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Heading Constraint Algorithm Based on WiFi Fingerprint Positioning

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Abstract

In order to solve the problem of low positioning accuracy caused by fluctuations in received signal strength, non-line-of-sight effects and time-varying factors in WiFi location positioning, this paper introduces a pedestrian heading calculation algorithm (PDR) to solve the problem of low WiFi fingerprint positioning accuracy. The WiFi fingerprint database is used to calculate the similarity of the real-time signal strength in the fingerprint database through the fuzzy weighted nearest neighbor matching algorithm (FW-KNN) to estimate the target position, and then the pedestrian heading calculation algorithm is used to estimate the target position. Finally, the WiFi is used to The estimation of the target position uses the particle filter method to constrain the heading of the PDR, which ultimately improves the accuracy and robustness of the positioning coordinates.

Keywords

Fingerprint positioning; FW-KNN; particle filter; heading calculation.

1. Introduction

The wide application of WiFi technology has made new progress in indoor pedestrian positioning technology. Although it has made up for the lack of accuracy of traditional positioning methods, the WiFi signal strength is unevenly distributed. In places with weak signals, the real-time positioning is severely limited, so This time, a new positioning method is proposed, combined with inertial navigation technology, to solve real-time problems, and achieve the effect of learning from each other and complementing each other[1]. It mainly includes two parts: the first part uses WiFi fingerprinting method to obtain the estimated position of pedestrians, and the second part uses inertial navigation technology for correction, and the two jointly locate the accurate pedestrian positions. In order to test the effectiveness of this method, simulation results show that compared with ultrasonic positioning method, radio frequency identification positioning method and infrared positioning method, the performance of this method is superior. It not only achieves the positioning accuracy requirement target, but also ensures the positioning accuracy real-time[2].

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method is superior[3]. It not only achieves the positioning accuracy requirement target, but also ensures the positioning accuracy real-time.

2. Positioning Method

2.1. Based on WiFi Fingerprint Positioning Method

The WiFi fingerprint positioning method is mainly divided into offline training phase and online positioning phase. In the offline training phase, the sampling points of the area to be located are planned, and the sampling points are sampled multiple times to establish a fingerprint database. In the online positioning phase, the current RSSI data information acquired by the current terminal is matched with the database fingerprint data to determine the current location of the point to be measured. Due to the uneven distribution of indoor APs, the effect of blurring the AP points can reduce the impact of the distance between the AP point and the positioning point. In the positioning stage, the fuzzy weighted nearest neighbor matching algorithm (FW-KNN) is used to estimate the current position. The positioning principle is shown in Figure 1.

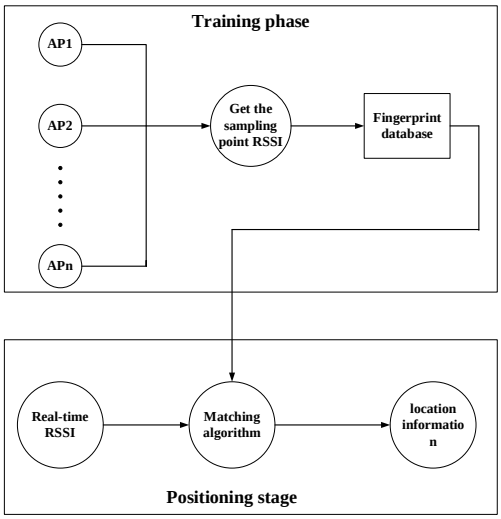

Figure. 1 Schematic diagram of WiFi fingerprint positioning principle

In the offline training phase, the fingerprint location of the area to be located is divided, the fingerprint collection point is determined, the RSSI sequence of each sampling point is collected and a database is established. The database contains the location information of the sampling point and the fingerprint information of each AP point[4]. The WiFi fingerprint on the i-th reference point (RP_i) is:

$$FW_i = \left\{ (x_i, y_i), (ssid_{i,1}, rssi_{i,1}), (ssid_{i,2}, rssi_{i,2}) \cdots, (ssid_{i,m_j}, rssi_{i,m_j}) \right\} \tag{1}$$

Among them: (x_i, y_i) is the position coordinates of point RP_i; $ssid_{i,m_j}$ and $rssi_{i,m_j}$ are the service set identification and signal strength of AP nodes received at point RP_i respectively; m_i is the number of AP nodes received at point RP_i.

