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Indoor localization and navigation using smartphone sensory data

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Abstract In the cloud age, it is quite easy to collect sensory data from smartphones. With these sensory data, it is desired to provide various kinds of applications to serve the user. In this research, we aim at developing an indoor navigation system on smartphone using solely smartphone sensory data. There are many researches on indoor localization and navigation in the literature. Nevertheless, environmental sensors and/or wearable sensors are usually needed. This can be costly and inconvenient. In this paper, we propose a smartphone indoor localization system using only accelerometer and gyroscope data from the smartphone. The Pedestrian Dead Reckoning (PDR) approach is used to build this system. The PDR approach is simple and efficient though seems traditional. The major weakness of the PDR is that the estimation error would accumulate over time. Thus we propose to add so-called calibration marks which look like short arrows and are placed on both the floor plan and the ground. To use the system, the user first finds a calibration mark on the ground, stands on it and faces the right direction. He/she then moves the android icon (representing the user) on top of the calibration mark on the floor plan on the smartphone. When the user starts to move, the android icon also moves on the floor plan following the real-time estimation of step length and moving direction change for each step from accelerometer and gyroscope data. This is a prototype of an indoor navigation system that can become fully functional after an optimal path planning module is included. Experimental results of estimated walking trace tests show high accuracy. The system is promising and useful as long as a floor plan and calibration marks are built in advance.

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1 Introduction

The smartphone is equipped with various kinds of sensors, which allows us to detect the movements and behavior of the user. The sensors include accelerometer, gyroscope, G-sensor, proximity sensor, light sensor, camera, etc (Ma et al. 2013). The sensory data from the smartphone can be transmitted to the cloud for storage and processing. If the networking environment is permitted, the processing on the cloud and the resulted automated services can be performed in real time. The storage of the sensory data might be huge, but the service can be fast to fulfill the need of human user. This creates many possibilities for developing useful applications. A smartphone can be used for lip reading via an app (Kim et al. 2009). Recognition of poses and gestures of human users can also be achieved via a rule-based approach (Hachaj and Ogiela 2014). Fall detection systems are introduced in Bai et al. (2012) and Viet et al. (2012), which are helpful for emergency care of the elderly. As for movement detection, the app in Pernek et al. (2012) and Hsu et al. (2015) can estimate and record activity intensity of the user. This can also be extended for health care need to help the user tackle obesity (Gao et al. 2009).

Another possibility of smartphone applications is indoor localization and navigation. The indoor navigation system could be very useful when people are in an unfamiliar public places. The system can also push notifications or commercials to the user if his/her location is known. Localization or positioning of the users is essential in developing such a system. GPS (global positioning system) is usually used to decide the location of the user in the outdoor navigation system. It has become a standard equipment for automobile navigation nowadays (Niu et al. 2012). For indoor navigation, GPS is not a possible option because the satellite signals cannot be detected in an indoor environment. Therefore, researchers have developed different technologies in the indoor scenario. Most of such technologies are based on WiFi (Koo and Cha 2012) or RFID (Yang et al. 2013). Martin et al. (2010) proposed a multimodal solution using a few sensors of the smartphone. They claimed to reach an accuracy of up to 1.5 m. However, these solutions require massive deployment of WiFi AP's or RFID tags in the environment. This can be very costly and troublesome if not possible. Furthermore, it is essential to properly deploy the WiFi AP's and RFID tags to achieve high accuracy in localization.

This research hope to design a simple solution with low cost for indoor navigation. We propose to develop a smartphone application with the built-in sensors of the smartphone to estimate the moving direction and distance when the user walks in a building. If the current location is known and the estimates of the moving direction and distance are accurate, we can decide the next location of the user on a floor plan at any time. This solution is called PDR (Pedestrian Dead Reckoning) (Ausmeier et al. 2012; Shin et al. 2012; Zhang et al. 2013). The concept of Dead (Ded, Deduced) Reckoning was first used in marine navigation before the Eighteenth century. Though the concept might be old and traditional, it is simple and useful.

Accelerometer and gyroscope are built-in sensors in all smartphones. In our design, accelerometer data are used to detect the step length of each step of the user. Gyroscope data are used to decide the moving direction. An Android application is developed for the estimations of step length and moving direction. The calculations are simple and the sensory data need not to be uploaded to the cloud for complex processing. There are two limitations on this application: (1) The user needs to hold the smartphone in an up-right position in front of his/her chest at all time. If the user holds the smartphone casually or places it in a pocket or a bag, accelerometer and gyroscope data would be different and the estimations of walking distance and direction would be wrong. Nevertheless, we think that it is natural to hold the smartphone that way when the application is extended for indoor navigation. (2) Calibration marks on the ground and on the floor plan are necessary. A problem with this approach is that the estimation error accumulates. Thus, it is necessary to design a mechanism to reset the system error. We propose to add a few calibration marks on the ground and on the corresponding floor plan positions. The calibration marks look like short arrows which show both the location and direction. With this design, the user can reset the system easily when the positioning error becomes unbearable.

This paper is organized as follows. Section 2 discusses related work in indoor localization, including how to estimate walking direction and distance. Section 3 introduces the proposed approach for indoor localization and navigation. Section 4 presents the implementation of the indoor localization application and the experimental results. Limitations of the implementation and directions for future improvement are also discussed. Finally, conclusions are drawn in Sect. 5.

