RPNOS: Reliable Pedestrian Navigation on a Smartphone

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Abstract. This paper presents a novel solution using smartphone inertial sensors for pedestrian navigation application. Pedestrian dead reckoning (PDR), which determines the relative location of a pedestrian without the need for additional infrastructure assistance, is utilized to locate pedestrians in our work. A robust step detection technique leaves out the preprocessing of raw signal and reduces complex computation. Since the estimation model is related to different walking modes, a stride length estimation algorithm using a linear combination of step frequency and acceleration variance is developed. Heading determination is carried out by detecting the gravity crossings of acceleration, which is effective to infer the heading form smartphone's yaw angle. The experimental results indicate that the displacement is estimated with 1.79 % error of distance travelled in the best situation and 3.86 % in the worst situation.

Keywords: Pedestrian navigation, smartphone inertial sensors, PDR.

1 Introduction

As one of the most challenging application in the development of navigation technologies, pedestrian navigation has gained great concern in recent years. Pedestrian navigation system (PNS) is generally required to provide continuous positioning capability in all environments including urban canyons, indoors and undergrounds, where GPS and other radio navigation signals may degrade or even outage, due to the weak signal or non-line-of-sight (NLOS) conditions between the pedestrian and satellites or base stations. Therefore, an accurate and reliable PNS is an important and emerging technology for many location-based services (LBS) applications, such as commercial, public-safety and military fields [1]. As we known, most of existing PNS approaches rely on the dedicated inertial measurement units (IMUs) fixed on user body (e.g. foot and waist) for pedestrian tracking [2, 3]. Although the so-called zero velocity update (ZUPT) methodology is an effective way to reduce the error drift of an inertial sensor-based navigation system, the main drawback of this method related to inconvenience has been discussed by several researchers [4, 5]. They point out that the IMU module, in the ZUPT algorithm, has to be attached on the foot in all the experiment, which may bring some uncomfortable feelings for the pedestrian and thus limit its widely application in the actual situation.

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With the development of micro electromechanical system (MEMS) technologies and the evolution of the capabilities in handheld devices, it becomes universal to integrate MEMS sensors (e.g. accelerometers, gyroscopes and magnetometers) into personal navigation devices, such as smartphones and tablets. Consequently, pedestrian navigation relies on smartphones only becomes a potential solution with acceptable accuracy using reliable PDR algorithms. Moreover, pedestrian navigation on a smartphone embedded with MEMS sensors has several advantages over the GPS system, such as small size, light weight and especially low power consumption, which are the major concerns for pedestrian navigation applications. However, to achieve reliable positioning of pedestrians using smartphones, we face several significant challenges as follows:

- Low-cost MEMS inertial sensors in smartphones are only able to provide required accuracy for brief moments due to the sensor errors arise from random zero bias and oscillation noise.
- During walking, the smartphone can be placed in different positions including the pedestrian's hand and pocket, which leads different smartphone orientations and affects the heading determination of PDR algorithm.
- While the smartphone is in the pedestrian's hand, the flexibility and complexity of hands activities make the reliable step detection difficult. Furthermore, the pedestrian may switch modes such as from swinging the hand to texting or taking a phone call.

In the recent years, several pedestrian navigation technologies that leverage MEMS sensor in a smartphone have been researched [5-7]. However, there exist many unsolved problems that arise from the challenges mentioned above in these systems, such as limited degree of freedom of smartphone orientations, constant stride length estimation, and lacking heading determination, etc.

In this paper, we present Reliable Pedestrian Navigation on a Smartphone (RPNOS), a scheme using PDR algorithm for pedestrian navigation application. To tackle the low-cost inertial sensors, RPNOS focuses on the topic of the designing of a robust step detection algorithm. Using the local gravity value crossings detection and autocorrelation operation of measured acceleration signals, we detect steps with low false alarm probability, which makes sure that the algorithm is not susceptible to the actual situation and independent of walking patterns, routes, distances and terrains. Then the stride length is estimated in RPNOS based on the relationship between stride length and stride interval (reciprocal of stride frequency). In order to find out the most appropriate parameters for the pedestrians, the stride length estimation models are established and are tested repeatedly according to extensive experiments that were performed by subjects with different physical profiles such as gender, height and weight. Heading determination is acquired through inferring the offset between the pedestrian and her smartphone and gained from the yaw angle of the smartphone sensors.