In the online positioning stage, the real-time position is estimated based on the currently measured RSSI information. The fingerprint matching algorithm used in the online positioning phase is the FW-KNN algorithm, that is, by calculating the Euclidean distance between the real-time positioning point and the reference point in the database, the K fingerprint points with the highest similarity to the real-time positioning point are found, and the K fingerprints are weighted. The weight of the point and the estimation result from it. The Euclidean distance between the real-time positioning point and the reference point is:

$$EDis = \sqrt{\sum_{m_i}^{i=1}\left(rssi_{i,m_j} - rssi_{0,m_j}\right)^2} \tag{2}$$

Among them: $rssi_{0,m_j}$ is the WiFi signal strength measured in real time at the current location. Under normal circumstances, the value of K is 4. Select the K fingerprint nodes with the smallest Euclidean distance as the neighbor points, and calculate the Euclidean distance from the signal strength of the real-time positioning point to each neighbor point:

$$EDis_i = \sqrt{\left(rssi_{i,m_j} - rssi_{0,m_j}\right)^2} \tag{3}$$

Fuzzy $EDis_i$ performs normalization processing on K fingerprint nodes according to a certain weight, and obtains the weight ω_{i,m_j} of each $rssi_{i,m_j}$. Calculate the weight of WiFi fingerprint points, and estimate the coordinates of the current point to be measured according to the weight of each WiFi fingerprint point.

2.2. PDR Positioning Method

2.2.1. Gait detection

The walking process of a person is a cyclical alternating action, which is divided into two actions: stepping and closing feet. When a person is walking, the center of gravity will move up, and the direction of acceleration will be upward; when the foot is retracted, the overall center of gravity will move down, and the resulting acceleration will be downward, so when a person is walking continuously, the acceleration will show periodic changes, And the number of cycles of change is regarded as the number of walking steps[5].

Gait detection can be realized by a three-axis acceleration sensor in the user's mobile terminal. When the user carries the mobile terminal and completes the continuous walking action, the built-in acceleration sensor collects the acceleration value at regular intervals to obtain the acceleration change law. However, because the three-axis acceleration sensor collects acceleration signals, it will be affected by interference factors, resulting in quality degradation. Therefore, it is necessary to process the acquired original acceleration signals to eliminate interference. The processing mainly includes three items: mean filtering and elimination of random errors. And noise interference.

$$Y_i = \frac{\sum_{\frac{w-1}{2}}^{j=-\frac{w-1}{2}} Y(i+j)}{w}, i = \frac{w-1}{2}+1, \frac{w-1}{2}+2, \cdots, N-\frac{w-1}{2} \tag{4}$$

in the formula, Y_i represents the i-th mean filtered data; w is the window length; N is the number of data to be processed.

Low-pass filtering to eliminate gravity interference:

$$\begin{cases} y_1 = y_2 + r\left(y_3 - y_2\right) \\ y_2 = y_1 \end{cases} \tag{5}$$

in the formula, y_1 is the data processed by low-pass filtering; y_2 is the data processed by the previous low-pass filtering; y_3 is the original acceleration data obtained at this moment; r is the filter coefficient, and the value is [0, 0.5].

The three-axis acceleration synthesis eliminates the interference of the mobile terminal's posture during the walking process.

$$Y_{total} = \sqrt{y_x + y_y + y_z} \tag{6}$$

In the formula, Y_{total} is the synthesized acceleration; y_x, y_y, y_z are the acceleration values of the x-axis, y-axis, and z-axis, respectively.

2.2.2. Step calculation

The step length is also one of the basic data to realize the estimation of the target position. Due to differences in individual height, weight, and striding habits, there are also large differences in step length. In order to accurately calculate the individual step length, calculations need to be carried out according to the following three models.

Constant step length estimation model: Build a step length storage table based on a large number of experiments, and then select the corresponding value from the table according to the acceleration value of the target object.

Non-linear step length estimation model:

$$G = v \times \sqrt[4]{f_{\max} - f_{\min}} \tag{7}$$

In the formula, v is the training model parameter; $f_{\max}$, $f_{\min}$ maximum and minimum acceleration in the gait cycle.

