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Research Article

Fingerprinting Localization Method Based on TOA and Particle Filtering for Mines

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Accurate target localization technology plays a very important role in ensuring mine safety production and higher production efficiency. The localization accuracy of a mine localization system is influenced by many factors. The most significant factor is the non-line of sight (NLOS) propagation error of the localization signal between the access point (AP) and the target node (Tag). In order to improve positioning accuracy, the NLOS error must be suppressed by an optimization algorithm. However, the traditional optimization algorithms are complex and exhibit poor optimization performance. To solve this problem, this paper proposes a new method for mine time of arrival (TOA) localization based on the idea of comprehensive optimization. The proposed method utilizes particle filtering to reduce the TOA data error, and the positioning results are further optimized with fingerprinting based on the Manhattan distance. This proposed method combines the advantages of particle filtering and fingerprinting localization. It reduces algorithm complexity and has better error suppression performance. The experimental results demonstrate that, as compared to the symmetric double-sided two-way ranging (SDS-TWR) method or received signal strength indication (RSSI) based fingerprinting method, the proposed method has a significantly improved localization performance, and the environment adaptability is enhanced.

1. Introduction

The Internet of Things and pervasive computing technology have continually progressed since their inception [1, 2]. At present, the Internet of Things technology has become increasingly used in a variety of fields. For example, Internet of Things technology for the mining industry was developed in order to obtain the status of coal mining and control mine production safety. It is crucial to know and manage the dynamic distribution of underground personnel for both mine enterprise management and emergency rescue in case of accidents [3]. Therefore, determining how to achieve an accurate localization of mine underground personnel has become a popular research topic.

Mine target localization usually utilizes the range-based method; that is, the location estimation is based on the distance measurement. In mine localization, the most used parameters are the RSSI of a wireless signal, the angle of arrival (AOA), the time of arrival (TOA), and the time difference of arrival (TDOA). In addition, some researchers used range-free methods to solve the problem of target localization. For example, problems such as node connectivity [4, 5] and beacon drift [6] are new research fields in the localization algorithm.

Because the underground environments of coal mines are complex and personnel mobility is relatively high, it is very difficult to achieve accurate positioning of underground personnel. The effect of NLOS propagation is the main source of wireless localization error in the underground environment. At present, the methods for reducing NLOS error can be divided into direct methods and indirect methods. The direct methods directly process the measurement results to reduce NLOS propagation error. Commonly used direct methods include the Wylie and Holtzman method [7], Kalman filtering [8], particle filtering [9], and mean filtering. Indirect methods avoid the direct processing of wireless signals or measurement results; instead, they utilize different localization methods to improve the robustness of the measurement results. Fingerprinting localization technology

is an indirect method. This technology is also one of the most commonly used mine localization technologies, and it is usually divided into two phases: the offline Training phase and Online Matching phase. The task of the offline Training phase is to collect the signal characteristic parameter, which is usually the RSSI from different APs at the reference points. These collected parameters are then used to construct the fingerprinting database. In the Online Matching phase, the similarity matching between the current collected data with fingerprinting database is conducted to obtain the best estimation.

Because fingerprinting localization methods have low computational complexity and good performance for suppressing NLOS error, there has been a lot of research published on fingerprinting localization methods in the past few years. Lin et al. [10] proposed a method to construct a fingerprint database by using the correlated RSSI of adjacent nodes. The Markov chain prediction model was used to assist the localization. Guzmán-Quirós et al. [11] applied directional antennas to the RSSI-based fingerprinting localization method, which reduced the required number of sensors and improved the localization success rate. To reduce the workload of collecting fingerprint data in the offline phase, Gu et al. used compressed sensing to reduce the amount of collected fingerprint data [12].

Although the TOA-based ranging method can overcome some shortcomings associated with RSSI, NLOS propagation still seriously impacts the localization accuracy. In this paper, a TOA fingerprinting localization method based on particle filtering is proposed according to the characteristics of the fingerprinting localization method and TOA ranging technology. The TOA ranging result vectors are stored in a fingerprint database, and the k-nearest neighbour (KNN) algorithm is used to estimate the positions. The proposed method uses both direct and indirect methods to suppress the NLOS error. When NLOS interference exists, the TOA localization result can be greatly optimized. The structure of the paper is as follows. Section 2 summarizes the work related to the field of particle filtering and fingerprinting localization. Section 3 details the proposed method for constructing a TOA fingerprint database based on particle filtering, and the position estimation is performed by the KNN matching localization method. In Section 4, the localization performance of the proposed method is experimentally tested. Section 5 concludes the paper.

2. Related Works

Because indoor positioning technology offers wide application prospects, many researchers have proposed different indoor wireless positioning technologies in the past few years, and consequently, a large number of research results have been published on the topic. One such example is the first developed RADAR system [13], which utilizes empirical data and the attenuation factor model. The localization of a moving target is achieved using a pattern recognition method after the completion of data acquisition. The MoteTrack system [14] and Horus system [15] are also indoor positioning system based on RSSI. These works laid a good foundation for further improving the accuracy and robustness of indoor positioning.

