Mine personnel location system based on Internet of things

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Abstract. For the problems that the RSSI fingerprint location algorithm was easily influenced by underground environment, and it is prone to coordinate jumps, and the pedestrian dead reckoning algorithm(PDR) had accumulative error. This paper proposes a fusion personnel location method based on RSSI fingerprinting algorithm and PDR algorithm. The positioning terminal uploads the collected inertial sensor data and RSSI data to location server on the ground through the underground WiFi network. The location server uses particle filter to fuse the RSSI fingerprint location algorithm and the location information of the PDR location algorithm to achieve the positioning of the underground personnel. The results shows that the proposed fusion algorithm cannot only improve the environmental interference caused by the use of the RSSI fingerprint algorithm alone, but also avoid the cumulative error caused by the use of the pedestrian dead reckoning algorithm alone. The average location error is 2.5m, achieving the accurate location of underground personnel.

1. Introduction

The newly revised “Coal Mine Safety Regulations” requires that the mine should be equipped with a mine personnel positioning system with the precise positioning of coal mine personnel [1]. At the same time, the precise positioning of coal mine personnel is also a problem that must be solved in the implementation of coal mine rapid and effective emergency rescue [2].

According to the research and application analysis of the methods for locating underground personnel at home and abroad, there are mainly positioning methods based on wireless signal strength, angle measurement and time based distance measurement [3]. At present, most of the mine positioning systems use a positioning method based on wireless signal strength. The positioning technology is mature and does not require additional technical equipment, and the cost is low. The literature [4,5] uses RSSI fingerprinting algorithm to achieve underground positioning, but it needs to collect signals at certain intervals, which is time-consuming and labor-intensive and costly. The traditional RSSI fingerprinting algorithm is applied directly to the underground. In [6], the PDR algorithm was used to achieve the underground positioning, but the initial positioning position alignment problem was not mentioned.

This article chooses the miner as the research object. For the problems of RSSI fingerprint positioning stability is poor and the estimation error of PDR is unprecise, we combined the advantages of the two algorithms, a particle filter fusion positioning method is proposed. The method effectively improves the problem that the RSSI fingerprint positioning is greatly affected by the environment, and avoids the cumulative error problem caused by using the inertial navigation alone. The average positioning error of the system is 2.5m, which is suitable for the location of moving targets in the underground.
2. System architecture
The underground personnel positioning system is mainly composed of a ground monitoring center, an industrial Ethernet ring network, an intrinsically safe AP, and a portable location terminal. The intrinsically safe AP constitutes the underground wireless network, forming the coverage of the underground wireless network. The ground monitoring center realizes the position monitoring of the positioning terminal through Industrial Ethernet and wireless networks. The overall architecture is shown in Figure 1.

![Figure 1 Composition of mine personnel location system](image1)

The positioning terminal is carried by miners and its composition is shown in Figure 2. The inertial sensor adopts MPU9150 chip, which integrates accelerometer, gyroscope, magnetometer, it has low power consumption, high performance. The GS1011 controller integrates WiFi module, which uploads the acceleration, angular velocity, and magnetic field direction collected by the inertial sensor and the RSSI data received by the positioning terminal to location server on the ground. The RSSI fingerprint database and the PDR algorithm are used to perform particle filter fusion position.

![Figure 2 Composition of location terminal](image2)

3. Fingerprint location based on RSSI and pedestrian dead reckoning

3.1. RSSI fingerprint location algorithm
The RSSI fingerprint location algorithm includes off-line sampling stage and positioning matching stage [7]. In the off-line sampling stage, RSSI information is collected for some calibration positions, and RSSI fingerprint database of sample point is principle of RSSI fingerprint location algorithm established. The location matching stage matches the signal strength obtained by the terminal with the fingerprint information in the fingerprint database, and finally obtains the location of the terminal. Commonly used matching algorithms are deterministic algorithms, neural network algorithms, and K-nearest neighbor algorithms. This article uses the K-nearest neighbor algorithm. Its matching criteria are follows.

\[
D_i = \sum_{m=1}^{n} A_i \left(RSSI_{m} - RSSI_i\right)^2, \quad i=1,2,\ldots,m
\]

(1)

\[
A_i = \frac{1}{\sum |RSSI_i|}
\]

(2)

Where $D_i$ represents the improved Euclidean distance of all received APs’ RSSI values and corresponding RSSI averages in the area where the terminal is located. $n$ is the number of RSSI received the AP, $RSSI_i$ is the value of RSSI received the ith AP, $RSSI_i$ is the average value of RSSI received the ith AP, $A_i$ is the weight of the ith AP.
After all Euclidean distance are completed, the K samples with shortest Euclidean distance are taken. Then find centroids of K sample, whose centroids are the estimated position of the anchor points. In order to further improve the accuracy of the positioning, the Euclidean distance based weighted centroid algorithm is used to calculate the position of the centroid.

\[
(x, y) = \sum_{i=1}^{k} a_i \ast (x_i, y_i) , \quad a_i = \frac{1/D_i}{\sum 1/D_i}
\]

(3)

Where \(a_i\) is the weighting factor, \((x_i, y_i)\) is the coordinates of the calibration position, \((x, y)\) is the coordinate of centroid.

