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Unscented-Kalman-Filter Based UWB and INS Fusion Positioning for Firefighters Application

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Abstract. Firefighter positioning is an important application field of Internet of things (IOT) technology. This paper aim at the problem that it is difficult for the fire command center to obtain firefighter location data under the influence of complex environment around the fire site and indoor non-line-of-sight (NLOS), ultra wideband (UWB) and inertial navigation system (INS) fusion positioning and NLOS detection algorithm based on unscented Kalman filter (UKF) is proposed. UKF avoids ignoring the high-order term of the nonlinear observation equation, which can effectively improve the solution accuracy of the nonlinear equation. The UKF fusion positioning framework takes the more accurate initial positioning coordinates obtained by the INS in a short time as observed values of UKF, and uses the initial positioning coordinates to detect the NLOS error, and uses the residual matrix constructed by the residual values to adjust the measurement noise matrix in UKF to reduce NLOS error. The simulation and experimental results show that the data for the position root mean square error (RMSE) of the proposed algorithm are 0.091m, 0.096m and 0.127m respectively in different groups of NLOS experimental environments. So, the method proposed in this paper has high positioning accuracy in the NLOS environment.

Keywords: internet of things, ultra wideband, inertial navigation system, unscented Kalman filter, firefighter positioning

1. Introduction

Fire safety is an important application field of Internet of things (IOT) technology. The rational use of Internet of things technology in fire protection can further improve the efficiency of fire protection and ensure the life safety of firefighters [1]. In a complex fire environment, it is difficult for firefighters to determine their specific position. When the life safety of firefighters is threatened, it is difficult for commanders to rescue the firefighters in time. Therefore, it is particularly important to use the Internet of things (IOT) positioning technology to obtain the position data of firefighters in the fire scene. At present, IOT indoor positioning technologies mainly include Wi-Fi, Bluetooth, ZigBee, infrared and other technologies [2]. However, these positioning technologies have the low anti-interference ability, and it is difficult to locate firefighters in a complex fire environment accurately.

Ultra wideband (UWB) positioning technology has the advantages of GHz bandwidth and strong anti-interference ability [3], and has obvious advantages in positioning and navigation [4]. Inertial navigation system (INS) can quickly calculate pedestrian position by using pedestrian dead reckoning (PDR) [5], [6]. Although UWB positioning technology and inertial positioning technology have their advantages in the indoor positioning process, the fire environment is complex and changeable. In the process of positioning using UWB, the positioning accuracy may be affected by [7] some factors such as multipath and non-line-of-sight (NLOS). Although the inertial measurement unit (IMU) has high-precision positioning results in a short time, due to the influence of complex factors such as the sensor itself and pedestrian walking habits, there are cumulative errors in positioning. With the passage of time, the positioning trajectory will deviate from the reality [8].

Single positioning method has limitations, and multi-technology fusion positioning can improve the accuracy and reliability of positioning. As in [9], a UWB/IMU fusion positioning method was proposed. However, the accuracy of the positioning results obtained by this method under NLOS conditions is limited. As in [10], the authors proposed an INS/UWB fusion positioning method, which can still provide reliable and continuous positioning even in an NLOS environment. As in [11], the authors proposed a method of fusion positioning of UWB and INS. Accurate positioning information is obtained by combining the positioning of the two technologies, which reduces the impact of the LOS/NLOS environment on positioning accuracy. However, the positioning error is still insufficient to meet some high-precision positioning requirements. As in [12], a UWB/INS fusion positioning algorithm based on EKF was proposed, the positioning accuracy of the algorithm reached 10cm, but when the nonlinearity of the system is high, the positioning accuracy will be reduced. As in [13], a Wi-Fi/INS fusion positioning method based on long short-term memory (LSTM) network was proposed. Although this method has good robustness, it can only provide meter-level positioning accuracy. However, the system deployment difficult and cost high. As in [14], a fusion positioning method based on Wi-Fi/Bluetooth/PDR was proposed, which overcomes the problem of INS cumulative error, but how to determine the weighting factor of different scenes remains to be studied.