The NLOS propagation phenomenon caused by obstacles is an important factor affecting wireless positioning accuracy for coal mines. For this reason, direct or indirect optimization can be used to eliminate or reduce the influence of NLOS. Direct optimization methods primarily include Kalman filtering, particle filtering, convex relaxation [16, 17], and iterative minimum residual method [18]. Indirect optimization methods mainly include the fingerprinting positioning method, Chan algorithm [19], and geometric projection method [20]. However, the system performance of a single optimization method has certain limitations. Therefore, to suppress the NLOS propagation error, this paper utilizes both the particle filtering and fingerprinting method to combine the advantages of direct optimization and indirect optimization.

Particle filtering combines the Bayesian filtering method with the Monte Carlo method. It approximates the posterior probability distribution of random variables in a system by a series of weighted discrete random sampling points. There are many kinds of particle filtering. The most commonly used are auxiliary particle filtering [21], regularized particle filtering [22], adaptive particle filtering, and so forth. Particle filtering has a wide range of application in the field of mine positioning and indoor positioning. Jiang et al. [23] combined particle filtering with Wi-Fi-based positioning information and motion sensor information to obtain a more accurate and smooth target moving trajectory. Based on the idea of gradient fingerprinting positioning technology, Shu et al. [24] combined multiple dynamic detection results with extended particle filtering to obtain positioning for users and equipment. Moreno-Cano et al. [25] used particle filtering to track and predict the position and trajectory of moving targets in positioning systems based on RFID and thermal infrared. Ma and Li [26] improved the positioning accuracy of mine rescue robots using modified particle filtering. Zhu and Yi [27] proposed a mine underground positioning system based on UWB, and the NLOS interference in the mine underground is suppressed by using particle filtering.

Fingerprinting localization includes an offline phase and an online phase. The key to the Online Matching phase is the design and selection of the pattern-matching algorithm, which directly determines the positioning accuracy. Presently, the KNN algorithm and the weighted k-nearest neighbour (WKNN) algorithm [13] are the most commonly used matching algorithms. In [28], Li et al. proposed a KNN algorithm based on feature scaling. Although their algorithm does consider the fact that the distance between RSSI vectors in the fingerprint database and the actual distance are not perfectly matched, their algorithm does not completely overcome the disadvantage that the RSSI can easily attenuate. At present, most of the fingerprinting localization methods are based on RSSI; however, in practical applications, the complex mine environment will affect the way the RSSI changes, usually resulting in low positioning accuracy for RSSI-based methods. In order to overcome the shortcomings of RSSI-based localization technology, Taok et al. proposed an UWB fingerprinting localization method based on neural network

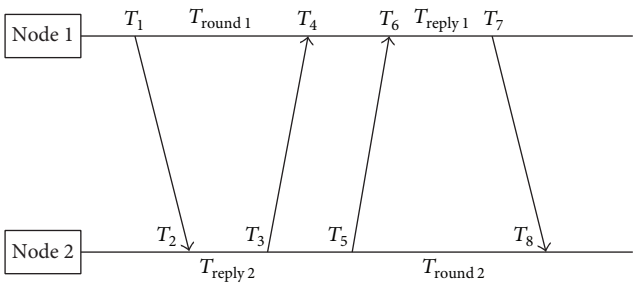


Figure 1: Frame of SDS-TWR.

for coal mine underground [29]. Their method obtains better localization accuracy using the channel impulse response (CIR) instead of RSSI to construct the fingerprint database. Sun and Li [30] proposed a mine TOA localization method based on Kalman filtering and fingerprinting. However, their results lack validation experiments in different environments to compare the suppression performance for NLOS errors. In [31], Kabir and Kohno also discussed the applications of a UWB-based fingerprinting localization method in an NLOS environment. However, the vast majority of currently used mine intelligent terminals cannot support the use of UWB. Instead, Wi-Fi, ZigBee, and other technologies are more popular.

3. TOA for Fingerprints

This paper proposes a TOA fingerprinting localization method based on particle filtering. The distance measurements based on TOA are first carried out using a SDS-TWR algorithm to suppress errors, such as synchronization delay, in the process of ranging. Then, the excess delay errors caused by the NLOS propagation in the mine underground are suppressed by particle filtering. Finally, the fingerprint database is constructed according to the obtained accurate TOA ranging information. The target position estimation is then completed.

3.1. Distance Measurements Based on SDS-TWR. The TOA data serves as the basis for constructing the fingerprint database and positioning. After the ranging system finishes the ranging work, the ranging result vectors are stored in the fingerprint database for matching positioning. At present, the most commonly used TOA ranging algorithms mainly include one-way ranging (OWR) [32], two-way ranging (TWR) [33], and SDS-TWR [34]. In this paper, the SDS-TWR algorithm is used. The errors caused by the clock synchronization error can be eliminated as far as the wireless signal undergoes on a round trip between the two nodes. Therefore, the system robustness is improved.

