frequency-domain approach, and feature clustering. Time-domain approaches include thresholding [6], peak detection [7], zero-crossing counting [8], and auto-correlation [9]. [6] introduced a strap-down pedestrian dead reckoning system with thresholding detection. Its mode of occupation is waist-worn which limits its application. [8] proposed an independent step counting algorithm for smartphones and got good results. [10] compared traditional step length estimation methods with its improved algorithm. But the longest distance of walking experiments in that paper is 40 m which is not representative enough.

This paper presents an improved algorithm for step detection and counting. In order to take full advantage of the continuity in walking, the accelerations are filtered and differentiated. The peak detection method is used to detect whether a stepping behavior occurs. In addition, the traditional step length estimation algorithm has been improved and performs well in experiments.

II. RELATED WORK

A. Transformation of Coordinate Systems

The commonly used coordinate systems are geographic coordinate system, carrier coordinate system, and navigation coordinate system [11]. Since the coordinate system in which the smartphone is located is different from that in which the user walks, the sensor data need to be transformed between the two coordinate systems.

North, east, and vertical direction compose the geographic coordinate system which can be represented by axes of N, E, and D. The body coordinate system determines the multi-sensor system in the smartphone. Head, starboard, and bottom can be represented by X_b, Y_b, and Z_b.

The body coordinate system (also named frame b) which presents the body's attitude can be obtained from geographic coordinate system (also named frame n) through three sequential rotation angles heading(φ), pitch(θ), and roll(ϕ). In this paper, we define vector x^n in frame n and vector x^b in frame b. The transformation matrix from frame n to frame b can be expressed as [5]

$$x^b = C_n^b x^n \tag{1}$$

Where C_n^b presents the transformation matrix and can be written as (2).

B. Filter

Due to a pedestrian's walking process has the certain periodicity, the trend of acceleration waveform is similar to sine wave with a lot of burrs at the same time. These burrs are caused by the shaking of the body and the error of the smartphone's accelerometer itself. Generally, in order to get smoother and more obvious acceleration change trends, we

$$C_n^b = \begin{bmatrix} \cos\varphi\cos\theta & \sin\varphi\cos\theta & -\sin\theta \\ -\sin\varphi\cos\phi + \cos\varphi\sin\theta\sin\phi & \cos\varphi\cos\phi + \sin\varphi\sin\theta\sin\phi & \cos\theta\sin\phi \\ \sin\varphi\sin\phi + \cos\varphi\sin\theta\cos\phi & -\cos\varphi\sin\phi + \sin\varphi\sin\theta\cos\phi & \cos\theta\cos\phi \end{bmatrix} \tag{2}$$

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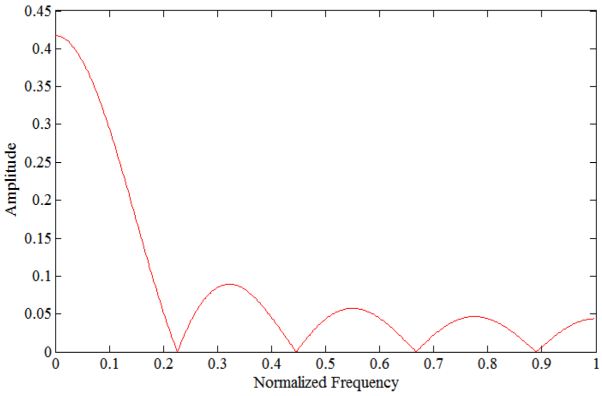

Fig. 1. The frequency response of the filter.

first filter the original accelerations measured by the acceleration sensor in the smartphone.

This paper uses a minimum square linear filter whose sampling frequency is set to 50 Hz and filter order is set to 8. The frequency response of the filter is shown in Fig. 1.

III. Improved Step Detection and Step Length Estimation

A. Step Detection

To detect a step, this paper utilizes the accelerometer in a smartphone to read the acceleration values. Since the Earth's gravity is much greater than three axes accelerations of pedestrian's walking, removing the effect of gravity is necessary. Processing of the original accelerations can be expressed as

$$\begin{bmatrix} a^N \\ a^E \\ a^D \end{bmatrix} = C_n^b \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} - g \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{3}$$

Where a^N, a^E, and a^D are accelerations in the geographic coordinate system. a_x, a_y, and a_z are accelerations obtained by smartphone. g is local acceleration of gravity.