### 3.2. PDR algorithm

The PDR algorithm uses the data provided by the inertial sensors, combines the initial position to estimate the motion pitch, step, and direction angles, and uses equation (4) to estimate the position of the next moment.

\[
\begin{align*}
    x_{k+1} &= x_k + l_{k+1} \sin \phi_{k+1} \\
    y_{k+1} &= y_k + l_{k+1} \cos \phi_{k+1}
\end{align*}
\]

(4)

In equation (4): \((x_k, y_k)\) is the coordinates of the location of the person's k step, \(l_{k+1}\) is the step size of the k+1 step, \(\phi_{k+1}\) is the direction angle of the k+1 step. However, the key to track calculations is the estimation of the pitch, the step size, and the heading angle. According to the components of the \(a_x, a_y, a_z\) that the accelerometer given the direction of \(X, Y, Z\), we can acquire the original acceleration data \(a = \sqrt{a_x^2 + a_y^2 + a_z^2}\). Kalman filter is used to filter high-frequency noise, peak detection is used to detect the step frequency. The step estimation model has the machine step estimation model, the linear relation step model, the Non-linear relation step model and the neural network step model [9]. To meet the present situation and the convenience of calculation, the step estimation is carried out using a non-linear model with moderate stability and complexity, as shown in the equation (5).

\[
L = K \ast 4\sqrt{a_{\text{max}} - a_{\text{min}}}
\]

(5)

Where L represents the length of the pedestrian’s steps, \(a_{\text{max}}\) is the value of the maximum acceleration measured by the pedestrian during this step, \(a_{\text{min}}\) represents the pedestrian’s minimum acceleration measurement. K is the parameters of the nonlinear relationship step model, it can be corrected according to the actual step size.

The system uses the four-number method [9] to estimate the heading angle, uses the four-number method to solve the attitude matrix, calculates the attitude angle of the terminal, and obtains the pedestrian's movement direction.

### 4. Particle Filter Fusion Positioning

After receiving the RSSI data from the location terminal and the inertial sensor data, the locating server estimates the step frequency, step length and direction angle by the PDR algorithm, and uses the improved Euclidean distance and K nearest neighbor algorithm to match the RSSI data, and estimates the location result. Finally, the initial position of PDR location is obtained by WiFi location, and the fusion location is achieved by particle filter. The fusion positioning process is shown in Figure 3.
4.1. Particle Initialization
Assuming that the pedestrian’s initial position is \((x_0, y_0)\), and the particle’s structure is \(X_i = [x_i, y_i, \omega_i, \theta_i]^T\), indicates the two-dimensional coordinates of the pedestrian, \(\omega_i\) is the position weights, \(\theta_i\) is the heading angles. Each particle represents a pedestrian’s possible movement status information.

4.2. Particle propagation model
Adopting pedestrian dead reckoning techniques to estimate the position of pedestrians, different directions will produce different location information. Therefore, the particle propagation model is given by:

\[
\theta_i' = (1 - \omega_{i-1}) \times \theta_{i-1} + \omega_{i-1} \theta_i
\]  

(1)

Where \(\theta_i\) is the Kalman filter merges the heading information after the magnetometer and the gyroscope, \(\theta_i'\) is the heading information of the ith particle, \(\omega_{i-1}\) is the weight value of the ith particle.

4.3. Pedestrian Coordinate Estimation and Particle Weight Update
Pedestrian position calculation formula is given by

\[
X_i' = \begin{bmatrix} x_i' \\ y_i' \\ \omega_i' \\ \theta_i' \end{bmatrix} = \begin{bmatrix} x_{i-1}' \\ y_{i-1}' \\ \omega_{i-1}' \\ \theta_{i-1}' \end{bmatrix} + \begin{bmatrix} L_i \times \cos \theta_i' \\ L_i \times \sin \theta_i' \\ n_x \\ n_y \end{bmatrix}
\]

(2)

Where \(x_i', y_i'\) is the position coordinates of the pedestrian, \(\theta_i'\) is the heading angle of the i particle, \(L_i\) is the step length at time \(t\), \(n_x, n_y, n_\theta\) are independent zero mean Gaussian white noises.

Therefore, the weight update equation of particle is given by

\[
\omega_i' = \frac{1}{\pi} \times e^{-\frac{1}{c} \sqrt{(x_i' - x) + (y_i' - y)^2}}
\]

(3)

Where \((x_i', y_i')\) is the position coordinate of the ith particle, \((x, y)\) represents the position coordinates of fingerprint positioning, \(c\) is the compensation constant.