As shown in Figure 1, the SDS-TWR algorithm calculates the distance between two nodes by accurately measuring the two-way arrival time and the internal reaction time. In the algorithm, T_{round1} is the time difference between the time when node 1 transmits the signal to node 2 and the time when the response signal is received from node 2. T_{reply2} is the time difference between the time when node 2 receives the signal from node 1 and the time when the response signal is sent to node 1. Similarly, T_{round2} is the time difference between the time when node 2 transmits the signal to node 1 and the time when the response signal is received from node 1. T_{reply1} is the time difference between the time when node 1 receives the signal from node 2 and the time when the response signal is sent to node 2. Assuming that the propagation velocity of the signal is v, the distance between node 1 and node 2 is

$$\frac{v}{4}\left[\left(T_{\text{round1}} - T_{\text{reply2}}\right) + \left(T_{\text{round2}} - T_{\text{reply1}}\right)\right]. \tag{1}$$

3.2. NLOS Error Optimization Based on Particle Filtering. NLOS propagation is a widespread phenomenon in the mine environment. The excess delay caused by the NLOS propagation greatly affects the ranging process and results in large ranging errors, which seriously decrease positioning accuracy. There are two main sources for excess delay in the mine environment. One is the stable excess delay caused by the special structure, fixed facilities, equipment, and pipelines in the mine. The other is the random excess delay caused by passing personnel and vehicles. The stable excess delay has certain regularity and can be analysed by the excess delay model. In contrast, the random excess delay has a large irregularity, which is difficult to analyse and predict. Furthermore, the random excess delay greatly impacts positioning accuracy. Therefore, corresponding algorithms are required to suppress these effects. This paper proposes a new method based on particle filtering to suppress the excess delay in order to reduce NLOS error and improve positioning accuracy.

The target node that needs to be located carries the Tag and moves in the mine tunnel. The AP deployed in the tunnel measures the distance between the AP and the Tag using the method described in Section 3.1. The moving of the positioning target can be regarded as uniform linear motion in a short sampling interval T_0. Assume that the state vector is $\mathbf{X}_k = \begin{bmatrix} s_k & v_k \end{bmatrix}^T \in R^n$, where s_k and v_k are the position component and the velocity component, respectively. Assuming that the observed value is Y_k, then the state equation and the observation equation are as follows:

$$\mathbf{X}_{k+1} = \boldsymbol{\varphi}\mathbf{X}_k + \boldsymbol{\gamma}\omega_k \tag{2}$$

$$Y_k = \mathbf{H}\left(\mathbf{X}_k\right) + \theta_k, \tag{3}$$

where $\boldsymbol{\varphi} = \begin{bmatrix} 1 & T_0 \\ 0 & 1 \end{bmatrix}$, $\boldsymbol{\gamma} = \begin{bmatrix} 0.5T_0^2 & 0 \\ 0 & T_0 \end{bmatrix}$. Both ω_k and θ_k are Gaussian white noise, and $\mathbf{H}(\mathbf{X}_k)$ is the distance relationship between the AP and Tag.

The above state transition equation only describes the motion state information of the Tag and the distance between the AP and the target node (i.e., observation value Y_k). Assuming that the coordinate of the AP is (x_s, y_s) and the coordinate of the Tag is (α, β), then the function $\mathbf{H}(\mathbf{X}_k)$ can be expressed as follows:

$$\mathbf{H}\left(\mathbf{X}_k\right) = \sqrt{\left(\alpha_k - x_s\right)^2 + \left(\beta_k - y_s\right)^2}. \tag{4}$$

The shape and structure of the mine tunnel make mine positioning a one-dimensional problem. Assuming that the

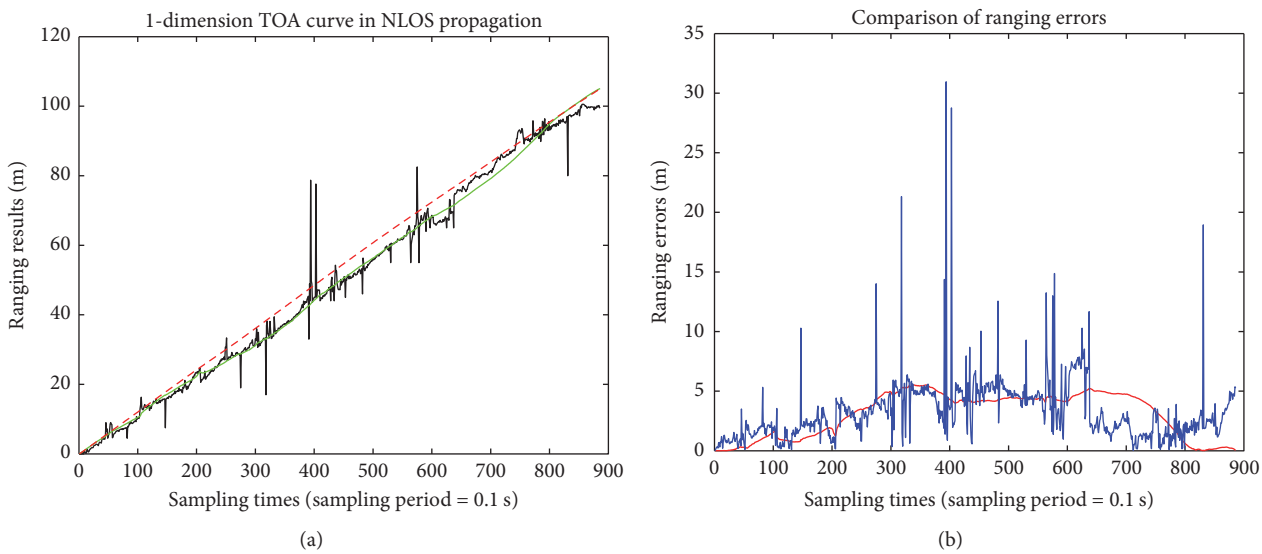


Figure 2: Comparison of ranging results before and after the particle filtering. (a) Comparison of positioning results under one-dimensional NLOS propagation conditions. (b) Comparison of positioning error between the original TOA and after particle filtering.