In this paper, a UWB/INS fusion positioning and NLOS detection algorithm based on UKF is proposed to obtain high accuracy positioning results and reduce the ranging error caused by NLOS in the actual situation. In the UKF fusion positioning framework, the accurate initial positioning coordinates obtained by INS in a short time are taken as the UKF observation values, the initial positioning coordinates are used to detect the NLOS error of UWB measurement values, and the residual matrix constructed by residual value is used to adjust the measurement noise matrix in UKF to reduce the NLOS error, so as to obtain more accurate position coordinates.

2. Firefights Indoor Positioning System

The firefighter's indoor positioning system consists of a UAV positioning base station and a positioning terminal, as shown in Fig. 1. When a fire broke out, a drone equipped with a UWB base station quickly lifted off and hovered around the windows of the building. The firefighter wears a positioning terminal to enter the fire scene. When the firefighter walks, the UWB module and the INS module will obtain the data for position calculation. Finally, the precise location information of the firefighter is obtained through the fusion positioning algorithm. The positioning system adopts the east north up (ENU) navigation coordinate system, in which the X, Y, and Z axes are the directions of true east, true north, and normal respectively. For the sake of simplicity, this paper only considers two-dimensional positioning.

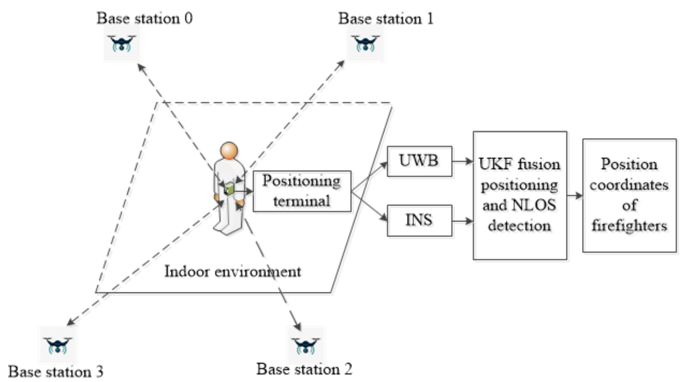


Fig. 1. System frame diagram.

3. Firefights Indoor Positioning System

3.1. INS Positioning Principle

INS usually uses the PDR algorithm to obtain the pedestrian's positioning trajectory, and PDR uses the data obtained by the inertial sensor to calculate the relative position of the pedestrian to achieve positioning. PDR positioning method is essentially a positioning method using relative position relationship, and its calculation formula is:

$$
\begin{cases} x_k = x_{k-1} + L_{k-1} * \cos\partial_{k-1} \\ y_k = y_{k-1} + L_{k-1} * \sin\partial_{k-1} \end{cases} \tag{1}
$$

where (x_{k-1}, y_{k-1}) represents the position coordinates of the previous moment, (x_k, y_k) represents the position coordinates at the current moment, k represents the number of steps, L_k represents the step size at the current moment, and ∂ represents the heading angle.

The commonly used models for step size estimation include constant step size estimation model, linear step size estimation model, nonlinear step size estimation model and artificial intelligence estimation model [15]. Considering the complexity and practicability of the algorithm, this paper uses the nonlinear step model to calculate the step size of firefighters during walking according to the acceleration amplitude information:

$$
L_{K-1} = K \bullet \sqrt[4]{a_{\max} - a_{\min}} \tag{2}
$$

where L is the step length, $a_{\max}$ represents the maximum acceleration value during walking, $a_{\min}$ represents the minimum acceleration value during walking, and K is the proportional parameter which is a constant. The value of K is related to everyone's height, weight and walking habits. In this paper $K = 0.45$.

There are three typical methods to solve the heading angle: the Euler angle method, direction cosine method and quaternion method. In this paper, the quaternion is updated by the Madgwick algorithm [16] to solve the heading angle.