In the rest of this paper, we describe first the position principle of PDR module and it is followed by detailed description of the algorithms for step detection, stride length estimation and heading determination. Afterward, the performance of proposed algorithms is evaluated through an outdoor experiment and is compared with ground truth. Finally, the conclusion and future works are drawn.

2 PDR Algorithm

Pedestrian dead reckoning (PDR) is a relative navigation technique, which determines the relative location of a pedestrian by using step detection, stride length estimation, and heading determination. The PDR algorithm can provide means of reducing the inertial error accumulation to the navigation solution by taking advantage of the sequential characteristics of the pedestrian motion [7]. Typically, the accelerometer measurements are utilized to implement step detection and stride length estimation, and heading determination is simultaneously implemented by fusing the information from gyroscopes and magnetometers. The block diagram of RPNOS system proposed in this paper is shown in Fig. 1.

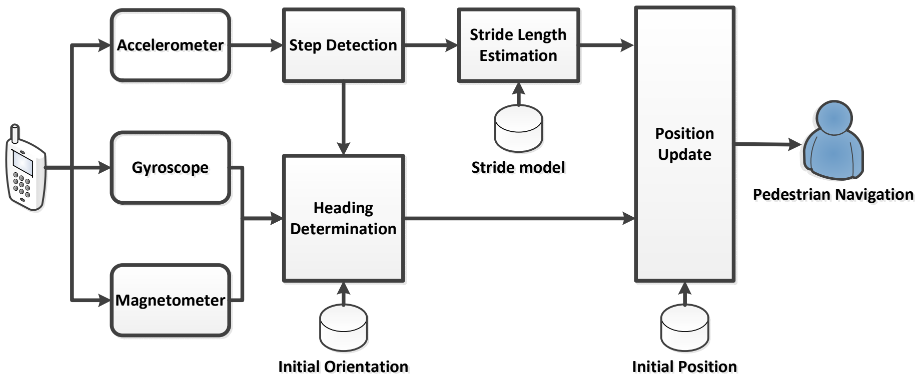


Fig. 1. Block diagram of RPNOS system

As shown in Fig. 1, the sensor data collected from a smartphone is used by the PDR modules for pedestrian navigation. Note that the stride model is trained offline and inputted to update the stride length online according to the stride frequency and acceleration variance. In addition, the system needs to get the initial position and orientation of the pedestrian in advance through GPS or user input, and then updates the position of the pedestrian at each step.

In the PDR system, the position of the pedestrian can be propagated as the following equations:

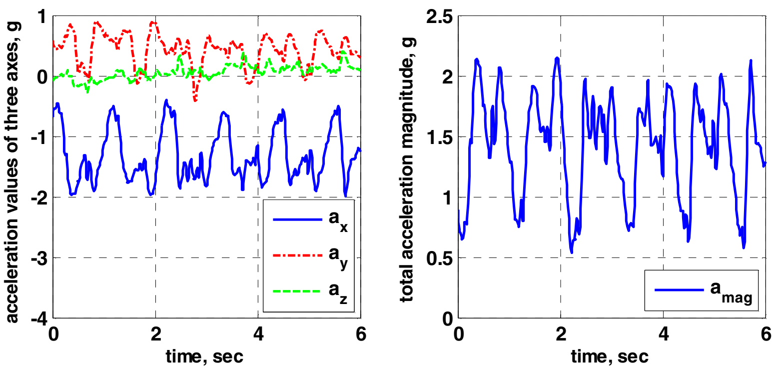
$$\begin{cases} X_{k+1} = X_k + SL * \sin(\theta_{k^*}) \\ Y_{k+1} = Y_k + SL * \cos(\theta_{k^*}) \end{cases} \tag{1}$$

where X and Y are the coordinates in north and east directions, SL is the stride length and θ is the heading at epoch k^*, which is not necessary same as subscript k that denotes the index of steps and defined in Heading Determination section. From the Equation 1, it is shown that we can estimate the position of the pedestrian at any moment provided that the initial position, the stride length and the heading of the pedestrian are known.