2 Related work

Accelerometer and gyroscope are the two major sensors in smartphone that we use in this research. Accelerometer detects the acceleration values in three axes when the smartphone is moving. The values can be used to estimate the distance that the smartphone moves (Hsu and Yu 2009). They can also be used to decide the activities of the user (Dernbach et al. 2012; Fahim et al. 2012; Oner et al. 2012). In this research, we use the acceleration values to calculate the step length and the step count. On the other hand, gyroscope senses the angular velocities the smartphone rotates about three axes (Barthold et al. 2011). In this research, we use the angular velocities to compute the direction change of the user.

There are various approaches for indoor localization. Pressure sensors can be deployed on the floor to detect the location of the user (Sousa et al. 2013). But this requires extensive work in building such floors. We can use the signal strength from three WiFi access points to estimate the location as long as a proper signal strength model can be built (Koo and Cha 2012). The estimation is more accurate if more WiFi access points are deployed. Active RFID technology can be used for localization in a similar manner. The most famous method is called LANDMARC (Ni et al. 2004; Jin et al. 2006; Polito et al. 2007). The cost of RFID is lower than the cost of WiFi. But massive deployment of RFID readers is also necessary.

The PDR approach needs no sensor deployment in the environment. This makes it an ease-of-use approach with low cost (Gusenbauer et al. 2010; Ausmeier et al. 2012; Pratama et al. 2012; Shin et al. 2012; Zhang et al. 2013). Gusenbauer et al. (2010) introduces a seamless positioning solution for indoor and outdoor environments. It uses accelerometer data for activity classification, step detection and step length estimation. It also uses electronic compass for step heading estimation. Ausmeier et al. (2012) focuses on building data storage and routing database design. The authors think it is sufficient for indoor navigation even though the location estimation using acceleration data is not that accurate. Pratama et al. (2012) shows a PDR-based positioning system without individual calibration. It presents a displacement analysis with 15 test subjects. Shin et al. (2012) emphasizes the importance of distance estimation. The authors use artificial neural networks to recognize the walking status of the user to improve distance estimation. They also use map matching to revise the estimated position. Zhang et al. (2013) utilizes a modified Kalman-filter-based approach to get more accurate orientation data. The approach minimizes the effect of magnetic field disturbance. There have been some hybrid approaches proposed in recent years. Radu and Marina (2013) develops HiMLoc which is based on PDR, but incorporates crowdsourced WiFi fingerprinting. Chen et al. (2015) proposes a sensor fusion framework to combine PDR, WiFi, and landmarks.

A pedometer counts the steps a user walked. It is a small device to help people know how much he/she has moved in a day. Jayalath and Abhayasinghe (2013) designs a pedometer algorithm using gyroscopic data. It can achieve a better estimation accuracy for low speed. Ying et al. (2007) describes three accelerometer-based step detection algorithms. They want to choose the best one to monitor locomotion of patients with Parkinson's disease. Marschollek et al. (2008) proposes and tests four accelerometer-based step detection algorithms. The experimental results show that the Wolf method and the Dual-Axial method are better. In this research, we tried these two methods and found that the Dual-Axial method is more suitable.

It is not easy to estimate the step length for different persons. The step length of a person can be estimated by his/her height. But the proportion of the body and the leg is different for different persons. Even for the same person, the step length could be varying during a walk. It is common to calculate the step length using the leg length and the accelerometer readings (Alvarez et al. 2006; Shih et al. 2012). It is troublesome that we need to know the leg length of the user first. Sayeed et al. (2013) introduces six methods for step length calculation. The experimental results show that the Weinberg's algorithm (Weinberg 2002) performed the best. Thus we adopt the Weinberg's algorithm in this research.

For direction estimation, Tundo et al. (2013) uses readings to judge the orientation of the smartphone. But it cannot be used to detect the direction change. Kang et al. (2012) combines the gyroscope and the digital compass to decide the direction. When either one of them is not stable, the system puts more weighting on another sensor to make the decision. In our experience, the digital compass reading is easily affected by the objects in an indoor environment and the estimation accuracy could be low. Since in this research we consider only indoor environments, the gyroscope reading is sufficient for direction change estimation.

3 Indoor localization and navigation

In this section, we will introduce the indoor localization system developed in this research. The system is an Android application which uses only the smartphone built-in accelerometer and gyroscope. It needs not deploy any kind of environmental sensors or devices in advance. Extension to a fully functional navigation system is also discussed.

3.1 System flow

Figure 1 shows the flow chart of the localization system. It is divided into two phases: (1) the setting phase and (2) the walking phase. The system flow is as follows.

(1) The setting phase (manually by the user)

Step 0 Load the floor plan to the system.
Step 1 Find a calibration mark on the ground and stand on it.
Step 2 Set the initial location on the corresponding calibration mark on the floor plan.

