Pedestrian Walking Model for Floor Plan Building Based on Crowdsourcing PDR Data

Guangda Yang[1], Yongliang Zhang[2], Lin Ma[2(✉)], and Leqi Tang[2]

[1] Mobile Communications Group Heilongjiang Co., Ltd., Harbin 150028, China
[2] Communication Research Center, Harbin Institute of Technology, Harbin, China
malin@hit.edu.cn

Abstract. Indoor navigation has gained lots of interest in the last few years due to its broad application prospect. However, indoor floor plan for position display is not always available. In this paper, we utilize the crowdsourcing pedestrian dead reckoning (PDR) data got from the smart phone to build the indoor floor plan. According to the crowdsourcing PDR data, we propose new walking model that reflects the distribution of indoor pedestrian trajectory. This model is can well express the pedestrian walking pattern. In addition, the proposed model can also estimate the hallway width through the PDR data in hallway. According to the proposed model, we can draw the floor plan with the width of hallway. We have implemented the proposed algorithm in our lab and evaluated its performances. The simulation results showed that the proposed algorithm can efficiently generate the floor plan in the unknown environments with lower cost, which can contribute a lot for indoor navigation.

Keywords: Floor plan · Mobile crowdsourcing · IMU · PDR

1 Introduction

Nowadays, several candidate methods can be employed in the future indoor navigation system, such as WiFi, Bluetooth and ZigBee [1]. Though these methods are different, all they require the same information, which is floor plan. As the indoor geographic information, floor plan contains wealth of geographic information, and it is necessary for the indoor navigation service. Floor plan will be standardized processed after collecting the geographical data, so that all of the navigation and positioning services can be established in the precise geographical space model [2]. With the help of floor plan, indoor navigation system can make specific database in the offline phase [3], and also show its location and navigation estimation clearly in a smart phone in the online phase. Therefore, the complete and accurate of floor plan are the basic conditions for indoor navigation and positioning system.

However, in some cases, floor plan is not always available, which greatly limits the development of indoor navigation service. Considering about the number of buildings or floors, it is unrealistic to make floor plan by SLAM due to the inevitable cost of economic or time [4]. Therefore, we need to find an effective way to build floor plan in the unknown indoor environment. In recent years, it becomes possible to use pedestrian trajectory to indicate the indoor path.

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The key idea of PDR algorithm is to count the step at a starting point by sensors, and combined with step estimation and heading calculation to realize the pedestrian trajectory estimation. Chen proposed a pedestrian indoor and outdoor seamless positioning method using multi-sensor positioning platform, which based on the fusion GPS and self-contained sensor [5]. Liu proposed a pedestrian positioning and navigation algorithm with a 6 degrees of freedom IMU equipment [6]. [7] proposed a system named CrowdInside, which used the crowdsourcing data to draw the indoor pedestrian trajectories through the smart phone sensors. In [8], Luo proposed an IMAP system, which can collect the smart phone sensor and construct the indoor floor map by detecting interest points, such as doors, elevators or stairs. In [9], Ma proposed a heading angle correction algorithm for PDR trajectory in the indoor corner environment. It turned the heading angle to right angle at the corner through the right angle detection algorithm. In [10], Zhou proposed a system called ALIMC, which can build an indoor floor plan in the unknown environment through an abstract link node model. However, there are still many problems remained for building the indoor floor plan with the crowdsourcing PDR data. The key problem is that all the methods stated above cannot provide the hallway width but only the indoor path. The hallway width is so important that it can help further decide the indoor structure, such as walls, doors and windows. Actually, the crowdsourcing PDR data contain lots of information about the indoor environment that are not well utilized.

