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Positioning of UWB Indoor Mobile Robot Based on Robust Kalman Filter

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Abstract

In UWB indoor location, the ranging process is interfered by non-line-of-sight error (NLOS), which reduces the accuracy and reliability of location. To solve this problem, an improved Kalman filter algorithm is adopted in this paper. Based on the linearized model of UWB indoor positioning system, a single new value is used to construct the resistance factor matrix, so as to eliminate the influence of non-line-of-sight ranging error. Experimental results show that this method can effectively eliminate the bad influence of NLOS ranging error on location and improve the accuracy and reliability of location solution.

Keywords

UWB indoor localization;Kalman filtering;NLOS ranging error.

1. Introduction

In the outdoor environment, mobile robots mainly rely on Global Navigation Satelite (GNSS) for positioning, but in the indoor environment, it is difficult to achieve precise positioning of mobile robots because GNSS signals are blocked by buildings[1]. At present, the sensors widely used in indoor positioning include UWB, LiDAR, camera, odometer, IMU, super god wave and so on[2-3]. Ultra Wideband(UWB) technology uses pulses with extremely low power spectral density and narrow pulse width to carry information, with extremely high time resolution and good penetration capability, and higher positioning accuracy than wireless positioning technologies such as WLAN, Bluetooth, and RFID[4].

UWB indoor positioning is generally achieved by measuring the distance, and common ranging technologies include： Time of Arrival(TOA), Difference of Time Arrival(TDOA), Angel of Arrival(AOA) , etc. In the indoor environment, due to the existence of walls and obstacles, UWB signals will be refracted and reflected, resulting in Non Line of Sight (NLOS) ranging errors, which greatly reduces the positioning accuracy[5-6].

In order to effectively suppress the non-line-of-sight error of UWB positioning and improve the positioning accuracy and reliability of indoor mobile robots, many scholars have done a lot of research[7-8]. Literature [9] proposed a TDOA localization algorithm based on Chan algorithm to identify and eliminate NLOS errors,Chan algorithm was used to obtain the initial estimation of target position, and then TDOA measurement error was used to identify non-line-of-sight errors. Finally, Chan algorithm was used to obtain the precise position of the target by replacing the modified measurement value into Chan algorithm. In literature [10], the new information vector and the corresponding covariance matrix are used to construct the adaptive factor, and the output value of the neural network is used to construct the pseudo-residual vector, so as to adaptively adjust the gain matrix and the covariance matrix of the measured noise. Literature [11] uses the new information vector to construct the equivalent covariance matrix of measurement information, so as to improve the anti-difference ability of the system.

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Aiming at the location error caused by NLOS interference in UWB positioning system, an improved Kalman filter algorithm is proposed in this paper. The algorithm uses the new information vector to distinguish LOS and NLOS environment, and constructs the measurement noise covariance matrix respectively, so as to eliminate the influence of NLOS location error and improve the accuracy and reliability of UWB indoor positioning.

2. UWB indoor positioning system

2.1. DS - TWR range

The Ranging method used in this paper is a Double Side Two Way Ranging (DS-TWR) algorithm based on TOA. DS-TWR does not require clock synchronization between communication parties, which can avoid the distance error caused by clock synchronization between two devices, reducing the difficulty of development. The packet sending process of DS-TWR algorithm is shown in Figure 1. Device A sends polling information with its own label to device B at the time T_{SP}. When device B receives polling information, device B records the receiving time T_{RP} and sends A reply message to device A, and records the sending time T_{SR}. After receiving the reply message, device A records the time T_{RP} and sends the time (T_{SP},T_{RP},T_{SF}.) recorded on the label to device B at the time T_{SF}. Thus, the delay time of device A is $T_{roundA} = T_{SP} - T_{RR}$, The response time of device B is $T_{replyB} = T_{RP} - T_{SR}$, The delay time of device B is $T_{roundB} = T_{SR} - T_{RF}$, The response time of device A is $T_{replyA} = T_{RR} - T_{SF}$.Thus, the unilateral flight time of UWB signal between device A and device B is:

$$TOF = \frac{1}{4}\left(\left(T_{roundA} - T_{replyB}\right) + \left(T_{roundB} - T_{replyA}\right)\right) \tag{1}$$

Due to the problem of clock drift in device A and device B, in order to reduce the ranging error caused by clock drift, literature [5] proposed an improved DS-TWR algorithm, and the improved TOF estimation is shown as follows:

$$TOF = \frac{T_{roundA}T_{roundB} - T_{replyA}T_{replyB}}{T_{roundA} + T_{roundB} + T_{replyA} + T_{replyB}} \tag{2}$$

Multiply TOF by the speed of light in the air (299792458m/s) to find the distance between device A and device B.