position of the AP is s and the position of the Tag is s_k, then (4) can be simplified as

$$\mathbf{H}(\mathbf{X}_k) = |s - s_k|. \tag{5}$$

It is further assumed that the Tag moves linearly from the origin. From (2), it can be seen that the actual distance can be approximated by a straight line. However, as shown in Figure 2, the equipment error and the excess delay caused by NLOS propagation cause a large irregular fluctuation in the measured data. However, the fluctuation amplitude of the ranging curve is greatly reduced after the particle filtering, which demonstrates that the ranging accuracy is greatly improved, and the NLOS error suppression performance is good.

3.3. The Construction of the Localization Fingerprinting Database Based on the Optimized Ranging Data. This section uses the optimized TOA data to construct the fingerprint database required for positioning. As mentioned above, the fingerprinting localization method includes an offline phase and an online phase. The fingerprint database is constructed in the offline training phase. For this purpose, the AP is first deployed according to the target area environment, and the position of the reference point is selected. The Tag is used to obtain the optimum distance (see Sections 3.1 and 3.2) at each reference point, which is used as the training vector $\mathbf{Dis}_{i,j}$. After the acquisition of all reference points, a Radio Map matrix is obtained, as shown in

$$\begin{bmatrix} \mathrm{Dis}_{1,1} & ,\ldots, & \mathrm{Dis}_{1,j} & ,\ldots, & \mathrm{Dis}_{1,J} \\ & & \cdots & & \\ \mathrm{Dis}_{i,1} & ,\ldots, & \mathrm{Dis}_{i,j} & ,\ldots, & \mathrm{Dis}_{i,J} \\ & & \cdots & & \\ \mathrm{Dis}_{I,1} & ,\ldots, & \mathrm{Dis}_{I,j} & ,\ldots, & \mathrm{Dis}_{I,J} \end{bmatrix}, \tag{6}$$

where I and J denote the total number of reference points (RP) and AP, respectively. $\mathbf{Dis}_{\mathbf{i,j}}$ is collected at the ith reference point, and it represents the distance information between the ith reference point and the jth AP. Furthermore, $1 \leqslant i \leqslant I$, $1 \leqslant j \leqslant J$. The ith row of vectors in the matrix represents the training vectors collected at the ith reference point, and $(\mathrm{Dis}_1 \ \cdots \ \mathrm{Dis}_j \ \cdots \ \mathrm{Dis}_J)$ represents the training vector collected by the Tag at the reference point.

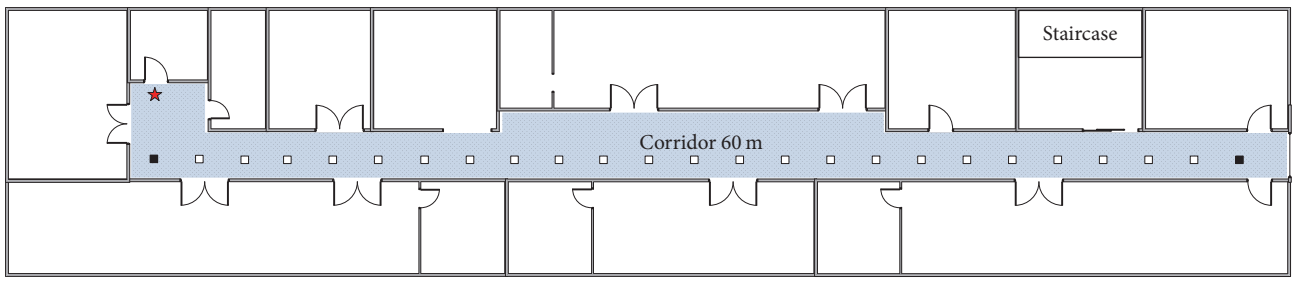
In the KNN algorithm, the similarity between the positioning vector $\mathbf{p}$ in the online phase and the training vector in the offline phase is usually used to estimate the target position. Numerous methods can be used to calculate similarity, such as the Euclidean distance, Manhattan distance, Chebyshev distance, and Spearman correlation. The similarity calculation method based on the Euclidean distance is the simplest, which is shown in

$$d_i = \sqrt{\sum_{j=1}^{J} \left(\mathrm{Dis}_{i,j} - p_j\right)^2}. \tag{7}$$

The results of Chen et al. [35], Farshad et al. [36], and Niu et al. [37] reveal that results of the Manhattan distance method are superior to those of other similarity calculation methods. The Manhattan distance is also called the City Block distance, which represents the sum of the distances projected on two axes for a line between two points in Euclidean space. The Manhattan distance is shown in

$$d_i = \sum_{j=1}^{J} \left|\mathrm{Dis}_{i,j} - p_j\right|. \tag{8}$$

Because the experimental conditions in this paper are very similar to those in the above works, the Manhattan distance is also selected to calculate the similarity.