Therefore, based on the crowdsourcing PDR data, in this paper, we propose a pedestrian walking model for floor plan building to provide not only the indoor path but also the hallway width. Since the crowdsourcing PDR data have inherent noise, it needs to be cleaned before building the floor plan. We assume the pedestrians prefer to walking in the long straight hallway along the central axis. And when turning happens in the corner, the pedestrians prefer to walk away from the central axis and gradually close to the corner in the rotation area. Finally, with pedestrians walk out rotation area, their path will be back to the hallway central axis again. Based on such a pedestrian walking model, we propose a crowdsourcing PDR data cleaning method. Different from the available literatures, we do non clean the PDR data based on each PDR trajectory but the trajectory point. We set up a simulation environment in our lab. And the experimental results show that the proposed method can better build indoor floor plan, substantially reduce costs. The remainder of this paper is organized as follows. Section 2 will introduce key ideas of the PDR algorithms and indoor walking model. Section 3 will introduce the proposed floor map building method based on PDR data. Section 4 will provide the implementation and performance analysis. Conclusion will be drawn in the last section.

2 System Model

2.1 PDR Overview

As a useful method to estimate the pedestrian trajectory, PDR algorithm can record the direction and distance from a known start position. The principle of the PDR algorithm is shown in Fig. 1. Each trajectory point represents the position of the pedestrian, and the line between two adjacent dots forms pedestrian trajectory.

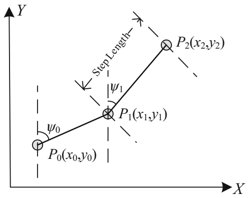


Fig. 1. The schematic diagram of PDR algorithm

We assume the initial trajectory point position $P_0(X_0,\ Y_0)$ is known. The next position is $P_1(X_1,\ Y_1)$, and the heading angle from P_0 to P_1 is ψ_0, the step length is $S(t_0)$. Then we have:

$$\begin{cases} x_1 = x_0 + S(t_0) \times \sin\psi_0 \\ y_1 = y_0 + S(t_0) \times \cos\psi_0 \end{cases} \tag{1}$$

The general relation from P_0 to P_k is:

$$\begin{cases} x_k = x_0 + \sum_{i=0}^{k-1} S(t_i) \cdot \sin\psi_i \\ y_k = y_0 + \sum_{i=0}^{k-1} S(t_i) \cdot \cos\psi_i \end{cases} \tag{2}$$

Due to the traditional gyro integration method for heading calculation will lead to deviation drift, the heading angle calculation is not accurate. Therefore, we utilize the quaternion method to acquire the high-precision heading angle.

2.2 Heading Angle Estimation Based on Quaternion

Quaternion is a mathematical method to describe a rotation of a vector relative to a certain coordinate system. It utilizes vector and scalar to define the rotation. Vector indicates the direction of rotation axis and the direction cosine value between rotation axis and coordinate axis. Scalar indicates the cosine of rotation angle in three demission. Equation (3) represents the expression of a new vector $R(t+1)$ getting from the vector $R(t)$ rotating at a certain angle in a reference coordinate.

$$R(t+1) = q \times R(t) \times q^{-1} \tag{3}$$

where $q = q_0 + q_1 i + q_2 j + q_3 k$, and i, j, k are unit vectors for the three Cartesian axes.

An object rotation can be described with roll γ, pitch θ and yaw ψ. If the initial rotation at time t_0 is known, we have:

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}_{t_0} = \begin{bmatrix} \cos(\gamma_0/2)\cos(\theta_0/2)\cos(\psi_0/2) + \sin(\gamma_0/2)\sin(\theta_0/2)\sin(\psi_0/2) \\ \sin(\gamma_0/2)\cos(\theta_0/2)\cos(\psi_0/2) - \cos(\gamma_0/2)\sin(\theta_0/2)\sin(\psi_0/2) \\ \cos(\gamma_0/2)\sin(\theta_0/2)\cos(\psi_0/2) + \sin(\gamma_0/2)\cos(\theta_0/2)\sin(\psi_0/2) \\ \cos(\gamma_0/2)\cos(\theta_0/2)\sin(\psi_0/2) - \sin(\gamma_0/2)\sin(\theta_0/2)\cos(\psi_0/2) \end{bmatrix} \tag{4}$$

Then, we can use the first order Runge-Kutta to update the rotation in quaternion from t_i to t_{i+1}:

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}_{t_{i+1}} = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}_{t_i} + \frac{(t_{i+1} - t_i)}{2} \begin{bmatrix} -\omega_\gamma q_1 - \omega_\theta q_2 - \omega_\psi q_3 \\ +\omega_\gamma q_0 - \omega_\theta q_3 + \omega_\psi q_2 \\ +\omega_\gamma q_3 + \omega_\theta q_0 - \omega_\psi q_1 \\ -\omega_\gamma q_2 + \omega_\theta q_1 + \omega_\psi q_0 \end{bmatrix}_{t_i} \tag{5}$$

The resolutions for γ, θ and ψ are:

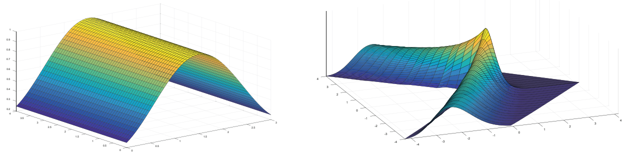
$$\begin{cases} \gamma_{i+1} = \arctan\dfrac{2(q_2q_3 + q_0q_1)}{q_0^2 - q_1^2 - q_2^2 + q_3^2} \\ \theta_{i+1} = -\arcsin(2(q_1q_3 - q_0q_2)) \\ \psi_{i+1} = \arctan\dfrac{2(q_1q_2 + q_0q_3)}{q_0^2 + q_1^2 - q_2^2 - q_3^2} \end{cases} \tag{6}$$

Thus, according to Eqs. (2) and (6), we can accurately estimate the PDR trajectory point.

3 Pedestrian Walking Model

3.1 Pedestrain Indoor Walking Habit Analysis

Generally, there are two common walking mode in the indoor environment, which are walking in straight and walking in corner. The probability model of pedestrian walking in straight is shown in Fig. 2(a). When pedestrians take turns, they tend to take "shortcut" in most cases. They will departure from the central axis and approach to the inside corner gradually. The probability model of the pedestrian walking in corner is shown in Fig. 2(b).



(a) Walking in straight (b) Walking in corner

Fig. 2. Pedestrian walking case

Based on the analysis above, we model the pedestrian walking habit with the Erlang distribution. Either in straight case or corner case, the trajectory point distribution can be described as:

$$f(x) = \frac{\lambda(\lambda x)^{k-1}}{(k-1)!} e^{-\lambda x} \tag{7}$$

where λ is the coefficient of Erlang, k is the order. When $\lambda = 0.5$, the distribution probability is shown in Fig. 3 to describe the PDR trajectory point distribution both for walking in straight and walking in corner.

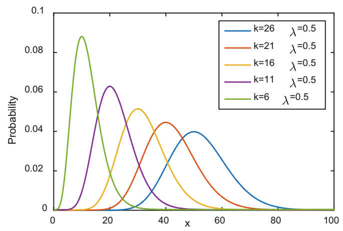


Fig. 3. Erlang distribution

In order to better analysis the distribution of trajectory points in corner, we illustrate a real crowdsourcing PDR trajectory points in Fig. 4, where the blue dots are PDR trajectory points and the red dash line are the hallway central. We further model the trajectory points distribution in Fig. 4 into three types of area as straight are, transition area and rotation area, which are used to describe the pedestrian walking in different cases in the hallway. We illustrated in Fig. 5.

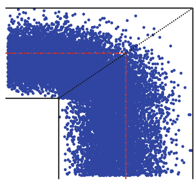


Fig. 4. Trajectory points distribution

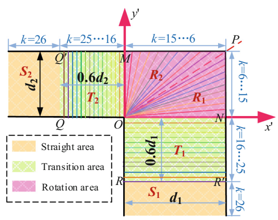


Fig. 5. Corner area division

As shown in Fig. 5, S_1 and S_2 are straight areas, which means pedestrian is walking in straight and does not tend to take a turn. T_1 and T_2 are the areas where pedestrian is ready to start or finish a turning. R_1 and R_2 are rotation areas, which means pedestrian is turning a corner. Suppose the hallway width of S_1 area and T_1 area are d_1, and the hallway width of S_2 area and T_2 area are d_2. The boundaries of S and T are QQ' and RR', and the boundaries of T and R are OM and ON respectively. The boundary of R_1

and R_2 is OP. According to our experiment results, we find that if the hallway width is d, pedestrian will start and finish the turning at $0.6d$. So, we set the length of OQ is $0.6d_1$ and the length of OR is $0.6d_2$ in transition area.