2.2.3. Heading acquisition

Heading acquisition refers to clarifying the user's walking direction. There are two ways to achieve it: the first is to obtain the heading through the direction sensor; the second is to obtain the heading through the gyroscope. Choose the latter here to complete the course acquisition.

The gyroscope can measure the angular velocity values around each axis of the mobile phone. Under the premise that the initial heading angle is known, a relative heading angle can be obtained through integration, and then converted into the real walking direction of pedestrians through coordinate conversion.

2.2.4. Location estimate

According to the different principle and mechanism of position calculation, it can be divided into two types: continuous integral positioning and pedestrian track calculation (PDR). The second kind of calculation is selected here, and the basic process is as follows.

Step 1: Parameter input. The initial position of pedestrian walking is $l_0(x_0, y_0)$, φ_0 course.

Step 2: Measure the pedestrian step length r_1, and calculate the pedestrian's current position $l_1(x_1, y_1)$ by the following formula (8).

$$\begin{cases} x_1 = x_0 + r_1 \sin(\varphi_0) \\ y_1 = y_0 + r_1 \cos(\varphi_0) \end{cases} \tag{8}$$

Step 3: Calculate the pedestrian position coordinates, the formula is as follows:

$$\begin{cases} x_{i+1} = x_i + r_{i+1} \sin(\varphi_i) \\ y_{i+1} = y_i + r_{i+1} \cos(\varphi_i) \end{cases} \tag{9}$$

3. Particle Filter Fusion Positioning

This paper proposes a positioning method that uses particle filtering to fuse WiFi fingerprint data and PDR data. The basic idea is: first generate a set of random particles from the initial state, calculate the weight of the particles through measurement, and then take the average value according to the weight to obtain the optimal estimate. The WiFi fingerprint location is used as the observation data, and the PDR data is used to model the user's motion behavior.

Suppose the particle set is $H = \{X^i \mid i = 1, 2, \cdots, n\}$, and n is the number of particles. The state space of the system is $X = (x, y, v_x, v_y)^T$, and the state space of the particle is $X^i = (x^i, y^i, v_x^{\,i}, v_y^{\,i})^T$.

Assuming that the position coordinate of the person at k-1 is (x_{k-1}, y_{k-1}), the duration from k-1 to k is Δt_k, the distance traveled in this time period is l_k, and the angle between the movement direction and the y-axis is θ, then the person is at The position coordinates at time k are:

$$\begin{cases} x_k = x_{k-1} + l_k \cdot \sin\theta \\ y_k = y_{k-1} + l_k \cdot \cos\theta \end{cases} \tag{10}$$

Assume that $v_{x,k}$ and $v_{y,k}$ are the speed of a person in the x direction and the y direction in the Δt_k period. Since the speed change during normal walking is a gradual process, and the speed change between two adjacent steps is very small, it can be considered that the speed at time k is approximately equal to the speed at time k-1, namely:

$$\begin{cases} v_{x,k} = v_{x,k-1} \\ v_{y,k} = v_{y,k-1} \end{cases} \tag{11}$$

When a new observation data is obtained from the WiFi fingerprint positioning at time k, the weights of all particles need to be updated, and particle re-sampling is performed, and particles with large weights are retained and particles with small weights are discarded. Update the weights of the particles in the geomagnetic field around the point to be measured. The distance between the particles around the point to be measured and the point to be measured obeys the Gaussian distribution, that is, the new weights of the particles are normalized:

$$\omega_k^i = \bar{\omega}_k^i / \sum_n^{j=1} \bar{\omega}_k^j \tag{12}$$

Particle resampling uses random resampling. According to the particle update weight, the particles are arranged in the [0,1] interval to form the particle weight interval. Randomly generate n [0,1] interval numbers, and copy and add the corresponding particle set according to the weight interval. Particles with a large weight occupy a longer interval and have a higher probability of being randomly selected, while particles with a smaller weight occupy a shorter interval and a smaller probability of being randomly selected, so that particles with a larger weight can be retained. According to the updated particle state and particle weight, calculate the current

$$X_k = \sum_n^{i=1} \omega_k^i \cdot x_k^i \tag{13}$$

(x_k, y_k) is the current position of the pedestrian.