3.2. UWB Positioning Principle

UWB usually uses the time difference of arrival(TDOA) positioning algorithm. The basic principle of TDOA is to measure the time difference between the signals transmitted by the tag and reach each base station. Multiply the time difference by the propagation speed of the electromagnetic wave to obtain the distance difference between the tag and each base station. Simultaneous equations can obtain the coordinates of the tag. Taking the first base station as the reference base station, the TDOA hyperbolic model can be expressed as shown in Fig. 2.

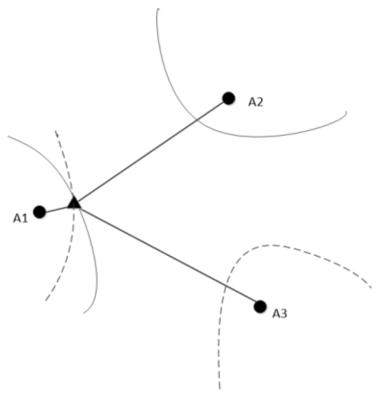


Fig. 2. TDOA positioning principle diagram.

A1, A2 and A3 are locating base stations, and the distances from the tag to the base station are d_1, d_2 and d_3. The distance difference between the tag and the base station A1 and the base station A2 is $d_{21} = d_2 - d_1$, and a certain point on the hyperbola with the base stations A1 and A2 as the focus is the position of the tag. In the same way, the distance difference between the tag and the base stations A1 and A3 is $d_{31} = d_3 - d_1$, and a certain point on the hyperbola with A1 and A3 as the focus is also the position of the tag. From this, the following equations can be obtained:

$$
\begin{cases} \sqrt{(x_2 - x)^2 + (y_2 - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)} = \\ d_{21} = d_2 - d_1 \\ \sqrt{(x_3 - x)^2 + (y_3 - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)} = \\ d_{31} = d_3 - d_1 \end{cases} \tag{3}
$$

Due to the clock synchronization between base stations, the time difference can be measured to obtain $d_{21} = c \cdot (t_2 - t_1)$ and $d_{31} = c \cdot (t_3 - t_1)$. The coordinates of the label are obtained by solving the above equations.

4. Fusion Positioning and Detection Algorithm

EKF is the Taylor expansion of the nonlinear function around the filtered value, eliminating the second-order and above terms. When the degree of non-linearity of the system model is very high, the extended Kalman filter will have a non-negligible error, and it is difficult to estimate the state of the target accurately. The unscented transform (UT) method and the KF algorithm are the theoretical basis of the UKF filtering algorithm. The UKF algorithm assumes that the state satisfies the Gaussian distribution and uses UT to generate Sigma points to approximate the nonlinear mean and variance, thereby obtaining a large number of observation default values, avoiding ignoring high-order problems in linearization. Therefore, compared with the EKF algorithm, the UKF algorithm shows higher calculation accuracy and stronger adaptability. This paper uses the position coordinates of the firefighter obtained by the PDR algorithm as the observation value of UKF:

$$X_{k+1} = FX_k + w_k \tag{4}$$

$$Z_k = H(X_k) + v_k \tag{5}$$

where $k \in \mathbf{N}$ represents the time variable and $X_k = [x_k, y_k, L_k, \partial_k]^T$ is the state variable of the system at time k, (x_k, y_k) represents the position coordinates of INS at time k, L_k represents the step size at time k, ∂_k represents the heading angle at time k, F represents the state transition matrix and the fourth-order identity matrix, $Z_k = [r_{2,1}, r_{3,1}, r_{4,1}, \cdots, r_{n,1}]^T$ represents the TDOA distance value obtained through UWB. W_k and V_k represent independent Gaussian white noise, zero mean, uncorrelated.