■ AP in LOS condition
□ Reference points
★ AP in NLOS condition

Figure 3: Schematic diagram of the line corridor environment and experimental deployment.

4. Experimental Results

This section evaluates the performance of the proposed TOA fingerprinting localization method based on particle filtering through experiments under various conditions. This proposed method is compared to the RSSI-based fingerprinting localization method and the traditional TOA localization method. In these experiments, all of the background control and data processing were completed by a PC with an Intel Core i7-3630QM and 8 GB RAM. The TOA ranging was completed using a NanoPAN 5375 wireless module.

4.1. The Experimental Setup. Here, the focus is on localization performance tests in long-distance corridor and tunnel environments because these environmental characteristics are more similar to mine tunnels. The APs are deployed at the two ends of the corridor or tunnel. When a line of sight (LOS) propagation path exists between APs, it is referred to as the LOS propagation condition. When there is no LOS propagation path between APs, it is referred to as the NLOS propagation condition. Taking into account the existence of a variety of practical scenes in mine tunnels, experiments in line corridors and curve corridors were carried out.

The line corridor structure is shown in Figure 3. This corridor is located in building A of the Internet of Things Research Center at China University of Mining and Technology, Xuzhou, China. The dimension of the corridor is 2.3 m by 60 m. A positioning AP is deployed at each end of the corridor. The distance between two APs is 57.6 m. A reference point is selected every 2.4 m between the two APs, and 23 reference points are selected in total to cover the entire corridor. During the experiment, the localization experiments were carried out at random positions in the corridor. The performance of the localization method was evaluated by the error between the localized results and the actual positions.

The curve corridor structure is shown in Figure 4. This corridor is located on the fourth floor of the School of Environment Science and Spatial Informatics, China University of Mining and Technology, Xuzhou, China. The width of the corridor is three meters, and the corner angle is approximately 121 degrees. The corridor corner is used as the midpoint, and the positioning APs are deployed symmetrically on both sides of the corridor. After multiple tests, it was determined that stable communications cannot be established when the distance between the AP and the corridor corner is greater than 12 meters. Therefore, the APs are deployed 12 meters away from the corridor corner; that is, the distance between the two APs is 24 m. Reference points are selected every 2.4 m between the two APs. There are nine reference points in total. Similar to the long straight corridor, the positions in the corridor are randomly selected for the positioning experiments. In order to accurately evaluate the particle filtering's ability to improve positioning accuracy, three lab assistants randomly walked in the test environments of both corridors to simulate the random excess delay in real positioning environments.

4.2. Experiments in LOS Propagation. Under the condition of LOS propagation, this paper compares the TOA-based localization method, RSSI-based fingerprinting localization method, TOA fingerprinting localization method without particle filtering, and TOA fingerprinting localization method based on particle filtering.

First, a localization experiment was carried out using the localization method based on TOA ranging. Two APs were deployed at both ends of the corridor, and their deployment locations are shown in Figure 2. During the experiments, a lab assistant walked from one AP to the other AP holding a Tag with constant speed. The localized results are compared to the real-time recorded actual positions.

Then, a localization experiment was carried out using the RSSI-based fingerprinting localization method under the same experimental environment. In this experiment, the AP is deployed in the same manner as in the previous experiment. The positions of the selected 23 reference points are shown in Figure 2. In the offline phase, the fingerprint database is constructed according to the fingerprint information collected at the reference points. The database is used for the matching positioning in the online phase. The KNN algorithm was used as the matching algorithm in the online phase, and the k value is set as 3 according to the experimental statistical data.

In the third experiment, a TOA fingerprinting localization method without particle filtering was used. Finally, the