For convenience, a_x', a_y', and a_z' present a^N, a^E, and a^D respectively. The changes of z axis accelerations can reflect the walking features of a pedestrian best, so this paper only uses a_z' to detect and count the step. a_z' after filtering can be expressed as

$$acc = a_z' - average(a_z') \tag{4}$$

$$b = firls(n, f, a) \tag{5}$$

$$acc = filter(b, 1, acc) \tag{6}$$

Where *firls* and *filter* are filter functions built in MATLAB. n is the order of the filter. f is the normalized frequency vector. a is the amplitude vector. The waveform of the *acc* before filtering is shown in Fig. 2, while the waveform of *acc* after filtering is shown in Fig. 3.

There are strong correlations between the accelerations of any two adjacent time points, and the correlations can be exploited by the differential computations of the accelerations. The difference equation is expressed as

$$delta\_acc(i) = acc(i) - acc(i-1) \tag{7}$$

delta_acc can be used to detect and count steps. Conduct the

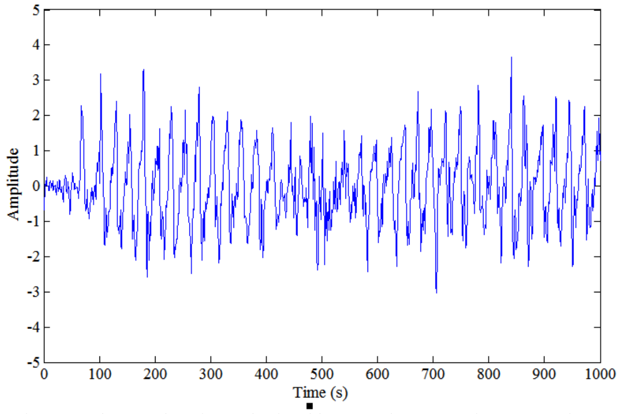

Fig. 2. The accelerations obtained by accerlerometer in a smartphone.

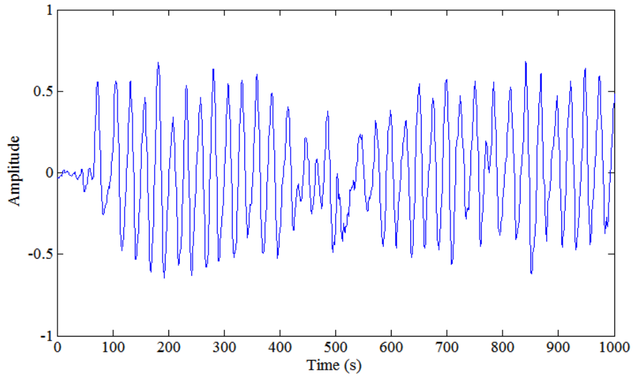

Fig. 3. The filtered accelerations.

the peak step counting algorithm to mark the possibility time of user's step events. This paper employs 5 conditions on the *delta_acc* to confirm a valid step event as following sets:

$$t_i^{peak} = \left\{ t \,\middle|\, \begin{array}{l} delta\_acc(i-1) > 0, delta\_acc(i) < 0, \\ acc(i) > a_\tau^{peak} \end{array} \right\} \tag{8a}$$

$$t_i^{valley} = \left\{ t \,\middle|\, \begin{array}{l} delta\_acc(i-1) < 0, delta\_acc(i) > 0, \\ acc(i) < a_\tau^{valley} \end{array} \right\} \tag{8b}$$

$$t_\tau = \left\{ \left| t_i^{peak} - t_{i-1}^{peak} > t_\tau,\ t_i^{valley} - t_{i-1}^{valley} > t_\tau \right. \right\} \tag{8c}$$

$$t_{\tau\tau} = \left\{ t \,\middle|\, t_i^{peak} - t_i^{valley} > t_{\tau\tau} \right\} \tag{8d}$$

$$-\left| acc_i^{peak} - acc_{i-2}^{peak} \right| < \sigma \tag{8e}$$

Where t^{peak} and t^{valley} are peak and valley points of time. a_τ^{peak} and a_a^{valley} are thresholds of step peak and step valley. t_τ is the time interval between the current peak and the previous peak or between the current valley and the previous valley. $t_{\tau\tau}$ is the time interval between the current peak and valley. σ is the threshold value of the difference in acceleration when the same leg (such as the left leg) is lifted two times. Only when all the formulas above from (8a) to (8e) are true do we consider that a complete step (including step peak and step valley) occurs. A full stride in this paper refers to the whole process from one foot up to the foot down [12]. Two strides make up a compound step.