The specific integration implementation process is as follows:

(1) Filter initial value:

$$\hat{X}_0 = E[X_0] \tag{6}$$

$$P_0 = E[(X - \hat{X}_0)(X - \hat{X}_0)^T] \tag{7}$$

(2) The set of sampling points and the corresponding weights are obtained through unscented transformation, and the sampling points are expressed as:

$$\begin{cases} \xi_0 = \bar{x} \\ \xi_i = \bar{x} + (\sqrt{(n+\lambda)P_x})_i, & i = 1, 2, ..., n \\ \xi_i = \bar{x} - (\sqrt{(n+\lambda)P_x})_i, & i = n, n+1, ..., 2n \end{cases} \tag{8}$$

The weight corresponding to each sampling point is expressed as:

$$\begin{cases} w_0^m = \dfrac{\lambda}{n+\lambda} \\ w_0^c = \dfrac{\lambda}{n+\lambda} + 1 - \rho^2 + \beta \\ w_i^m = w_i^c = \dfrac{1}{2(n+\lambda)}, & i = 1, 2, ..., 2n \end{cases} \tag{9}$$

where $(\sqrt{(n+\lambda)P_x})_i$ is the column vector of matrix $(\sqrt{(n+\lambda)P_x})$, $\lambda = \rho^2(n+K) - n$ represents the variable parameter, ρ represents a constant parameter with a value of 0.0001 ~ 1, which determines the diffusion degree of the sampling point near $\bar{x}$ (usually 0.01), K represents another constant, usually $3-n$ or 0. w_i^c represents the weight required to calculate the covariance, w_i^m represents the weight required to calculate the mean, β represents the state distribution parameter, $\beta \geq 0$, the system set as Gaussian distribution in this paper, and take $\beta = 2$.

(3) State prediction

$$\begin{cases} \xi_{k|k-1}^{(i)} = F(\xi_{k-1|k-1}^{(i)}), \qquad i = 0,1,...,2n \\ \hat{X}_{k|k-1} = \sum_{i=0}^{2n} w_i^m \xi_{k|k-1}^{(i)} \\ P_{k|k-1} = \sum_{i=0}^{2n} w_i^c (\xi_{k|k-1}^{(i)} - \hat{X}_{k|k-1})(\xi_{k|k-1}^{(i)} - \hat{X}_{k|k-1})^T + Q_{k-1} \end{cases} \tag{10}$$

where Q_k represent the variance of w_k .

(4) Observation and prediction

$$\begin{cases} \xi_{k|k-1}^{(i)} = H(\xi_{k-1|k-1}^{(i)}), \qquad i = 0,1,...,2n \\ \hat{Z}_{k|k-1} = \sum_{i=0}^{2n} w_i^m \xi_{k|k-1}^{(i)} \\ P_{z_k} = \sum_{i=0}^{2n} w_i^c (\xi_{k|k-1}^{(i)} - \hat{Z}_{k|k-1})(\xi_{k|k-1}^{(i)} - \hat{Z}_{k|k-1})^T \\ P_{x_k z_k} = \sum_{i=0}^{2n} w_i^c (\xi_{k|k-1}^{(i)} - \hat{X}_{k|k-1})(\xi_{k|k-1}^{(i)} - \hat{Z}_{k|k-1})^T + R_{k-1} \end{cases} \tag{11}$$

where R_k represent the variance of v_k .

(5) State update equation

$$\begin{cases} \hat{X}_{k|k} = \hat{X}_{k|k-1} + K_k (Z_k - \hat{Z}_{k|k-1}) \\ K_k = P_{x_k z_k} P_{z_k}^{-1} \\ P_{k|k} = P_{k|k-1} - K_k P_{z_k} K_k^T \end{cases} \tag{12}$$

where K_k is the Kalman gain of the system. The estimated value of the position coordinates of the fusion positioning of UWB /INS can be obtained through the whole process above.