2.1 Step Detection

Step detection algorithm, as a basic technique of PDR system, is crucial to influence the performance of the pedestrian navigation system. As previously mentioned, the accelerometer signal is usually used to detect the steps of the pedestrian. A number of papers have described the methods of step detecting for PDR systems, such as peak detection and Fourier transformation [8, 9]. However, with regards to the low-cost MEMS sensors in a smartphone and the flexibility of hands activities, the performance of these methods cannot be guaranteed when the experimental measurements are collected from accelerometers of smartphones.

In general, the output of accelerometer may present harmonic oscillation waveforms that result from walking behaviors. Fig. 2 shows the triaxial acceleration signal collected from a smartphone in hand during normal walking and its total acceleration magnitude.



(a) (b)

Fig. 2. Acceleration signal and its total magnitude during walking

As shown in Fig. 2, the total acceleration magnitude, as well as all the output acceleration signals of three axes, has approximately bimodal oscillation mode with interferences that arise from perturbations of the hand. And the magnitude a_{mag} can be expressed as:

$$a_{mag,k} = \sqrt{a_{x,k}^2 + a_{y,k}^2 + a_{z,k}^2} \tag{2}$$

where $a_{x,k}$, $a_{y,k}$ and $a_{z,k}$ are the measurements from the triaxial accelerometer. Unlike other approaches that use vertical direction of the acceleration to detect steps, the total acceleration magnitude is used in our algorithm, in view of its advantage of being insensitive to the orientation of the accelerometer sensor.

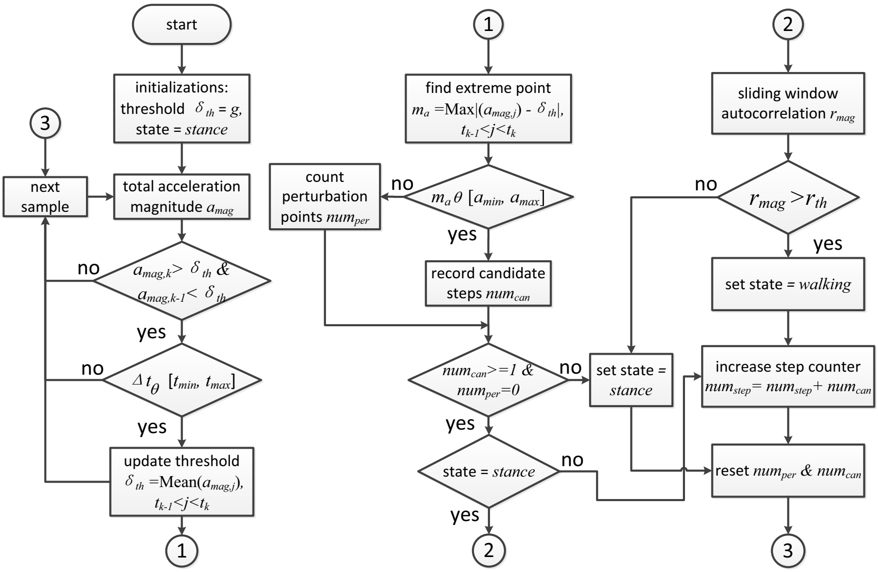


Fig. 3. Proposed step detection algorithm

Fig. 3 shows the flowchart of the proposed step detection algorithm. At the beginning of the algorithm, the thresholdδ_{th} is initialized to the local gravity acceleration value and the total acceleration magnitude a_{mag} is calculated. A candidate step is identified by following criterions:

C1. The total acceleration magnitude a_{mag} has to cross the thresholdδ_{th} from negative to positive.

C2. The time intervalΔt between two consecutive steps defined by C1 must be within t_{min} to t_{max}.

C3. The extreme value of a_{mag} during a step phase, denoted as ma, compared with the thresholdδ_{th}, has to be among a_{min} to a_{max}, otherwise a perturbation point is recorded.

The thresholdδ_{th} in C3 is updated dynamically according to the mean value over a step period. Then a sliding window of appropriate size is created and a finite state machine (FSM) is actuated. Under the premise that all the candidate steps and perturbation points in the sliding window have been recorded, the state can be determined as follows:

S1. *Stance*: there is no candidate step or there exists perturbation points in the sliding window.