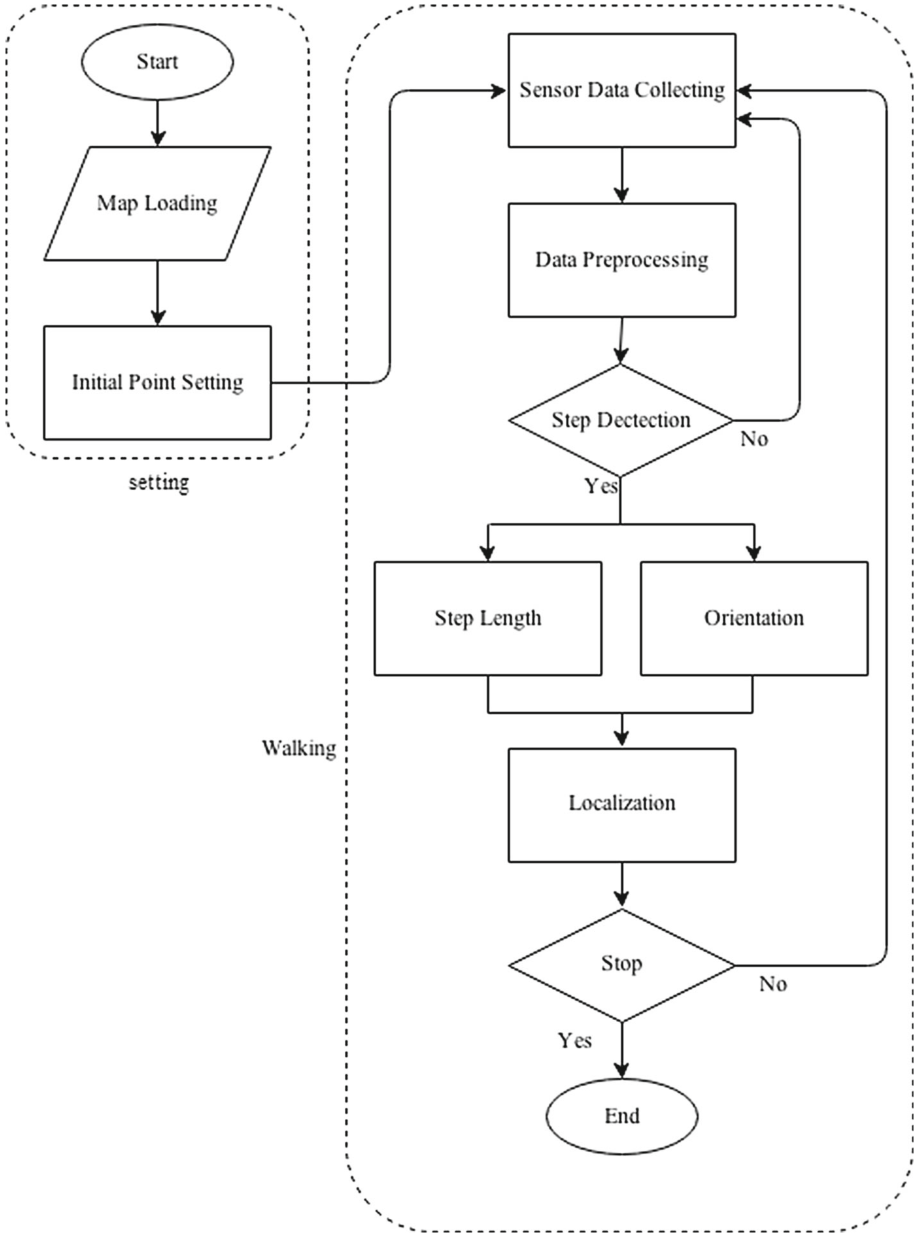

Fig. 1 System flow chart

Step 3 Face the moving direction (the arrow of the calibration mark) and press the START button.

(2) The walking phase (by the system)

Step 4 Collect sensory data.
Step 5 Preprocess the sensory data.
Step 6 Perform step detection.
Step 7 If no step is detected, go back to Step 4.
Step 8 Calculate step distance and direction change angle.
Step 9 Decide the new location by the distance and angle.
Step 10 If STOP is not clicked, go back to Step 4.
Step 11 Stop sensory data collection.

Since the system is aimed for indoor navigation, it is assumed that the user holds the smartphone in a near-upright position in front of the chest. When the system is running, sensory data from accelerometer and gyroscope are collected and preprocessed in real time. Considering the frequency of human walking is about 0.5–1.5 Hz and one step might take 0.6–2 s, we set the data fetching interval at 60 ms. It is one of the default data fetching intervals of Android – SENSOR_DELAY_UI.

To preprocess the sensory data, the three-axis data (x_a, y_a and z_a) from the accelerometer are combined into a signal called *Acc* using (1). For gyroscope data in (2), we take only the y-axis (y_g) and z-axis (z_g) since when the user turns with the smartphone hand-held in front of the chest, the x-axis data are mostly zero. A signal *Gyr* is thus resulted.

$$Acc = \sqrt{x_a^2 + y_a^2 + z_a^2} \tag{1}$$

$$Gyr = \sqrt{y_g^2 + z_g^2} \tag{2}$$

Acc is then smoothed by low-pass filtering (five-point moving average) to remove spikes or noises caused by unstable signals. Filtered *Acc* is used for step detection and step length calculation.

Next, the system starts to detect the movement of the user. When a step is detected, the application calculates both the step length and the direction change (orientation). With a combination of step length and direction change, the system can determine the next location of the user after the step. Details of the step detection, step length calculation and direction change calculation are given in the following.

3.2 Step detection

The Dual-Axial method combines the acceleration values of two axes to detect the step (Marschollek et al. 2008). Since we already combine the acceleration values of three axes in (1), we would just use the *Acc* value for the detection here. The *Acc* value is not affected by different orientations of the smartphone. It actually includes the acceleration of gravity (9.8 m/s^2). Thus all the *Acc* values are subtracted by 9.8 to remove the gravity component. A *zero-crossing* is a point where the sign changes. When the sign of the *Acc* value changes from positive to negative or from negative to positive, there exists a zero-crossing point. A step can thus be determined when two consecutive zero-crossing points are detected.