In the actual fire environment, it is difficult to ensure that the UWB signal between each base station and the tag communicates unobstructed. During the movement of the firefighter, there will inevitably be some obstructions between the base station and the tag. In this case, the acquired TDOA value will have a large NLOS error, and bringing these large error values directly into the UKF algorithm will make the positioning result contain a large error. Therefore, in order to solve the problem of low positioning accuracy due to NLOS errors, this paper proposes a UKF-based fusion positioning and NLOS detection algorithm. First, take advantage of the high positioning accuracy of INS in the initial short time of the system, and use the PDR algorithm to obtain preliminary results. Locate the coordinates, and then use the NLOS detection algorithm to alleviate the NLOS error. The NLOS detection steps are as follows:

• Calculate the distance difference

The initial positioning coordinate $(\hat{x}, \hat{y})$ is obtained by PDR algorithm, and then the absolute value of the difference between the distance value from the coordinate to each UWB base station and the TDOA measurement value is calculated:

$$R_i = \left\| \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} - d_i \right\| \tag{13}$$

where (x_i, y_i) represents the coordinates of each base station, and d_i represents the TDOA measured value.

• NLOS judgment

The main source of UWB positioning system error is NLOS error. By comparing the calculated by formula (14) with the threshold , it can be judged whether there is NLOS error:

$$R > \Delta \tag{14}$$

When $R < \Delta$, it indicates that the error of the TDOA measurement value is small and within the normal error range. When $R \geq \Delta$, it indicates that there is a large NLOS error in the TDOA measurement value. The size of the threshold is determined by the measurement accuracy of the device. Find the residual error of the TDOA measurement value with large NLOS error:

$$\varphi_i = \eta(R_i - \Delta) \tag{15}$$

where η represent the residual coefficient. All residual values are used to form a residual matrix. In the fusion framework, the residual matrix is multiplied by the measurement noise matrix in the filter to dynamically alleviate the NLOS error. The algorithm flow of fusion position and NLOS detection based on UKF is shown in Fig.3:

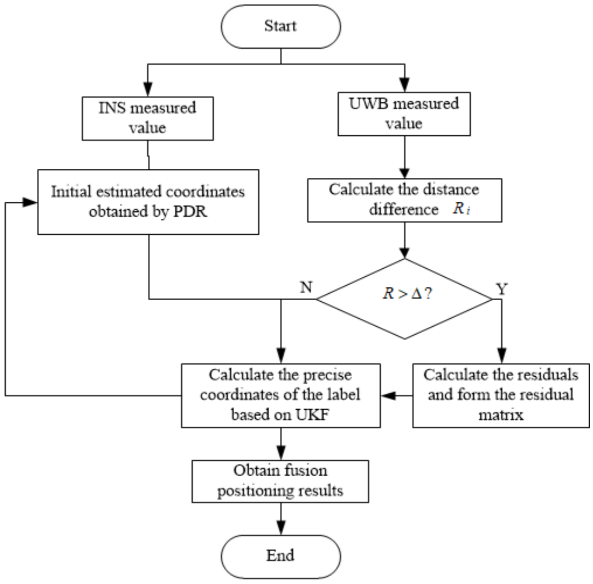


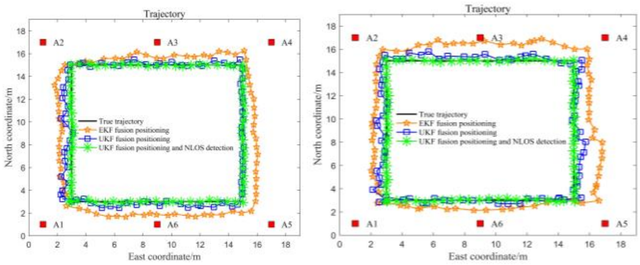
Fig. 3. Flow chart of fusion positioning algorithm.