B. Step Length Estimation

Estimating step length in each certain step event can figure up the total traveled distances. In summary, there are two approaches can be used to estimate step length. One is static model, the other is dynamic model. According to physiological characteristics of human body, the static model utilizes height to estimate the pedestrian's step length, and the formula is

$$L = k * h \tag{9}$$

Where h is height and k is a constant parameter depended on h. On the contrary, dynamic model allows any valid step has different length. Even a same pedestrian may have diverse step length between one step to the next step, that is why dynamic model matches the true situation more. Weinberg. H proposed a famous step length calculation formula as [13]

$$L = k * \sqrt[4]{acc^{peak} - acc^{valley}} \tag{10}$$

where k is a parameter which depends on pedestrian's gender, height, and weight. Kim proposed another step length estimation equation as [14]

$$L = k * \sqrt[3]{\frac{\frac{\sum_{i=1}^{N} |acc_i|}{N} - acc^{valley}}{acc^{peak} - acc^{valley}}} \tag{11}$$

where N is the sampling number of the current step. Both (9) and (10) ignore the time of each step which reflects the speed of walking. This paper proposes an improved method for estimating step length with *delta_acc* and step time. The step length is

$$L = k_1 * average(delta\_acc) * T_{step} + k_2 \sqrt[4]{acc^{peak} - acc^{valley}} + \gamma \tag{12}$$

Where k_1 and k_2 are scale factors. T_{step} is the time of step process and γ is an offset.

IV. Experiments and Results

Experiments were conducted in the library of Xi'an University of Science and Technology where there were a large number of electronic equipments (such as computers) and serious electromagnetic interferences. The smartphone which is used to collect data is honor 8 of Huawei.

A. Step Detection

The outputs of step detection are shown in Fig. 4. As is shown in Fig. 4, almost every step has been detected, and false peak and valley points have been removed. This paper takes total 5 experiments with different speed and along different paths. The accuracy of step detection is shown in TABLE I. The highest accuracy of step detection is up to 100%, while the lowest accuracy of step detection is 98.84%.

B. Step Length Estimation

Fig. 5 shows influences of parameters k_1 and k_2 in the improved step length estimation algorithm. In order to get the best values of k_1 and k_2, this paper sets arbitrary initial values first, then get fitted values according to actual values This paper sets k_1=0.125, and k_1 =0.232. This paper sets a constant step length to 0.65 m. The comparison of user's step length values obtained by different step length estimation methods mentioned above is shown in Fig. 6, in which Algorithm 1 refers to (10), Algorithm 2 refers to (11), and Improved Algorith*m* refers to (12). The improved algorithm performs better than the other two algorithms. This paper does other experiments based on different step number and the results are

TABLE I. Results of Step Detection

Experiment	Values		
	Step Counting	***Reference***	***Accuracy (%)***
1	86	85	98.84
2	90	91	98.9.
3	50	50	100
4	65	65	100
5	216	214	99.07

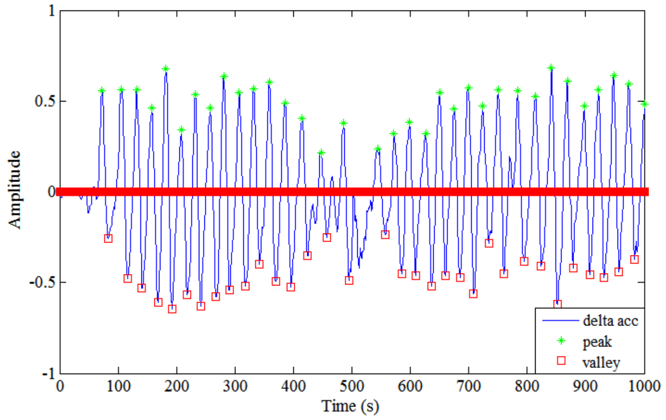

Fig. 4. The results of step detection.