3.3 Step length calculation

There are several ways to determine the step length of the user in the literature (Sayeed et al. 2013). The step length can be calculated from the height or leg length of the user or we can ask the user to input the value of his/her step length to the system in advanced. However, to use a fixed value for the step length may not be practical. The step length can be estimated quite accurately via the acceleration values (Weinberg 2002). The length of a step can be estimated by $\sqrt[4]{Acc_{max} - Acc_{min}}$, where Acc_{max} is the maximum of the acceleration values and Acc_{min} is the minimum of the acceleration values within a step. In (3), the step length (L) is calculated with an individual parameter η.

$$\mathrm{L} = \eta * \sqrt[4]{Acc_{max} - Acc_{min}} \tag{3}$$

The individual parameter $\eta = \frac{d_{real}}{d_{estimated}}$ is added to get the optimal estimation result. In the equation, d_{real} and $d_{estimated}$ are real walking distance and estimated walking distance ($\sqrt[4]{Acc_{max} - Acc_{min}}$), respectively. In this research, we do not consider this individualization and it could be added in the future.

3.4 Direction change calculation

The built-in orientation sensor on the smartphone can be used to decide the direction change of the user. However, it is not suitable in the indoor environment because the reading is easily affected by magnetic fields from electric cables, appliances and other electronic devices. Therefore, we choose to use the gyroscope data to decide the direction change. When the user holds the smartphone in front of his/her chest, the gyroscope value of the x-axis does not change even if the user turns to a different direction. In (4), the sign of Gyr is determined by the sign of z_g. In (5), the orientation (direction change) can be determined by multiplying the combined gyroscope data from (4), the time interval and a parameter 57.29578 (180/2π). The parameter converts the orientation value from radians to degrees.

$$Gyr = \begin{cases} \sqrt{y_g^2 + z_g^2}, & z_g \geq 0 \\ -\sqrt{y_g^2 + z_g^2}, & z_g < 0 \end{cases} \tag{4}$$

$$Ori = \sum_k (Gyr_k * Time_k * 57.29578) \tag{5}$$

In Fig. 2, the results of a direction change test are presented. The user turned to the right four times (about −90 °, −180 °, −270 ° and −360 °, respectively). When the value of *Ori* reaches −360, it was reset to 0. He/she then turned to the left two times (about 90 ° and 180 °). This shows that (4) and (5) can be used to estimate the direction change.

3.5 Indoor localization by PDR

A problem with the PDR approach for indoor localization is that the error would accumulate. Thus a mechanism is needed to reset the accumulated error to zero via pointing out the right location and facing direction on the floor plan. A so-called calibration mark is designed to be placed on both the floor plan and the real floor. It is an arrow sign that indicates both the location and the facing direction. The user can choose to stand on a calibration mark on the floor and face to the right direction whenever he/she feels that the accumulated error is somewhat big. He/she then click the corresponding calibration mark on the floor plan on the smartphone to reset the error. Figure 3 shows such calibration marks on a floor plan.

Fig. 2 Results of the direction change test

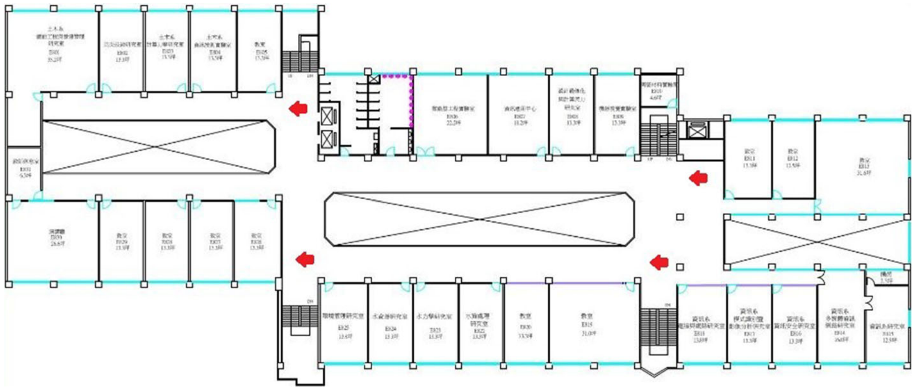

Fig. 3 Calibration marks on a floor plan

When a user enters a public building, he/she can find a calibration mark on the ground near the entrance. After the initial setting of loading the floor plan on the smartphone and marking his/her location on the floor plan, he/she can start to walk inside the building with the smartphone held in front of the chest. For each detected step, the application can decide the next location of the user by the estimated step length and direction change angle. An Android icon representing the user will move on the floor plan along with the movement of the user. When the user passes by another calibration mark, he/she can choose to reset his/her position if the accumulated error is big. The developed system is able to locate and track the user in real time.

3.6 From indoor localization to indoor navigation

In this research, the optimal path planning algorithm is not studied and implemented. With such an algorithm, we can extend the developed indoor localization system into an indoor navigation system. The path planning algorithm for indoor navigation would be quite different from the ones considering only nodes and distances among these nodes. For indoor navigation, there could be open spaces and the user might need to move between different floors via escalator, elevator or stairs. We think the problem is more complicated and would like to point this out as an interesting research issue.

4 Implementaiton and experimental results

In this section, we first introduce the developed indoor localization application with its user interface and functions. We then present the experimental results on walking trace estimation. Finally, we further discuss the pros and cons of the system.

4.1 Indoor localization application

An Android application is implemented in this research. Figure 4 shows the user interface of the developed application. The user can initiate the system by click the Start button at the lower-right corner. The button turns into Stop when it is clicked. On this screenshot, the floor plan has been loaded, the system is initiated, and the user (the Android icon) is walking. The Android icon will always stay at the center of the screen, but the background floor plan will move to reflect the location of the user. On the upper right corner, the estimation of the direction change angle in both radian and degree is displayed in real time. The estimation of the step count is also shown at the bottom. On the lower-left corner, the user can choose to room-in or room-out the floor plan.