5. Experiment and Analysis

5.1. MATLAB Simulation Design

In order to verify the performance of this algorithm, this algorithm is compared with the fusion positioning algorithm based on EKF and the fusion positioning algorithm based on UKF in the same simulation environment. Then, the algorithm's performance is evaluated by the simulation results and the root means square error (RMSE) of the positioning results. In the simulation experiment, the base station remains fixed, and the coordinates are A1 = [1, 1], A2 = [1, 17], A3 = [9, 17], A4 = [17, 17], A5 = [17, 1], A6 = [9, 1]. The simulated walking track is a square, and the coordinates of the four vertices are [3, 3], [3, 15], [15, 15], [15, 3]. In this paper, two groups of simulation experiments are carried out. The first group randomly adds 30 1.0m forward deviations to base stations A4 and A5 to simulate the error caused by NLOS, and the second group randomly adds 30 1.0m forward deviations to base stations A2, A5 and A6 to simulate the error caused by NLOS.

Fig.4 is trajectory diagrams obtained using different fusion positioning algorithms in different conditions. It can be seen from the trajectory diagram that the fusion positioning result of UWB/INS based on EKF has a large deviation because EKF truncates the Taylor expansion of nonlinear function by first-order linearization and ignores other high-order terms to convert the nonlinear problem into linearization. The error of EKF in a strongly nonlinear system is very large; The fusion positioning result of UWB / INS based on UKF is better than the former, but there will still be a large deviation in the positioning result at some times. Although UKF avoids ignoring the higher-order terms of UWB and INS nonlinear observation equations and can effectively improve the accuracy of solving nonlinear equations, it does not take into account the NLOS environment in reality; The result of fusion positioning and NLOS detection algorithm based on UKF is obviously better than that of the previous two algorithms. At the same time, the UWB measurement error in the NLOS environment is detected and mitigated so that the final positioning result is closer to the real walking track.



a) A4, A5 are in NLOS (b) A2, A5, A6 are in NLOS

Fig. 4. Simulation trajectory in different conditions.

RMSE is used to measure the positioning accuracy. The RMSE calculation formula is as follows:

$$RMSE = \sqrt{\frac{1}{m-1}\sum_{j=1}^{m}\left(\left(x_j - x_r\right)^2 + \left(y_j - y_r\right)^2\right)} \tag{16}$$

where $\left(x_j, y_j\right)$ represents the positioning coordinate, $\left(x_r, y_r\right)$ represents real coordinates, m represents the number of positioning points. Table I respectively show the position RMSE under two different NLOS conditions. Through the position RMSE in the table, it can be seen that the positioning results of the proposed algorithm are significantly better than the other two algorithms.

TABLE I. POSITIONING RMSE(M)

Algorithm	*NLOS base station: A4, A5*	*NLOS base station: A2, A5, A6*
Fusion positioning algorithm based on EKF	0.930	1.267
Fusion positioning algorithm based on UKF	0.446	0.606
Fusion positioning and NLOS detection algorithm based on UKF	0.091	0.096

5.2. Field Test Verification and Analysis

1) Experimental equipment and environmental layout

The preliminary positioning terminal used for firefighter positioning is shown in figure5. From left to right, the modules are UWB module, main control module, and INS module in Fig.5.

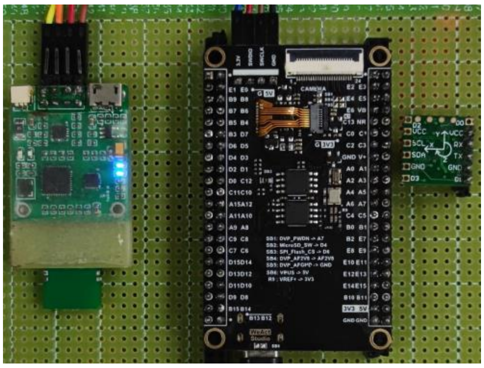


Fig. 5. Positioning terminal.