3.2 Pedestrian Walking Model

We assume pedestrians start from the S_2 area and passes through S_2-T_2-R_2-R_1-T_1-S_1 in clockwise. When they are walking in the S_2 area, they tend to walking in a straight central axis of hallway. Then the order of Erlang distribution is $k = 26$. When pedestrians pass QQ' and walk into the T_2 area, their walking paths are gradually approaching to the inside corner point O. In this area, k gradually decreases from 25 to 16, until pedestrians cross OM into the R_2 area. When pedestrians are in turning state, their walking trajectories are gradually close to the corner point O. Until walking to the cross section OP, the pedestrians are closest to the corner O. The order of Erlang distribution k now gradually decreases from 15 to 6. When pedestrians cross the diagonal OP and continue to walk, their paths are gradually away from O and return to the central axis of the hallway. The path will be back to the axis of the hallway on RR'. The returning process is similar to the turning process and the order k is increased from 6 to 25. In this way, we divide T_2, R_2, R_1, and T_1 equally. T_1 and T_2 areas are divided into 10 segments, and the order of Erlang distribution k is from 16 to 25. R_1 and R_2 areas, taking the inner corner as the center of the circle, are equal divided into 10 segments, where k varies from 6 to 15. As shown in Fig. 3, the width and position of Erlang major distribution area are changes with the change of k. So, we introduce scaling coefficient t to make the width of Erlang major distribution area consistent with the hallway cross section. And we introduce deviation coefficient a/λ to make Erlang major distribution area corresponding to the actual location of PDR trajectory. In this way, Eq. (7) can be rewritten as follows:

$$f(x, \alpha_i, k_i) = \frac{\lambda[\lambda(tx + a/\lambda)]^{k_i - 1}}{(k_i - 1)!} e^{-\lambda(tx + a/\lambda)} \tag{8}$$

$$\lambda = b\left[(d_1 \cos\alpha_i)^2 + (d_2 \sin\alpha_i)^2\right]^{-1/2} \tag{9}$$

where $a = 0.062k_i - 3.463$, $b = 0.151k_i + 2.478$.

Combining the coordinate translation and the change matrix, we can unify all cases to the coordinate system shown in Fig. 4 (Fig. 5). The coordinate translation in S_2, T_2, R_2, R_1, T_1, and S_1 is:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\alpha_i & -\sin\alpha_i \\ \sin\alpha_i & \cos\alpha_i \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ y_{step} \end{bmatrix} \tag{10}$$

Thus, we can get the probability density distribution of trajectory point in different areas as follows:

$$f = \frac{\lambda[\lambda(10x' + a/\lambda)]^{k_i - 1}}{(k_i - 1)!} e^{-\lambda(10x' + a/\lambda)} \tag{11}$$

So in different areas, we have different a and k. In straight area S_1 and S_2:

$$\alpha_i = 0, \quad k_i = 26 \tag{12}$$

In transition area T_2:

$$\alpha_i = \frac{\pi}{2}, \quad k_i = 26 - \left\lceil 10 + \frac{x'}{0.06d_2} \right\rceil \tag{13}$$

In rotation area R_2:

$$\alpha_i = 0.1i \ \arctan(d_2/d_1) + \arctan(d_1/d_2), \quad k_i = 6 + i \tag{14}$$

In rotation area R_1:

$$\alpha_i = 0.1\, i \arctan\left(d_1/d_2\right), \quad k_i = 16 - i \tag{15}$$

where we have i = 0,…,10. In transition area T_1:

$$\alpha_i = 0, \quad k_i = 26 - \left\lfloor 10 + \frac{y'}{0.06d_2} \right\rfloor \tag{16}$$

where α_i is the angle of rotation, k is the Erlang coefficient.