4.2 Experimental results

In our previous work, we performed experiments on step detection, direction change estimation and step length estimation (Hsu et al. 2014). In the experiments of step detection, the average step count error is 0.7 step for 50 steps. Six out of 10 experiments are 100% correct. The accuracy is very high as long as the user holds the smartphone steadily during the test. In the experiments of direction change estimation, the user was asked to turn right or left 90°. The average errors in percentage are 2.58 and 3.51%, respectively. The error rate is quite good considering that part of the errors is caused by the user since it is not possible that the user would turn exactly 90°. In the walking distance estimation experiments, the user was asked to walk 10 m. The error rates are less than 6.5% (65 cm) mostly except for two experiments. Again, the errors can be caused by the user because he/she could have held the smartphone in a casual way. Also, to reach the 10-meter mark, the final step could be shorter or longer than normal ones. This might generate errors, too. From the results of those experiments, we think that accurate estimation of walking direction and distance via our approach is possible. By combining the results of step detection, direction change estimation and step length estimation, the system can decide the movement of one step and the next location of the user.

We examined the overall performance of the system by comparing the actual trace and the estimated trace in a set of experiments. First, the user walked a rectangle route, going up first and turning right three times to go back to the origin (the starting point). Figure 5a presents a bad result and Fig. 5b shows a good result selected from a set of experiments. In Fig. 5a, the system produces some error in direction estimation at the very beginning and the error stays. Even though the subsequent estimations look quite good, the end point is a bit far from the origin. On the contrary, the estimated trace in Fig. 5b is almost perfect. The end point is very close to the origin. In this case, the user tried hard to hold the smartphone as steady as possible during the test, which proved to be very useful in producing good results.

Next, we performed more tests to evaluate the system. The user can walk freely from a designated initial point to a destination point without following a predefined route. Here we present two sets of experimental results. The first set is for an experiment of short distance walk. The shortest distance for the walk is 34 m with the initial coordinates at the origin (0,0)

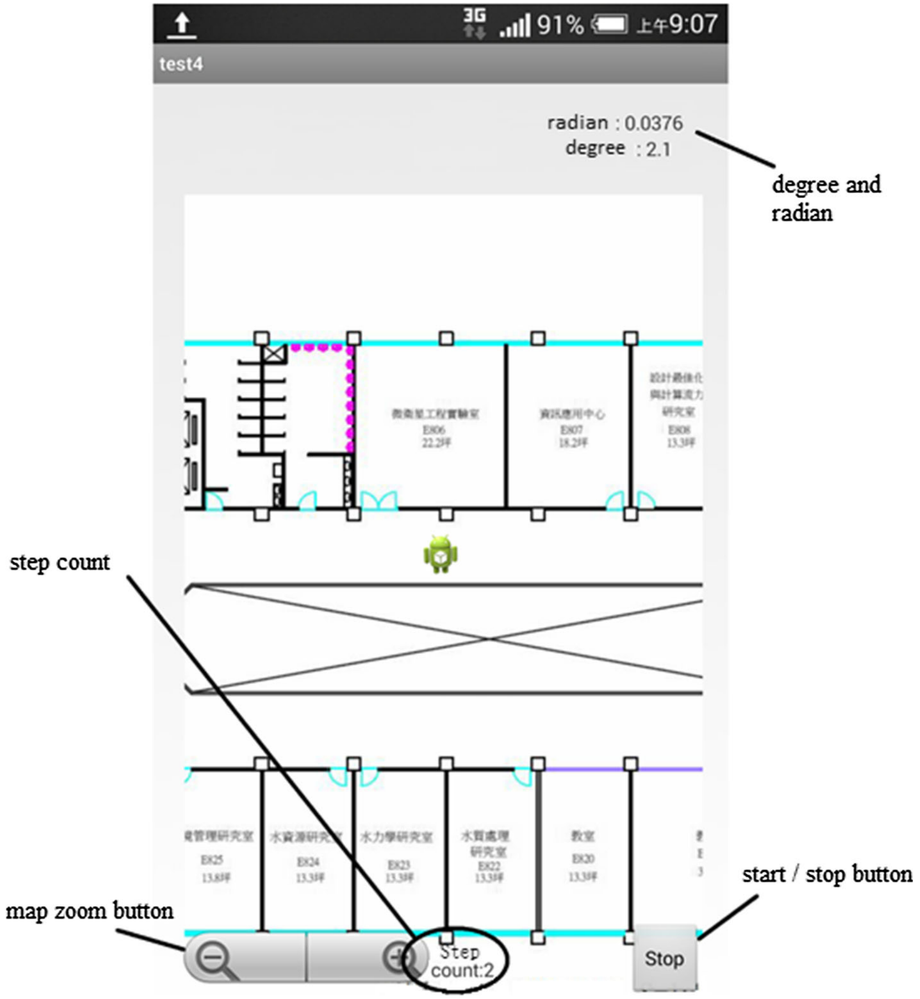

Fig. 4 User interface of the smartphone application

and the destination coordinates at (800, 0). The unit of the coordinates is cm. The results of 10 tests are shown in Table 1. The average error is 1.18 m with a maximum at 1.91 m and a minimum at 0.53 m. The second set is for an experiment of long distance walk. The shortest distance for the walk is 72.54 m with the initial coordinates at the origin (0,0) and the destination coordinates at (1636, 5618). The results of 10 tests are shown in Table 2. The average error is 2.54 m with a maximum at 4.94 m and a minimum at 0.88 m. These experimental results are actually very good except for Test #1 of the long distance walk experiment (Table 2).