In this experiment, The East Laboratory of Xi'an University of Posts and telecommunications is selected as the experimental site to verify the actual positioning performance of the proposed algorithm. The experimental site includes tables and chairs, bars, lockers and other items. Fix the base station in the experimental site and set the position of the base station in advance. In the experiment, A0 is used as the host station, A0 [0.50, 0.75], A1 [0.50, 8.50], A2 [8.50, 8.50], A3 [8.5, 0.75]. Base stations A0 and A1 are placed in the corridor during the experiment to form NLOS communication between the base station and the tag. The actual layout of the base station is shown in Fig.6. The enlarged part in the figure is the actual working state of the base station. During the test, the positioning terminal is connected to the computer through USB-TTL. The tester walks with the computer according to the specified rectangular route, collects the positioning data of UWB and INS, and then transmits it to the computer for storage through USB-TTL. Finally, the positioning results are analyzed through the algorithm. The schematic diagram of the experimental environment is shown in Fig. 7.

Fig. 6. Schematic diagram of base station layout.

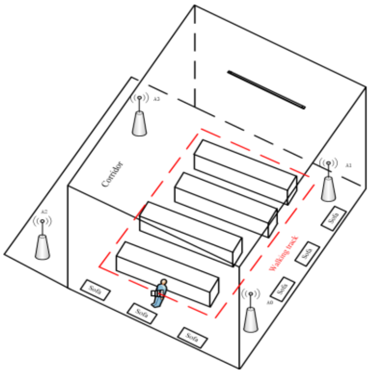


Fig. 7. Schematic diagram of experimental environment.

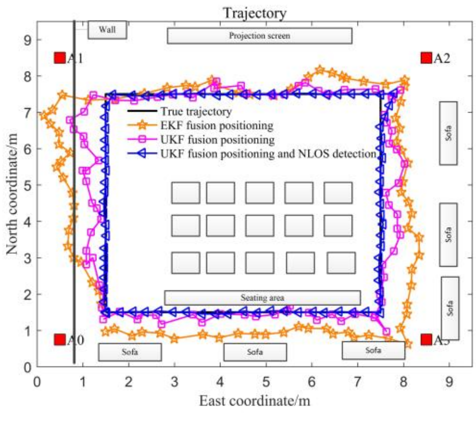


Fig. 8. Actual position trajectory.

2) Experimental results and analysis

Fig.8 is a simulation diagram of the actually measured positioning trajectory. It can be seen from the figure that when the base stations A2 and A3 are in the NLOS environment, the data fusion result of UWB/INS using EKF, and the data fusion result of UWB/INS using UKF and Compared with the real trajectory, there is a larger error. The reason is that the positioning base station is in the NLOS environment during the positioning process, which causes a large error in the positioning result. However, the positioning results of the UKF fusion positioning and NLOS detection algorithm proposed in this article have a smaller deviation from the real trajectory. There are two reasons. On the one hand, UKF is more suitable for strong nonlinear environments than EKF. On the other hand, there is NLOS detection to alleviate the NLOS error in the algorithm framework. Table II respectively show the position RMSE of the positioning trajectory, the RMSE of the position based on the EKF fusion positioning algorithm is 1.329m, and the RMSE of the position based on the UKF fusion positioning algorithm is 0.638m, and the RMSE of the algorithm proposed in this paper is 0.127m. Therefore, the positioning results of this algorithm in the NLOS environment are significantly better than the other two positioning algorithms mentioned above.

TABLE II. POSITIONG RMSE

Algorithm	*Position RMSE(m)*
Fusion positioning algorithm based on EKF	1.329
Fusion positioning algorithm based on UKF	0.606
Fusion positioning and NLOS detection algorithm based on UKF	0.127

6. Conclusion

This paper uses IOT positioning technology to obtain positioning data of firefighters on the fire site. It integrates UWB and INS for positioning so that UWB technology and INS technology complement each other. This method overcomes the problem of low positioning accuracy of single positioning technology in complex environments. The algorithm in this paper combines the UKF data fusion with the NLOS detection algorithm, which reduces the impact of the difference obtained in the NLOS environment on the positioning results and obtains a higher positioning accuracy. The NLOS detection algorithm takes advantage of the fact that INS can obtain more accurate positioning coordinates at the initial positioning stage. It detects the NLOS error by calculating the difference between the initial positioning coordinates to the base station and the TDOA measurement value, calculates the residual, and constructs the residual matrix. In the UKF fusion algorithm, the residual matrix and the measurement error matrix are multiplied to alleviate the NLOS error dynamically. Finally, through simulation and experimental testing, the algorithm proposed in this paper has good positioning accuracy. It provides an effective solution for the high-precision positioning of firefighters in the fire scene. However, there is room for further improvement in the stability of the algorithm.