In summary, the pedestrian trajectory points distribution in hallway can be expressed as follows:

$$f' = f(x', \alpha_i, k_i) \tag{17}$$

where α_i and k_i can be summarized as follows:

$$\alpha_i = \begin{cases} 0.1i \arctan\frac{d_1}{d_2} & i = 0, \ldots, 10 \\ 0.1(i - 10) \arctan\frac{d_1}{d_2} + \arctan\frac{d_1}{d_2} & i = 11, \ldots, 20 \\ 0 & \text{others} \end{cases} \quad k_i = \begin{cases} 16 - i & i = 0, \ldots, 10 \\ i - 4 & i = 11, \ldots, 20 \\ i - 5 & i = 21, \ldots, 30 \\ 25 & \text{others} \end{cases} \tag{18}$$

And the step of each part can show as follows:

$$y_{step} = \begin{cases} 0 & \text{rotation area} \\ l \times n_i/n & \text{others} \end{cases} \tag{19}$$

where l is the length of hallway, and n_i/n is step radio.

In above equations, all the parameters are known without the hallway width d_1 and d_2. We will estimate the hallway width in the following subsection.

3.3 Hallway Width Estimation

Large number of experiment data show that when the pedestrians are far away from the starting point, their trajectory points will be more divergent leading to errors. There are two reasons causing errors. The first one is PDR algorithm will inherently accumulate the measurement error. With the extension of the walking distance, the error accumulation of the PDR algorithm will lead to a divergence of the trajectory. The second reason is the accumulated error generated by gyroscope of smartphone. The error caused by calculate of heading angle will lead a divergence phenomenon when the PDR trajectory passes the turning point. Thus, PDR trajectories obtained by crowdsourcing users will be partially inaccurate as shown in Fig. 6.

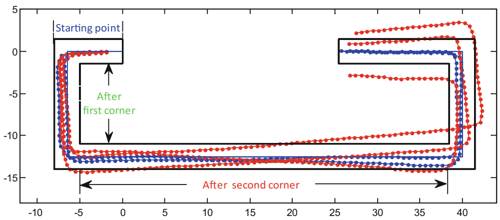


Fig. 6. PDR trajectory diagram

At different locations, the trajectory points distribution at the cross section of hallway are shown in Fig. 7.

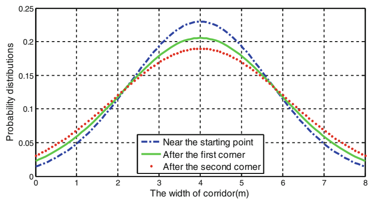


Fig. 7. The relationship between starting point and probability distributions

Because of the PDR error, some PDR trajectory points will be outside the real hallway. If we select these outliers to estimate the hallway width, a larger hallway width maybe got. To solve this problem, we introduce the turning factor m and the correction factor ξ to estimate the hallway width as:

$$d = \xi(\sigma - m \times \gamma) \tag{20}$$

where γ is the number of corners that one PDR trajectory turns, σ is the standard deviation of Erlang probability distribution function. On account of the standard deviation can reflect the dispersion of the random variables, we use σ to describe the major distribution area of Erlang distribution.

As we known, though two straight hallways are connected by one corner, they do not always have the same width. We should estimate the hallway width respectively. The next step is to distinguish trajectory points which are belong to the same straight areas. As shown in Fig. 8, there are lots of PDR trajectories start nearly from the middle of the floor plan, which are actually to show pedestrians walk from the elevators. And then pedestrians turn left or right for their ways.

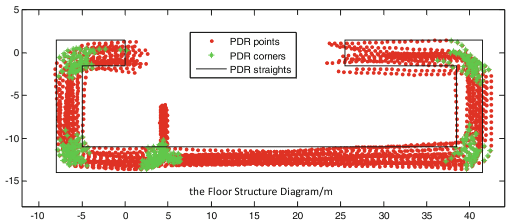


Fig. 8. The filter result of PDR trajectory points in corner (Color figure online)

The estimation of hallway width can be seen as the estimation of major distribution area of PDR trajectory points projected to the cross section of hallway. Therefore, we further process the PDR data of straight hallway (red point in Fig. 8) by clustering method to distinguish whether the PDR trajectory point is belong to the straight area or not. We then segment the straight hallway evenly and project the trajectory points to the hallway cross section. Therefore the histogram of occurrence is established and fitted with the Erlang distribution of $k = 26$. Finally, we can get σ for different straight area. According to analysis of massive straight hallway PDR data, we can further get the parameter m and γ.