S2. *Walking*: the candidate step number is more than one and there is not any perturbation point within the sliding window, and the autocorrelation value r_{mag} is more than threshold r_{th}.

The autocorrelation in S2 is used for distinguish walking motions from other pedestrian activities (refer to Fig. 4), and it needs to be computed only when the state transits from *stance* to *walking*. The purpose of this scheme is to effectively reduce unnecessary calculations. As a result, the step counter num_{step} is incremented if the state is *walking* and the candidate steps counter num_{can} and the perturbation points counter num_{per} are reset to zero for the next sample.

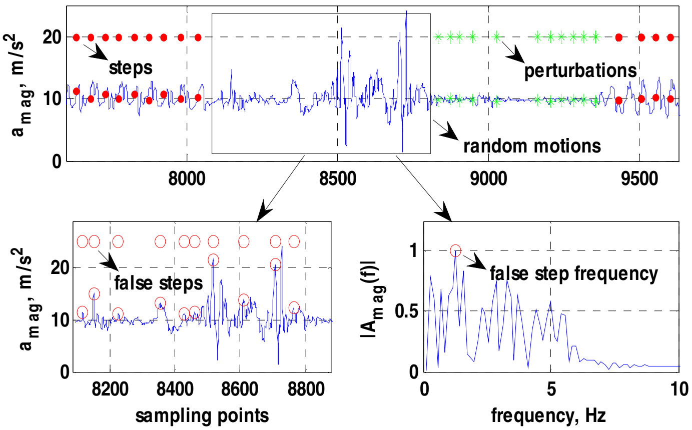


Fig. 4. Step detection for activities during actual walking

The top of Fig. 4 shows that the experimental results of step detection using proposed algorithm by which activities including steps, perturbations and random motions all can be detected and classified with high accuracy. However, for peak detection and FFT, random motions that occur during changing actions are difficult to be distinguished from real walking behaviors. As a result, a large number of false steps are introduced into the detection process (see the bottom of Fig. 4). Therefore, compared with peak detection and FFT, the algorithm proposed in this letter is more adaptive to the flexible and complex hands activities during walking motions.

2.2 Stride Length Estimation

In the PDR system, stride length estimation, combined with heading determination, is utilized to compute the traveled distance and update the position of the pedestrian on condition that the previous position is known. As described in related IMUs based PDR system, the step length of a pedestrian is not constant and varies with walking speed, step frequency, and inclination of the walking route [10]. In order to estimate the travel distance of the PDR system accurately, adaptive stride length estimation must be adopted according to these variations.

In RPNOS, the stride length is estimated using a linear combination of step frequency and acceleration variance [11]. The stride length is estimated through following equations:

$$\text{Stride Length } L = \alpha \cdot f + \beta \cdot v + \gamma \tag{3}$$

where f is step frequency, v is acceleration variance during one step; α and β are weighting factors of step frequency and acceleration variance; γ is constant. And the step frequency and acceleration variance in Equation 3 are obtained as:

$$\begin{aligned} f_k &= 1/(t_k - t_{k-1}) \\ v_k &= \sum_{t=t_{k-1}}^{t_k} \frac{(a_k - \bar{a}_k)^2}{n} \end{aligned} \tag{4}$$

where f_k and v_k are step frequency and acceleration variance at t_k ; t_k means timestamp of the step k ; a_k is acceleration signal and $\bar{a}_k$ is average acceleration during on step; n is the number of sensor sampling points.