7. Acknowledgements

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8. References

[1] Zhang W P, Research on the application of the Internet of Things in the field of fire safety[J]. Firefighting community, 2016 (12): 65-65.

[2] Zafari F, Gkwlias A, Leung K K. A Survey of Indoor Localization systems and Technologies [J]. IEEE Communications Surveys & Tutorials, 2019, 2568-2599.

[3] KG A, TA A, AB B, BG A, AC A. Indoor positioning of metal parts by fingerprinting using passive RFID - Science Direct [J]. Procedia CIRP, 2020, (88), 60-63.

[4] Feng D, Wang C, He C, Zhuang Y, Xia X. Kalman filter based integration of IMU and UWB for high-accuracy indoor positioning and navigation[J]. IEEE internet of things journal, 2020, 7(4):3133-3146.

[5] Tian Q, Salcic Z, Kevin I, Pan Y. A multi-mode dead reckoning system for pedestrian tracking using smartphones[J]. IEEE Sensors Journal, 2015, 16(7): 2079-2093.

[6] Zhang W, Wei D, Yuan H, Yang G. Cooperative Positioning Method of Dual Foot-Mounted Inertial Pedestrian Dead Reckoning Systems[J]. IEEE Transactions on Instrumentation and Measurement, 2021, 70: 1-14.

[7] Zhang Y L. Research on indoor positioning technology based on UWB/PDR combination[D]. Beijing: Beijing University of Architecture and Architecture, 2021.

[8] Liu F. Research on high-precision seamless positioning model and method based on sensor fusion[D]. Xuzhou: China University of Mining and Technology, 2020.

[9] Wang G, Qin S, Lv Q, Wei F, Liu H, Liang B. UWB and IMU system fusion for indoor navigation[C]//2018 37th Chinese Control Conference (CCC). IEEE, 2018: 4946-4950.

[10] Zhong Y, Liu T, Li B, Yang L, Lou L. Integration of UWB and IMU for precise and continuous indoor positioning[C]//2018 Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS). IEEE, 2018: 1-5.

[11] P. Li, Y. Xu, T. Shen and S. Bi, INS/UWB integrated AGV localization employing Kalman filter for indoor LOS/NLOS mixed environment. International Conference on Advanced Mechatronic Systems, 2019, pp. 294-298.

[12] Yang G, Zhu S, Li Q, Zhao K. UWB/INS Based Indoor Positioning and NLOS Detection Algorithm for Firefighter s[C]//2020 IEEE 22nd International Conference on High Performance Computing and Communications; IEEE 18th International Conference on Smart City; IEEE 6th International Conference on Data Science and Systems (HPCC/ Smart-City/DSS). IEEE, 2020: 909-916.

[13] Zhang M, Jia J, Chen J, Deng Y, Aghvami A. Indoor Localization Fusing WiFi with Smartphone Inertial Sensors Using LSTM Networks[J]. IEEE Internet of Things Journal, 2021.

[14] Zhu Y, Luo X, Guan S, Wang Z. Indoor Positioning Method Based on WiFi/Bluetooth and PDR Fusion Positioning [C]//2021 13th International Conference on Advanced Computational Intelligence (ICACI). IEEE, 2021: 233-238.

[15] Cai J, Chen Z, Sun L.Design of WiFi/PDR fusion indoor positioning system based on extended Kalman filter[J]. Single Chip Microcomputer and Embedded System Application, 2020, 20(08):56-60+64.

[16] Hasan M A, Rahman M H. Smart phone based sensor fusion by using Madgwick filter for 3D indoor navigation[J]. Wireless Personal Communications, 2020, 113(4): 2499-2517.