4. Experimental Verification

The second floor of the 1st teaching building of Chongqing University of Posts and Telecommunications was selected as the experimental site. During WiFi fingerprint collection, sampling points are set on the two stair buckles on the 2nd floor. The experimental scene is shown in Figure 2.

Finally, through the path of pedestrians from point A to point B, the final actual trajectory of the WiFi fusion PDR is used. Figure 4 shows that the deviated position is calculated at some positioning positions, and the two kinds of data are merged by particle filter, which can effectively solve the calculation. The position returns to the original route, and the positioning accuracy is high. Joint positioning based on particle filtering can improve the accuracy and stability of indoor positioning.

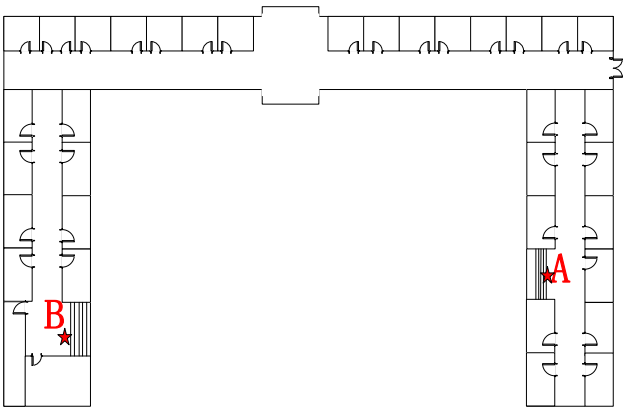

Figure. 2 Test scene on the 2nd floor of Teaching 1

Figure 3 shows the collection of the number of WiFi for 30 minutes at point B.

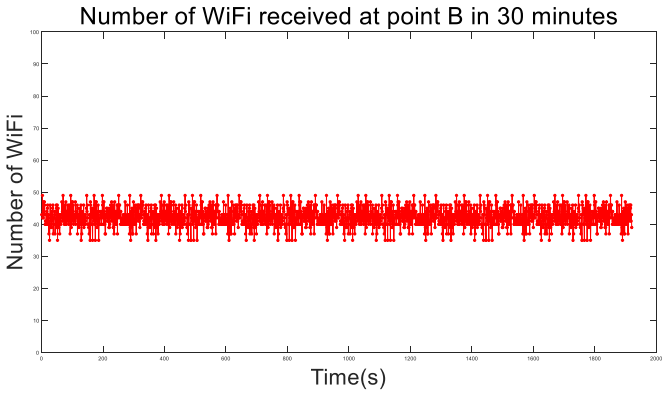

Figure. 3 Collecting the number of WiFi at point B in 30 minutes

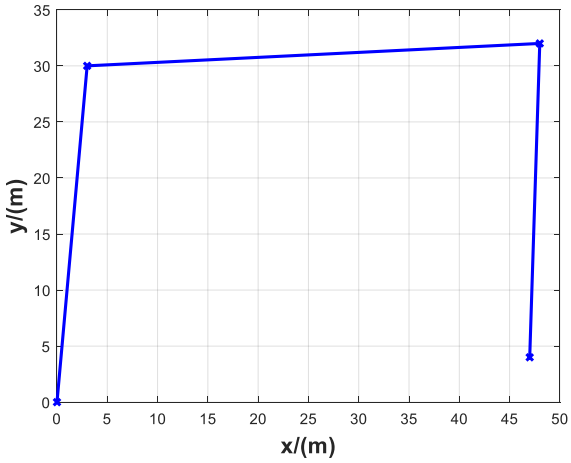

Figure. 4 Particle filter fusion positioning trajectory

5. Summary

In order to improve positioning accuracy and positioning stability, this paper proposes a joint positioning method based on particle filter fusion WiFi and PDR. In the aspect of PDR detection and positioning, the idea of dynamically setting the threshold to detect gait is proposed. In the aspect of WiFi positioning, the fuzzy weighted WiFi fingerprint solution method is proposed, and the particle filter algorithm is used to fuse the data. The use of this solution eliminates the cumulative error of inertial navigation, improves the stability and continuity of WiFi positioning, and improves positioning accuracy. However, for higher-precision indoor positioning requirements, such as centimeter-level precise positioning effects, and

technologies used in high-precision indoor positioning requirements, follow-up research remains to be done.

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