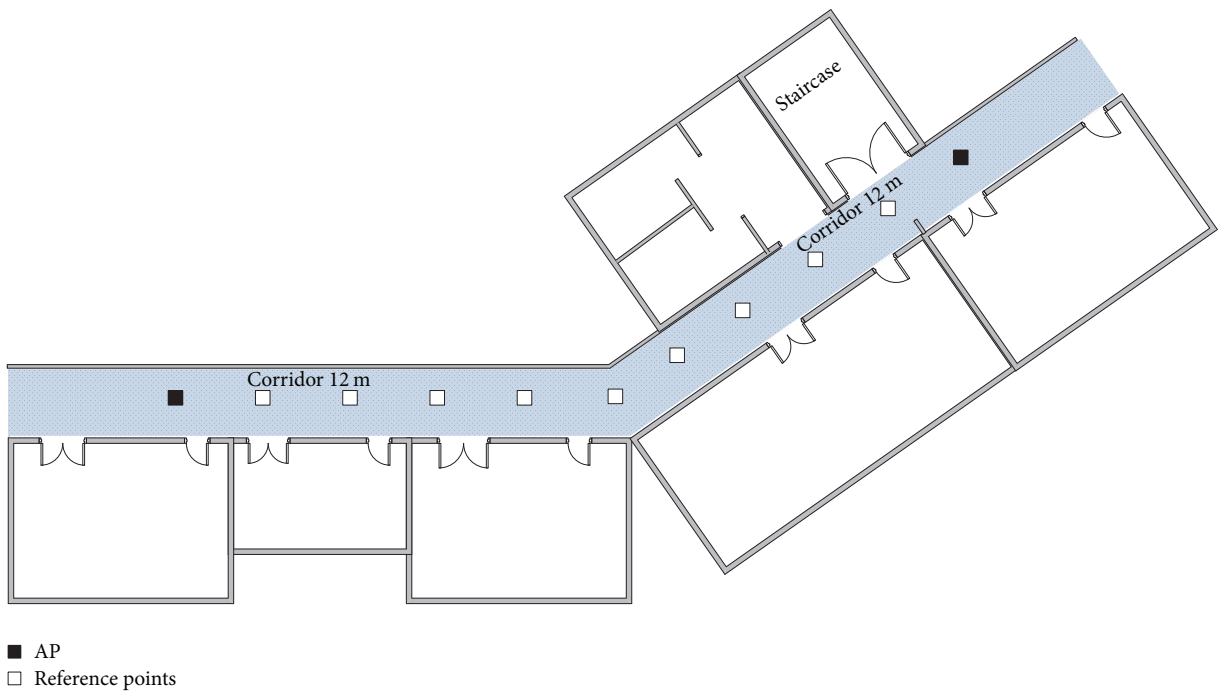


Figure 4: Schematic diagram of the curve corridor environment and experimental deployment.

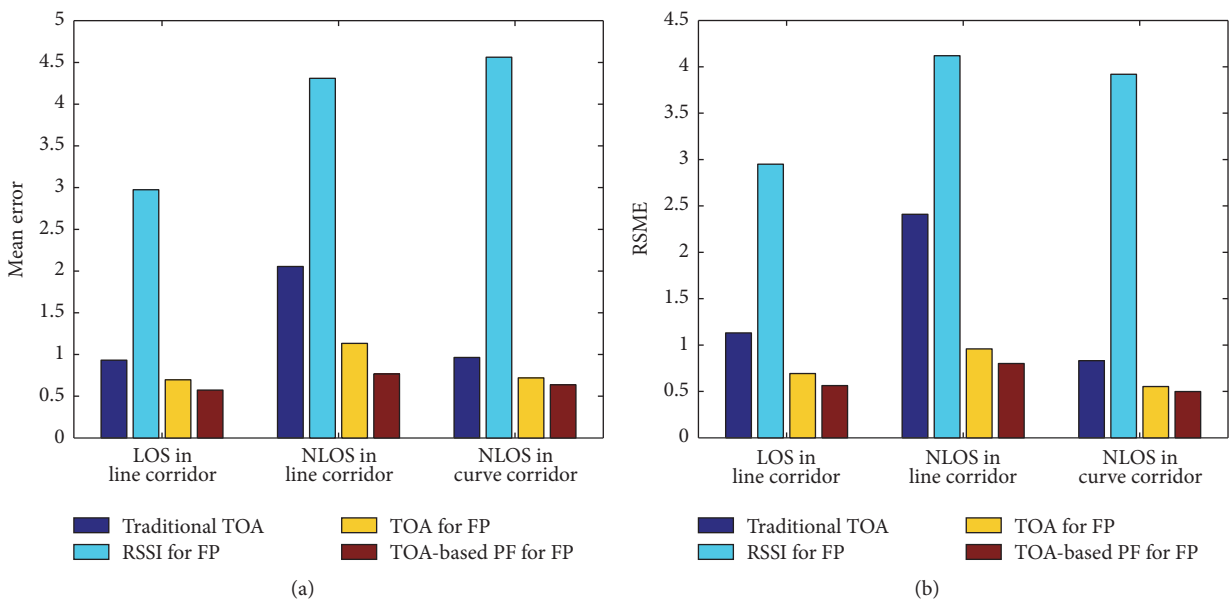


Figure 5: Performances of the four localization methods under different experimental conditions. (a) The mean error under different experimental conditions. (b) The root mean square error under different experimental conditions.

proposed TOA fingerprinting localization method based on particle filtering was used for the localization experiment. All experimental parameters and k values are the same as those of the second experiment.

From the experiments, it was determined that the RSSI-based fingerprinting localization method has the highest positioning error (2.974 m) by comparing the positioning results of the four experiments (see Figure 5). In contrast, the positioning accuracy of the TOA-based positioning method is much better (0.932 m); however, the localization accuracy is further improved using the TOA fingerprinting localization method without particle filtering, which produced an average positioning error of 0.696 m. Finally, the positioning accuracy is only 0.574 m for the proposed TOA fingerprinting localization method based on particle filtering. As compared to the traditional TOA localization method and

the TOA fingerprinting localization method without filtering, the proposed method results in 38.4% and 17.5% increases in positioning accuracy, respectively. The root mean square error of the traditional TOA localization method is 1.131, the root mean square error of the TOA fingerprinting localization method without particle filtering is 0.693, and that of the TOA fingerprinting localization method based on particle filtering is 0.563.