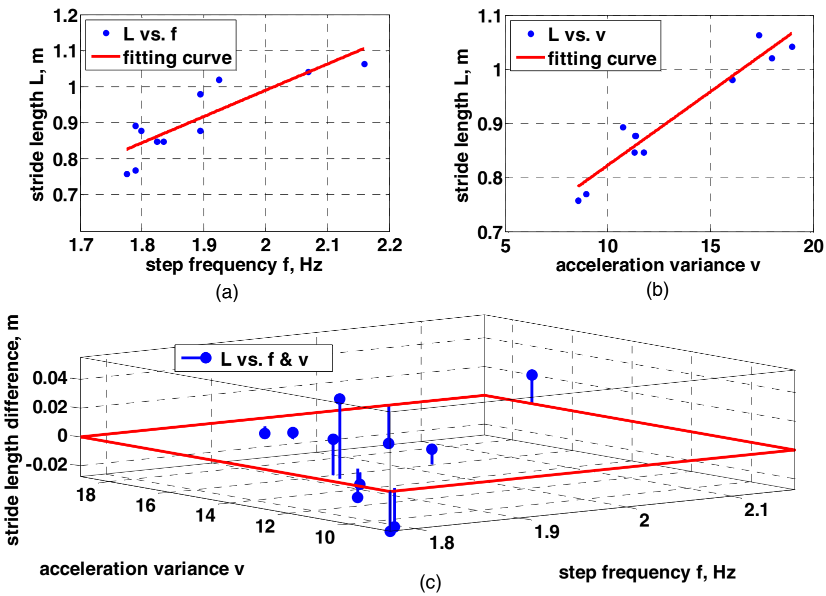


Fig. 5. Unary and binary polynomial fitting of step frequency and acceleration variance for stride length estimation

Fig. 5 shows that the relations between stride length and variations including step frequency and acceleration variance. From this figure, we can find that stride length is approximately proportional to the step frequency and acceleration variance. And the binary polynomial fitting is better than unary fitting due to the root mean square error (RMSE) decrease from 0.0571 to 0.02937.

2.3 Heading Determination

Heading determination in PDR is like heart in a body, because the error in heading leads to quadratic growth of localization error. To obtain the heading of phone, one has to deal with the altitude of the sensor which can be represented in the form of quaternion. RPNOS calculates the altitude quaternion by adopting a gradient-descent attitude and heading reference system (AHRS) algorithm using MARG sensor arrays (including accelerometers, gyroscopes and magnetometers) [12], which calm to be both computationally inexpensive and effective at low sampling rates. Some PDR systems use body mounted MARG to provide accurate heading information. However, a smartphone has ways of placements and much higher degree of freedom. We usually use it to text, to make a call; it may be swinging with hands or be placed in pocket.

RPNOS deals with these situations and provides reliable heading determination in following four scenarios:

- Compass: User is holding the smartphone stably with the screen up. She/he may be checking the map or texting.
- Calling: User is making a call, so the smartphone is close to her ear.
- Pocket: Smartphone is placed in the user's trousers' pocket.
- Hand-swinging: User is holding the smartphone in hand, and the smartphone is swinging with the hand.

We first assume that the offset between sensor yaw and pedestrian heading is known. This is reasonable because there always be a chance for the user to check her smartphone when he points the smartphone at her direction. With the knowledge of heading offset, first two situations can be solved. However, in the situation 3 and 4, even the user walks straight ahead, sensor's yaw angle still can change dynamically. To determine the heading in dynamic state, RPNOS takes advantage of the characteristics of walking behaviors.

As demonstrated before, when a pedestrian is walking, the MARG attached to her body will give a periodic signal which represents the walking motion. The magnitude of acceleration is not only useful in detecting steps but also effective in determining the pedestrian's heading when the smartphone is in pocket or swinging with the hand. As illustrated in Fig. 6, despite of the dynamic changing of sensor's yaw angle, the moment to access the true heading is determined by the time when the magnitude of acceleration cross the threshold of gravity. This is reasonable since smartphone will have the same offset heading to pedestrian when the magnitude of acceleration crosses the gravity. Fig. 7 shows the result of heading determination according to gravity value crossings of acceleration. As can be seen in this figure, the algorithm estimates the heading well due to accurate crossings detection.