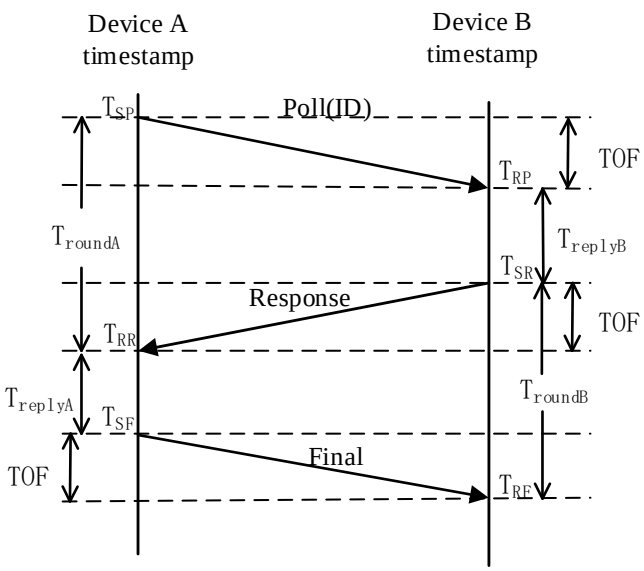

Figure 1: Steps based on DS-TWR

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2.2. UWB positioning model

In this paper, the UWB indoor positioning system consists of four reference stations, a tag and a local server. The UWB tag is installed in the geometric center of the four-wheel omnidirectional mobile robot, and the local server is used to write the control program of the mobile robot and obtain positioning information. The composition of the UWB indoor positioning system is shown in Figure 2.

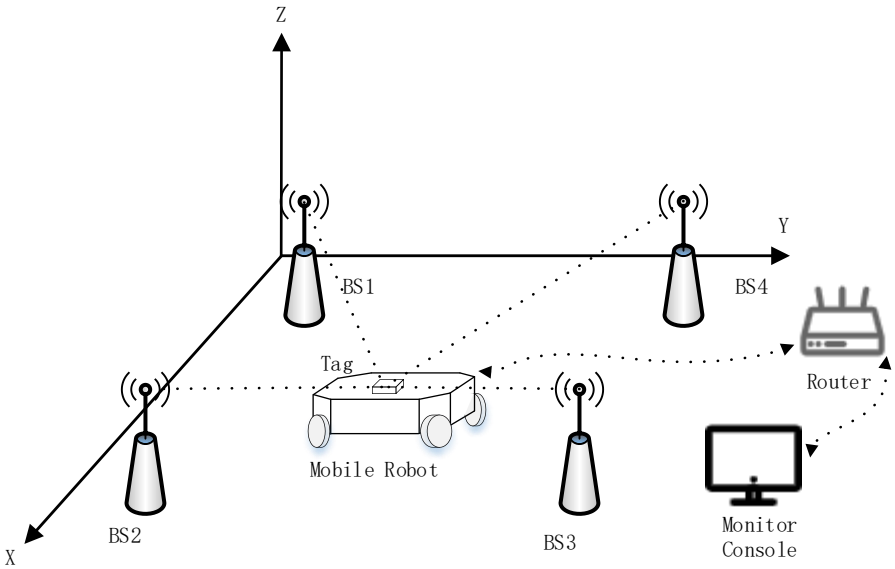


Figure 2: The overall structure of UWB positioning system

In the indoor positioning system based on UWB, the position and speed of the tags in the two-dimensional plane are taken as the state variables of the system $X_k = [x_k \quad y_k \quad v_{x,k} \quad v_{y,k}]^T$, x_k and y_k are the abscissa and ordinate of the label at time of k, $v_{x,k}$, $v_{y,k}$ are the speed component of the label on the X-axis and Y-axis at time of k. So the equation of state of the system can be described as:

$$X_k = FX_{k-1} + W_k \tag{3}$$

Where, F is the state transition matrix, $F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$, T is the sampling time of the system; W_k is the systematic error, Assume that it is gaussian white noise with variance 0 and covariance matrix Q, and $E[W_k] = 0$, $Cov[W_k, W_j] = Q\delta_{kj}$.

δ_{kj} is Kronecker function,which mean:

$$\delta_{kj} = \begin{cases} 0, & k \neq j \\ 1, & k = j \end{cases} \tag{4}$$

As shown in figure 2, it is assumed that the location coordinates of the base station are respectively $(\tilde{x}_1, \tilde{y}_1, \tilde{z}_1), (\tilde{x}_2, \tilde{y}_2, \tilde{z}_2), (\tilde{x}_3, \tilde{y}_3, \tilde{z}_3), (\tilde{x}_4, \tilde{y}_4, \tilde{z}_4)$, the position coordinates of the label are (x_u, y_u, z_u). Since the actual ranging information is the distance in three dimensions, the actual ranging information needs to be converted in plane positioning, minus the difference on the Z-axis, which is:

$$d_{i,k} = \sqrt{(d_{i,k}^{UWB})^2 - (z_u - \tilde{z}_i)^2}, i = 1, 2, 3, 4 \tag{5}$$

Where, $d_{i,k}$ is the plane distance between the ith base station and the label at time of k; $d_{i,k}^{UWB}$ is the actual measured distance between the ith base station and the label at time of k.
Considering the ranging error, the ranging model in two-dimensional plane can be obtained as follows:

$$d_{i,k} = r_{i,k} + n_{i,k} \quad (i = 1, 2, 3, 4) \tag{6}$$

where, $r_{i,k}$ is the real distance between the label at time k and the ith base station,and $r_{i,k} = \sqrt{(x_k - \tilde{x}_i)^2 + (y_k - \tilde{y}_i)^2}$;$n_{i,k}$ is distance measurement error.