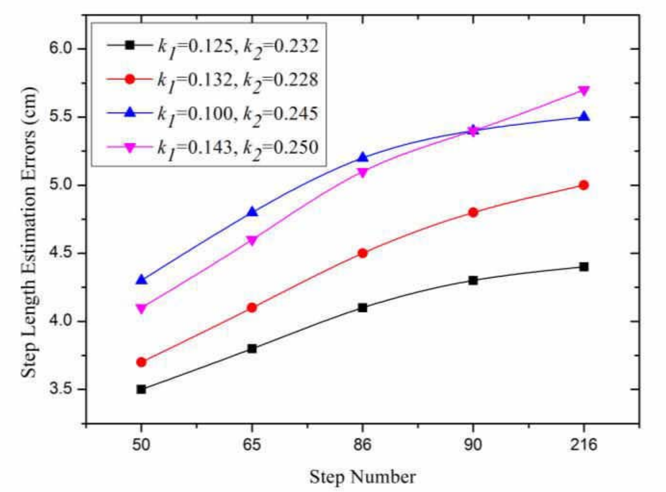

Fig. 5. The step length estimation errors based on different values of k_1 and k_2.

shown in Fig. 7. With the number of steps increasing, the improved algorithm carries out more stable performances, and the maximum error of step length estimation is less than 5 cm while the step number is 216.

V. Conclusion

This paper makes two contributions to the research on PDR. First, this paper proposes differential processing of acceleration, which provides a reliable basic for the following work. Second, this paper compares traditional step length estimation algorithms, then improve a step length estimation algorithm based on differential acceleration. Experimental results show that the results of improved step length estimation algorithm are better than the other two algorithms.

Each pedestrian may have his own special walking characteristics, that is why the noise covariance matrix varies from different pedestrians. As a result, choosing optimal parameters automatically and fleetly seems a hard task. For

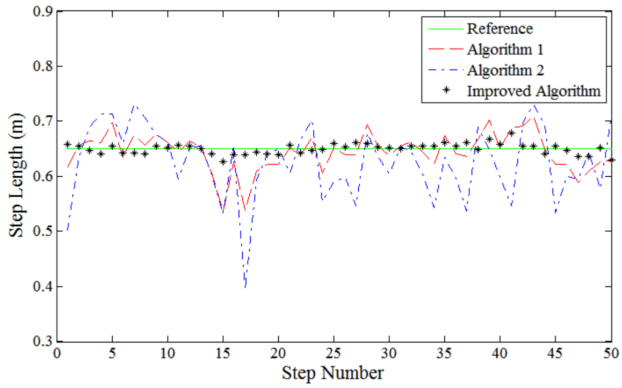

Fig. 6. The comparison of step length estimation based on different methods.

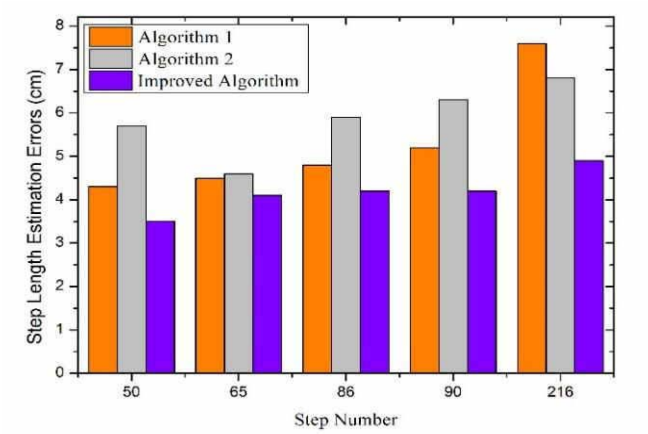

Fig. 7. The comparison of errors of step length estimation based on different methods.

PDR, there are three primary steps, step detection, step length estimation, and heading direction. In the future work, we are going to conduct more experiments in various conditions and studying the methods of heading direction estimation.

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