Figure 6 shows the estimated walking trace of the best test (0.53 m error) in the short distance walk experiment (Table 1). On the other hand, Figs. 7 and 8 show the estimated walking traces for the best test (0.88 m error) and the worst test (4.94 m error) in the long distance walk experiment, respectively. The estimated walking traces in Figs. 6 and 7 are almost perfect considering that the distances of the end points and the destination points are

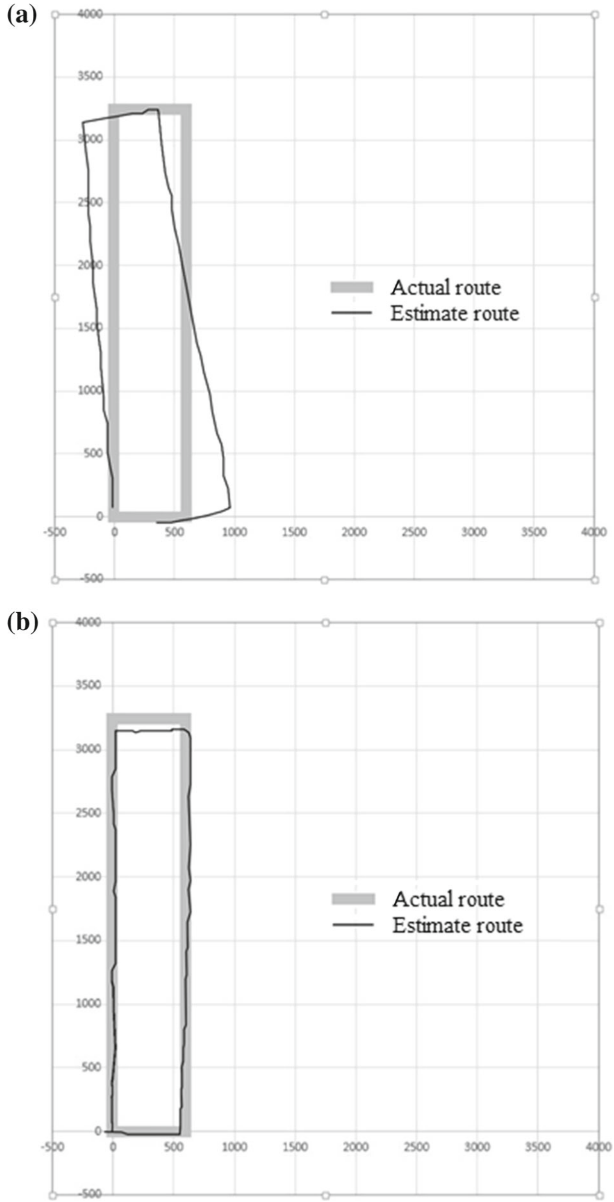

Fig. 5 Walking test results **a** casual movement **b** steady hands

less than 1 m, meaning, within one step. For the worst case in Fig. 8, the estimated walking trace passes through walls, which is not possible in the physical world. This can be used to fix the error before it gets worse.

Table 1 Estimated destination coordinates and error for short walking experiments with target coordinates at (800, 0)

Experiment no.	Estimated coordinates	Error (m)
1	(915.63, 26.31)	1.18
2	(978.81, −69.35)	1.91
3	(902.4, 10.84)	1.02
4	(865.72, 68.59)	0.94
5	(814.22, −51.07)	0.53
6	(938.06, −31.56)	1.41
7	(888.18, 51.31)	1.02
8	(925.21, 73.6)	1.45
9	(853.24, 32.68)	0.65
10	(957.04, 68.57)	1.71
Average	(903.85, 17.99)	1.18

Table 2 Estimated destination coordinates and error for long walking experiments with target coordinates at (1636, 5618)

Experiment no.	Estimated coordinates	Error (m)
1	(1363.07, 6030.88)	4.94
2	(1680.81, 5892.39)	2.78
3	(1574.25, 5844.07)	2.34
4	(1461.94, 5718.41)	2.00
5	(1376.77, 5810.95)	3.23
6	(1491.84, 5841.38)	2.65
7	(1454.43, 5738.20)	2.17
8	(1512.70, 5865.44)	2.76
9	(1510.25, 5730.38)	1.68
10	(1561.57, 5666.79)	0.88
Average	(1499.06, 5813.89)	2.54

4.3 Discussions

These experimental results show that the system has good tracking on the user and they are comparable to the results of other researches. In Koo and Cha (2012), the WiFi approach was used and the predicted errors were between 2.16 and 4.76 m. As for LANDMARK proposed in Ni et al. (2004), the RFID technology was used for localization. The errors were below 1.7 m when the RFID sensors were deployed at high density. But the errors were from 2.6 to 3.1 m with low RFID density. Moreover, our PDR-based approach requires no sensor deployment in the environment and is a relatively simple approach.

The PDR approach is simple, but the estimated error would accumulate. Thus calibration marks are designed to reset the error to 0 whenever it becomes unbearable. Furthermore, when the system shows that the user passes through walls or other types of barriers on the floor plan, the system needs another mechanism to issue a warning or correct such obvious errors. To extend this indoor localization system to an indoor navigation system, an optimal path planning algorithm is needed. Also, how to reach a destination at a different floor is another important problem and should be properly addressed.