The normalized formula for weights is shown as follows

\[
\omega_i' = \frac{\omega_i'}{\sum_{i=1}^{N} \omega_i'}
\]

(4)

4.4. Target position calculation
Through the three steps above, we can get the position information of pedestrians and their corresponding weights, and finally use the weighted criterion to estimate the final target location.
5. System test

In this experiment, the performance test of the system was performed in the straight roadway of Yongmei Coal Group. The laneway is a straight structure with a width of 3m. The length of the test area is selected to be 100m. In actual tests, two wireless access points (APs) are placed at both ends of the test area. In the off-line sampling phase, AP1 is used as the starting point, and the roadway travels at a constant speed of 1.5m along the roadway. The positioning terminal performs fingerprint sampling every 2m intervals. The sampling time is 60s. It traverses the required laneways and stores the collected data in the fingerprint database. In the positioning and matching stage, the user carries the positioning terminal and moves from AP1 to AP2. The walking distance is 100m. The time interval for positioning detection is 2s. The experiment has a total of 30 position points.

In order to more accurately evaluate the performance of the method, cumulative distributions of errors are used to show the cumulative distribution of errors in the method shown in Figure 4. The convergence probability of the fusion location algorithm converges to 1 at the fastest rate, which is greater than any single location algorithm. The probability of the fingerprint positioning algorithm error within 5m is 58.85%, the probability of the tracking algorithm deriving the positioning algorithm error within 5m is 50.25%, and the probability of the fusion positioning algorithm error within 5m is 86.21%. It is 1.46 times and 1.72 times the single fingerprint algorithm and the track estimation method.

![Figure 4 Cumulative distribution of positioning error](image1)

![Figure 5 Location Error of different location algorithms](image2)

| Location algorithm | Minimum error | Maximum error | Average error |
|--------------------|---------------|---------------|--------------|
| Fingerprint        | 0.32m         | 9.93m         | 3.82m        |
| PDR                | 1.06m         | 11.01m        | 5.41m        |
| Fusion             | 0.56m         | 5.50m         | 2.50m        |

From the positioning error analysis shown in Figure 5 and Table 1, it can be seen that the positioning effect is not stable by using RSSI fingerprint positioning alone, and the phenomenon of coordinate jumps is likely to occur. The short-term positioning accuracy is better by using the PDR location alone. But with the increase of time, there is a problem of error accumulation. However, in
this paper, using the fusion location algorithm, the maximum positioning error is 5.5m, the average positioning error is 2.5m, and the precision is significantly higher than the other two algorithms. For a few kilometers of roadway, fully meet the positioning accuracy requirements.

6. Conclusion
This article chooses the miner as the research object. In order to improve the positioning accuracy of the underground personnel, the localization method of particle filter fusion RSSI fingerprint positioning and pedestrian dead reckoning is proposed, and the particle propagation model is established. The results show that the fusion algorithm preserves the advantage of short-term positioning accuracy of PDR, weakens the phenomenon of fingerprint positioning coordinate jump, and effectively improves the accuracy and stability of positioning.

References
[1] Sun Jiping, Jiang Ensong. Target location method for curved roadway based on secondary reconstruction of ranging value[J]. Journal of China Coal Society, 2018, 43(01):287-294.
[2] Sun Jiping, Qian Xiaohong. Coal Mine Accident and Emergency Rescue Technical Equipment[J]. Mining and Industry Automation, 2016, 42(10): 1-5.
[3] Sun ZheXing, Wang YanWen. Accurate two-dimensional location method for mine personnel based on Kalman filter[J]. Mining and Industry Automation, 2018, 44(05): 31-35.
[4] Li Lu, Ding Enjie, Hao Lina, Zhang Lei. An Improved Fingerprint Matching Algorithm in Coal Mines[J]. Journal of Transducer Technology, 2014, 27(03): 388-393.
[5] Wang Tao. Research on mine location algorithm based on location fingerprint[D]. Xuzhou: China University of Mining and Technology, 2015.
[6] Li Shiyin, Wang Hao, Zhang Nan. Underground personnel location system based on MEMS inertial sensor[J]. Coal Mine Safety, 2017, 48(4): 111-114.
[7] Yao Zhifeng. Design and implementation of multi-information fusion indoor system based on Wi-Fi and inertial sensors [D]. South China University of Technology, 2016.
[8] Wang Long. Research on key algorithm for underground personnel location based on pedestrian dead reckoning [D].China University of Mining and Technology, 2015.
[9] Ma Jing. Research on Underground Mine Location Technology Based on Fingerprint Membrane and Track Derivation[D]. China University of Mining and Technology, 2017.
[10] Guo Longfei. A High Reliability Location Method Integrating RSSI and IMU Data[D]. Wuhan University, 2017.
[11] Sun Jiping, Li Chenxin. Mine TOA Location Method Based on Kalman Filter and Fingerprinting[J]. Journal of China University of Mining & Technology, 2014, 43(6): 1127-1133.
[12] Lu Q, Liao X, Xu S, et al. A hybrid indoor positioning algorithm based on WiFi fingerprinting and pedestrian dead reckoning [C]. IEEE, 2016.