4.3. Experiments in NLOS Propagation. In order to test the localization performance under NLOS propagation conditions, the localization experiments were carried out in both corridors with different structures as shown in Figures 3 and 4.

4.3.1. Line Corridor. In Figure 3, the deployment location of the left AP is changed to the red five-star location so that there is no LOS propagation path between the left and right APs. Under this NLOS propagation condition, the above four experiments were repeated.

As shown in Figure 5, in the NLOS propagation environment, the obtained positioning error of the RSSI-based fingerprinting localization method is relatively large (4.31 m). The localization error obtained by the TOA-based localization method also increased as compared to that of the previous experiment due to the NLOS interference, and the localization error is 2.054 m. The positioning error of the TOA-based fingerprinting localization method is 1.134 m when the particle filtering is not used. With the proposed TOA fingerprinting localization method based on particle filtering, the NLOS interference is effectively suppressed, and the localization error is only 0.767 m. As compared to the traditional TOA localization method and TOA fingerprinting localization method without filtering, the proposed method results in 62.7% and 32.4% increases in positioning accuracy, respectively. In this case, the root mean square error of the traditional TOA localization method is 2.41, whereas it is 0.801 for the TOA fingerprinting localization method based on the particle filtering. It is evident from the results that the proposed TOA fingerprinting localization method based on particle filtering greatly improves both the positioning accuracy and the root mean square error in the line corridor NLOS propagation condition.

4.3.2. Curve Corridor. For the curve corridor, the deployed positions of the APs and the selected nine reference points are shown in Figure 3. There is no LOS propagation path between the two APs, which is consistent with the NLOS propagation condition established in this paper. The above four experiments are repeated under this condition. Additionally, the deployed positions of the APs and the selected reference points are fixed in all four experiments. As mentioned above, the maximum distance between the APs for establishing stable communication is 24 m under this condition. This distance is much shorter than that in the line corridor.

In the curve corridor, the obtained positioning error of the RSSI-based fingerprinting localization method is still large (4.563 m). The obtained positioning error of the TOA-based positioning method is 0.964 m, which is roughly equivalent to the positioning error under the LOS propagation condition, and the positioning error of the TOA-based fingerprinting localization method is 0.719 m. The positioning error of the proposed TOA fingerprinting localization method based on particle filtering is only 0.637 m. As compared to the traditional TOA localization method and TOA fingerprinting localization method without filtering, the proposed method results in 33.9% and 11.4% increases in positioning accuracy, respectively. The root mean square error of the traditional TOA localization method is 0.832, and that of the TOA fingerprinting localization method based on particle filtering is 0.499. The mean error and root mean square error under the four experimental conditions are shown in Figure 5.

4.4. Results Analysis. Figure 6 shows the cumulative distribution function of errors of the four above-mentioned localization methods. It can be seen from Figure 6(a) that, under the LOS condition, the probability for errors less than 50 cm is 40% for the traditional TOA localization method. In contrast, the probability for the TOA fingerprinting localization method based on particle filtering is less than 20%. However, the positioning error for the TOA fingerprinting localization method based on particle filtering is always less than 1 m, whereas the probability for errors less than 1 m for the traditional TOA method is 64%. These have been reflected by the crossover points in Figure 6(a), which means the localization accuracy of traditional TOA method decreased more significantly with distance. The positioning accuracy fluctuates greatly that leads to instability of the system. For the RSSI-based fingerprinting localization method, the probability for positioning errors that are less than 2 m is 4.44%.

It can be seen from Figure 6(b) that, under the line corridor NLOS condition, the probability for positioning errors less than 1 m for the TOA fingerprinting localization method based on particle filtering is 44.4%, and its probability for errors less than 1.4 m is 97.78%. The probability for errors less than 1 m for the traditional TOA localization method is 11.1%. The positioning error is always larger than 3 m for the RSSI-based fingerprinting localization method, and its probability for positioning errors less than 4 m is 31.1%.

Figure 6(c) demonstrates that the error of the RSSI-based fingerprinting localization method is still large, and the probability for errors less than 4 m is 29.4%. For the traditional TOA localization method, the probability for errors less than 1 m is 70.59%. The error for the TOA fingerprinting localization method based on particle filtering is always less than 0.8 m, and its probability for errors less than 0.6 m is 82.35%.