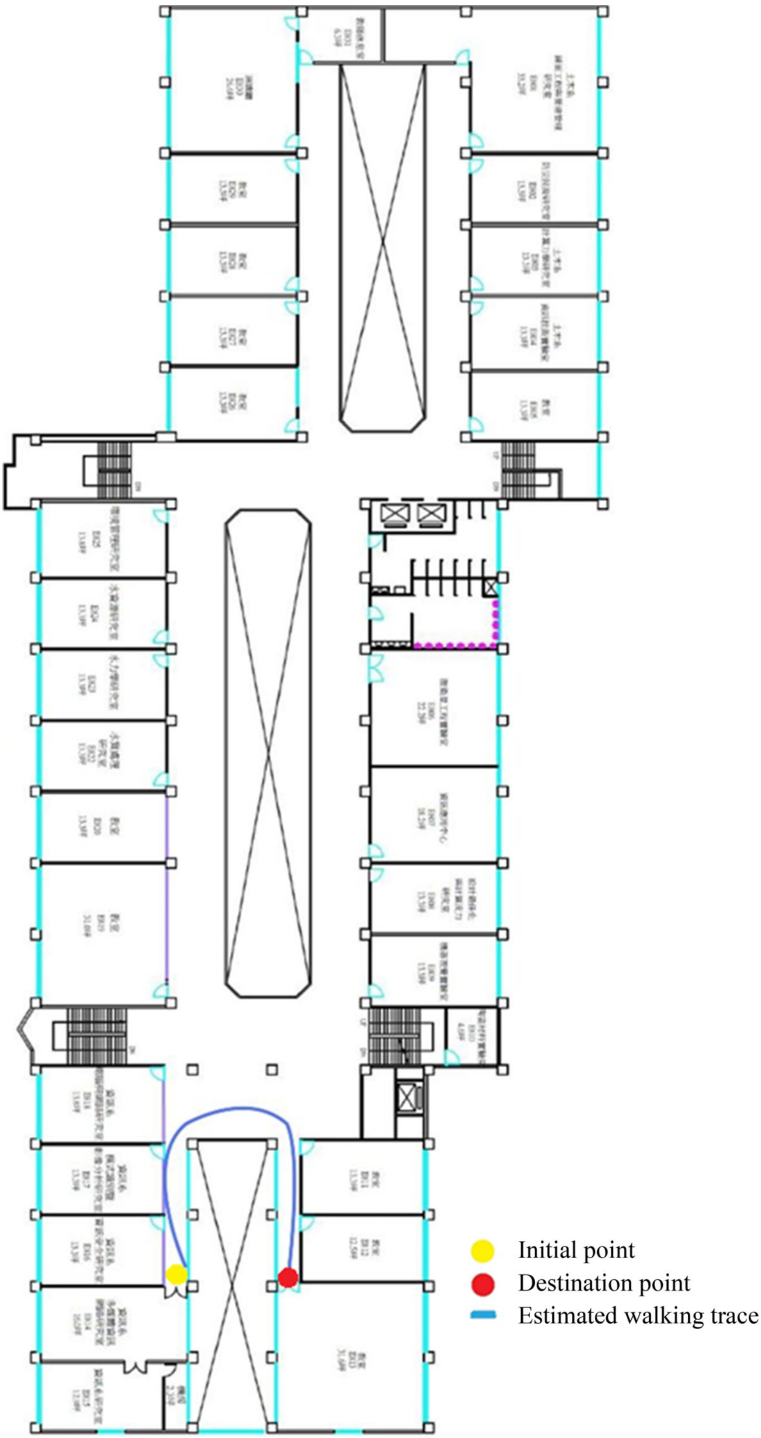

Fig. 6 Estimated walking trace for the best case in Table 1

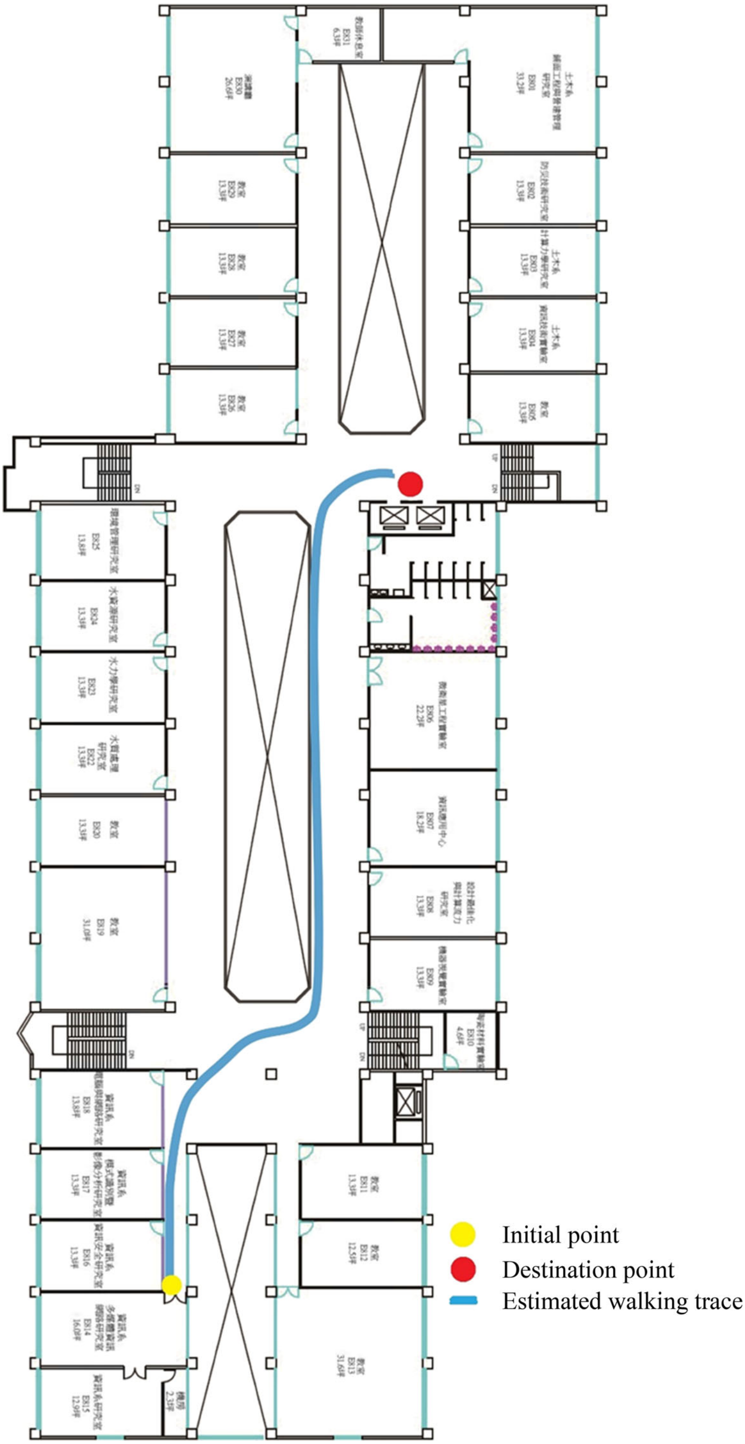

Fig. 7 Estimated walking trace for the best case in Table 2

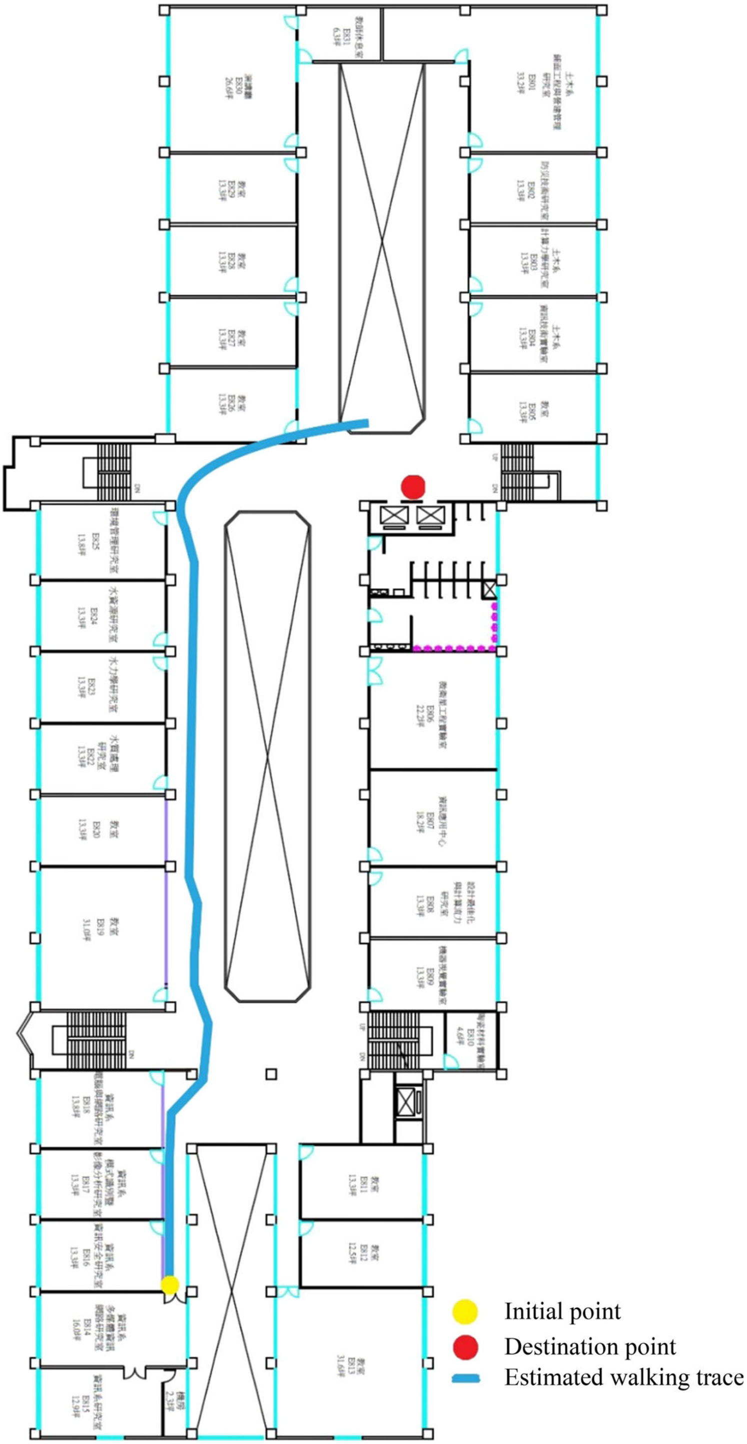

Fig. 8 Estimated walking trace for the worst case in Table 2

5 Conclusions

We have developed and presented an indoor localization system using only smartphone built-in sensors in this paper. A PDR-based approach is applied in the system. Estimations on step count, step length and direction change are necessary in such a system. With the real-time localization of the user, the system can track the user in real time. The experimental results show that this approach is practical and feasible. Calibration marks are designed to be added to the system for the user to reset the accumulated error at any time. The system can be further extended to an indoor navigation system by including an optimal path planning module. When a user enters a public place like government buildings, train stations, hospitals or museums, he/she can stop by a kiosk near the entrance to download a floor plan of the place to his/her smartphone and set the initial location and facing direction on the floor plan. The user then can choose a destination on the floor plan and the system can track his/her location on the floor plan and guide him/her to the destination.

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