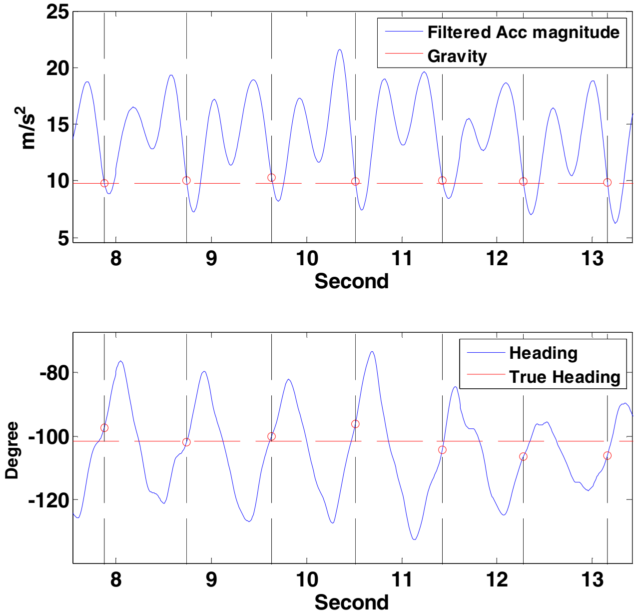


Fig. 6. Heading determination corresponding to acceleration magnitude

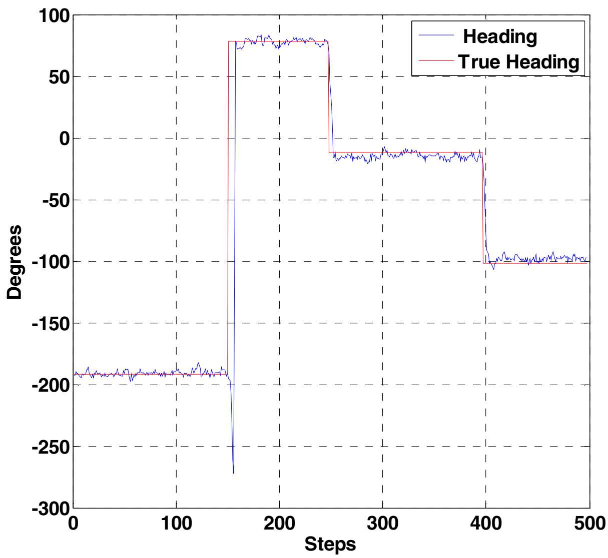


Fig. 7. Heading determination and its true heading

3 Experimental Results

In this section, to verify the performance of RPNOS in practical situations, an experiment with long distance was performed. The experiment site was situated at the football stadium of our university where the total length of one lap was about 345 m. The subjects, who participated in the experiment, walked in different postures naturally each lap as descriptions in heading determination section. In the experiment, an iPhone was utilized and the output rate of the smartphone was set to 32 Hz (the output rate of the data was increased to 64 Hz by interpolation when RPNOS system was in operation).

Fig. 8 shows that the estimated trajectory using RPNOS. The blue line, red line, yellow line and green line represent Compass, Calling, Pocket and Hand-swinging situations respectively. The results indicate that in most situations, the positioning accuracy of RPNOS is reliable and accurate. However, when the smartphone is placed in the pocket, it is hard to estimation the exact positions of pedestrians especially the headings due to the random shaking of the smartphone. Table 1 lists the detailed results of the experiments in four scenarios. Obviously, the best result is Compass situation, the maximum error is 11.6358 m and the error of distance travelled is only 1.79 %. And the worst one is Pocket situation, the maximum error is 19.4688 m and the error of distance travelled is 3.86 %.

Fig. 8. Estimated trajectory of pedestrian around the football stadium

Table 1. Estimated errors in four scenarios

Scenarios	Maximum error	Error of distance travelled
Compass	11.6358 m	1.79 %
Calling	15.0683 m	3.7 %
Hand-swinging	15.346 m	2.31 %
Pocket	19.4688 m	3.86 %

4 Conclusion

In this paper, a reliable smartphone based pedestrian navigation system named RPNOS is proposed. The system possesses an efficient performance in step detection and heading determination, and allows us to positioning pedestrians accurately using PDR algorithm with comparatively less amount of calculation. Experimental results show that RPNOS, which is applicable to diverse usage scenarios of smartphones, could be a prospective system for pedestrian navigation applications.

For future work, the system will be improved in all aspects of PDR algorithm and be tested in indoor environment where the heading determination may be seriously affected by various magnetic interferences, such as electric equipment, reinforced concrete, and so on. On the other hand, other technologies, such as WLAN, Bluetooth, RFID, etc., can be fused into RPNOS to improve the positioning accuracy.

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