By comparing the four experiments, it is apparent that using the SDS-TWR method to directly measure raw data is superior to using the RSSI-based localization method; however, the data still has a certain error, and most of the errors are within 2 m. When the excess delay is not suppressed by the particle filtering, the positioning accuracy is improved by combining the TOA and fingerprinting localization method. The average positioning error in such a case is 0.85 m. However, after using the particle filtering to suppress the excess

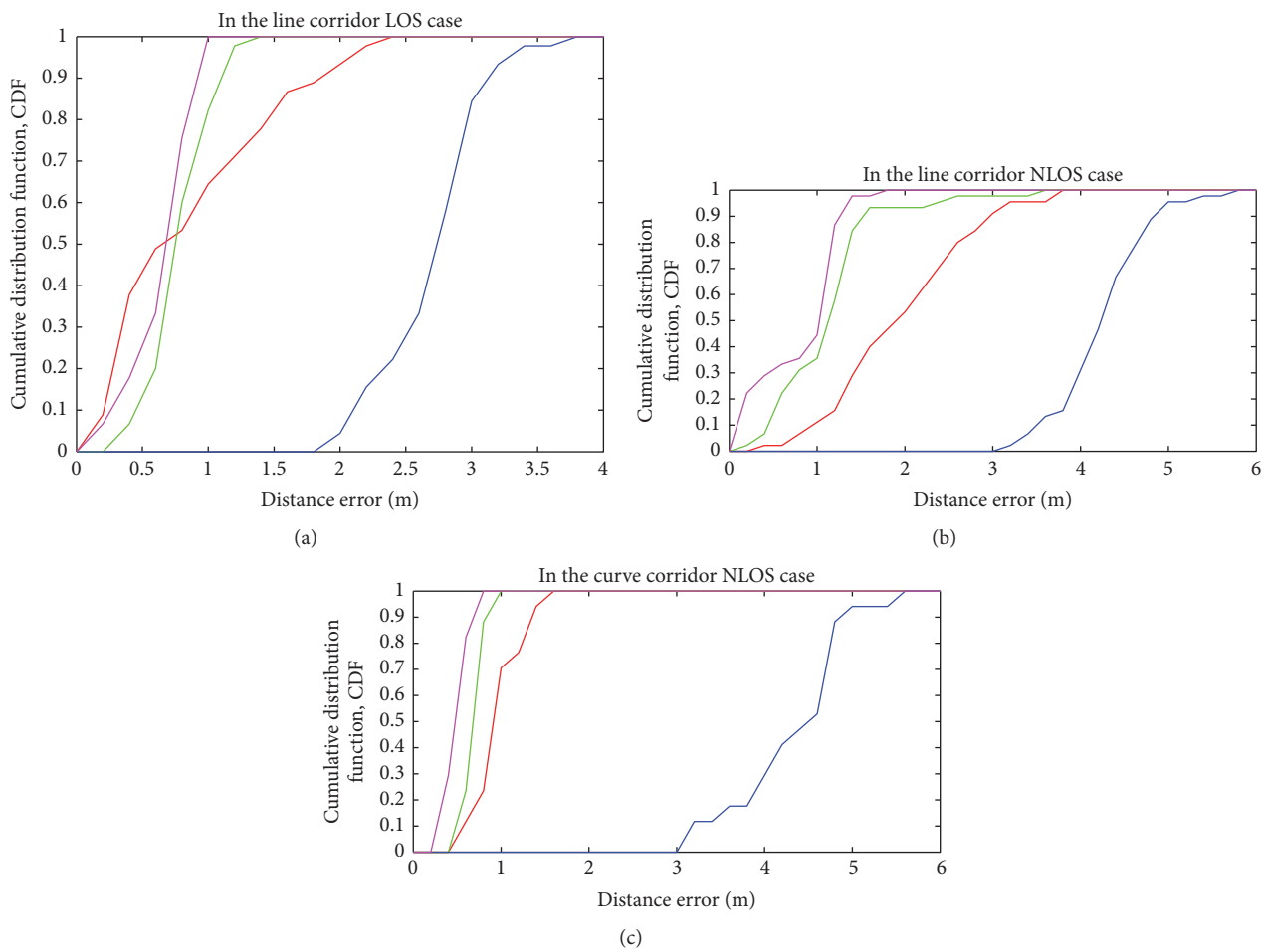


Figure 6: Cumulative distribution functions of errors of the four algorithms under different conditions. (a) Cumulative error distribution of four algorithms under line corridor LOS condition. (b) Cumulative distribution functions of errors of four algorithms under line corridor NLOS condition. (c) Cumulative distribution functions of errors of four algorithms under curve corridor NLOS condition.

delay, the average positioning error becomes 0.66 m. The localization performance is more stable, and it shows higher positioning accuracy and system robustness. Therefore, the proposed TOA fingerprinting localization method based on particle filtering can effectively eliminate the influence of excess delay. It provides more stable, higher positioning accuracy, and it has potential for greater application.

5. Conclusions

NLOS interference is the most common problem for wireless communication in the mine environment, and it is also the main factor that affects mine positioning accuracy. In this paper, a TOA fingerprinting localization method based on particle filtering is proposed for NLOS propagation in a mine environment. To further optimize the fingerprinting matching results, the proposed method uses TOA ranging data to construct a fingerprint database in the offline phase, and it uses the particle filtering to suppress the NLOS error that is caused by the excess delay in the online phase. Based on the original TOA ranging technique, the proposed method optimizes the localization results by direct and indirect optimization. The experimental results demonstrate that the proposed method can significantly improve the performance of NLOS interference suppression in a mine environment. It obtains a higher positioning accuracy and stronger system robustness with lower complexity. It has strong adaptability to different environments, and it is easily transplanted to other Internet of Things applications that cannot receive satellite-positioning signals.

Conflicts of Interest

The authors declare that there are no conflicts of interest with the publication of this paper.

Acknowledgments

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