4 Implementation and Performance Analysis

4.1 Experiment Environment

We make an experiment in our lab, which is located in Information building, Science Park of Harbin Institute of Technology, China, as shown in Fig. 9. In this building, the main experimental environment is the indoor hallway illustrated with blue part. The crowdsourcing PDR trajectory acquisition equipment are Google Nexus 4, Google Pixel and Redmi 3. We use the PDR algorithm to generate the PDR trajectories for indoor floor plan building, and the original data are collected based on the acceleration and gyro from the smartphones stated above.

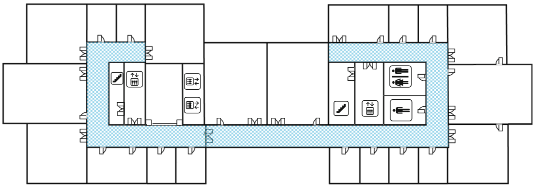


Fig. 9. The diagram of experimental environment in hallway (Color figure online)

4.2 Performance Analysis

In this experiment environment, there are 5 turnings, and there remains 6 different straight hallways as shown in Fig. 10. Different color represents the result of clustering, and the black points means the noise.

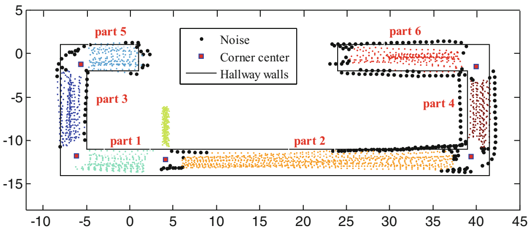


Fig. 10. Straight area diagram (Color figure online)

According to a large number of straight hallway data testing and simulation, we can get turning factor m and correction factor ξ as shown in Table 1.

Table 1. Results of hallway width estimation

	Part1	Part2	Part3	Part4	Part5	Part6
σ	0.660	0.668	0.863	0.844	0.960	1.078
m	1	1	2	2	3	3
$m \times \gamma$	0.216	0.216	0.432	0.432	0.648	0.648
$\xi(\sigma - m \times \gamma)$	3.108	3.164	3.017	2.884	2.184	3.011

In our proposed model, the correction factor $\xi = 7$, and the turning factor $m = 0.216$. Based on the summary of Table 1, the hallway width in the 6 part are respectively 3.1 m, 3.2 m, 3.0 m, 2.9 m, 2.1 m and 3.0 m. The width we estimate is similar to the true value of hallway width except part 5. Finally, we get the floor boundary as shown in Fig. 11, and this boundary is the indoor hallway environment floor plan based on crowdsourcing PDR data.

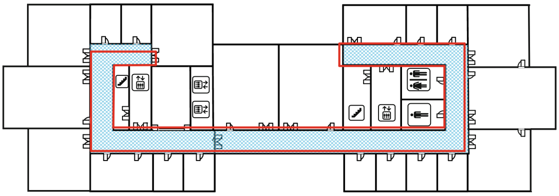


Fig. 11. The final generated floor plan in experiment environment

5 Conclusion

In this paper, we proposed a novel floor plan building method based on the crowd-sourcing PDR data. We build an indoor pedestrian walking mode, which includes walking in straight and walking in corner. Based on the analysis of the PDR trajectory points of straight hallway, the hallway width can be estimated. We use turning factor and correction factor to restore the width of the hallway well. Finally, by solving the hallway width, the contour of the PDR is generated, and the accurate indoor floor plan can be obtained. This algorithm can establish the floor plan more efficiently when lacking floor plan in an unknown indoor environment.

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