The square expansion of equation (6) gives:

$$\begin{cases} (\tilde{x}_1^2 + \tilde{y}_1^2) + (x_k^2 + y_k^2) - d_{1,k}^2 = 2\tilde{x}_1 x_k + 2\tilde{y}_1 y_k - m_{1,k} \\ (\tilde{x}_2^2 + \tilde{y}_2^2) + (x_k^2 + y_k^2) - d_{2,k}^2 = 2\tilde{x}_2 x_k + 2\tilde{y}_2 y_k - m_{2,k} \\ (\tilde{x}_3^2 + \tilde{y}_3^2) + (x_k^2 + y_k^2) - d_{3,k}^2 = 2\tilde{x}_3 x_k + 2\tilde{y}_3 y_k - m_{3,k} \\ (\tilde{x}_4^2 + \tilde{y}_4^2) + (x_k^2 + y_k^2) - d_{4,k}^2 = 2\tilde{x}_4 x_k + 2\tilde{y}_4 y_k - m_{4,k} \end{cases} \tag{7}$$

where $m_{i,k} = 2d_{i,k}n_{i,k} - n_{i,k}^2$. According to the equation (7), based on the first term in equation (7), x_k^2, y_k^2 can be eliminated by making difference with the following three terms respectively, thus obtaining:

$$\begin{cases} x_2^2 - x_1^2 + y_2^2 - y_1^2 + d_{1,k}^2 - d_{2,k}^2 = 2(\tilde{x}_2 - \tilde{x}_1)x_k + 2(\tilde{y}_2 - \tilde{y}_1)y_k - m_{2,k} + m_{1,k} \\ x_3^2 - x_1^2 + y_3^2 - y_1^2 + d_{1,k}^2 - d_{3,k}^2 = 2(\tilde{x}_3 - \tilde{x}_1)x_k + 2(\tilde{y}_3 - \tilde{y}_1)y_k - m_{3,k} + m_{1,k} \\ x_4^2 - x_1^2 + y_4^2 - y_1^2 + d_{1,k}^2 - d_{4,k}^2 = 2(\tilde{x}_4 - \tilde{x}_1)x_k + 2(\tilde{y}_4 - \tilde{y}_1)y_k - m_{4,k} + m_{1,k} \end{cases} \tag{8}$$

Therefore, the measurement equation of UWB positioning system is:

$$Z_k = H_k X_k + V_k \tag{9}$$

where, Z_k is the measured value of the system at time of k; H_k is the measurement matrix of the system at time of k. V_k is the measurement noise of the system at time of k, assuming that it obeys the normal distribution with mean value zero and covariance matrix R_k ,and $V_k \sim N(0, R_k)$,which are:

$$Z_k = \begin{bmatrix} x_2^2 - x_1^2 + y_2^2 - y_1^2 + d_{1,k}^2 - d_{2,k}^2 \\ x_3^2 - x_1^2 + y_3^2 - y_1^2 + d_{1,k}^2 - d_{3,k}^2 \\ x_4^2 - x_1^2 + y_4^2 - y_1^2 + d_{1,k}^2 - d_{4,k}^2 \end{bmatrix} \tag{10}$$

$$H_k = \begin{bmatrix} 2(\tilde{x}_2 - \tilde{x}_1) & 2(\tilde{y}_2 - \tilde{y}_1) & 0 & 0 \\ 2(\tilde{x}_3 - \tilde{x}_1) & 2(\tilde{y}_3 - \tilde{y}_1) & 0 & 0 \\ 2(\tilde{x}_4 - \tilde{x}_1) & 2(\tilde{y}_4 - \tilde{y}_1) & 0 & 0 \end{bmatrix} \tag{11}$$

$$V_k = \begin{bmatrix} m_{2,k} - m_{1,k} \\ m_{3,k} - m_{1,k} \\ m_{4,k} - m_{1,k} \end{bmatrix} \tag{12}$$

In UWB positioning system, complex and changeable indoor environment will bring errors to ranging information and reduce the accuracy and reliability of positioning. Therefore, it is necessary to use filtering algorithm to process the original ranging inf-ormation.According to formula X and X, the positioning system is a linear system, so the Kalman filter algorithm can be used for optimal estimation of the positioning resu-lts.KF can reduce UWB ranging error by analyzing historical data.

In LOS environment, the standard Kalman filter algorithm can be used to solve the lo-cation information of the target in UWB positioning system.The prediction process of the standard Kalman filter algorithm is：

$$\begin{cases} \hat{X}_{k,k-1} = F_{k,k-1}\hat{X}_{k-1} \\ P_{k,k-1} = F_{k,k-1}P_{k-1}F_{k,k-1} + Q_{k-1} \end{cases} \tag{13}$$

the update process is:

$$\begin{cases} K_k = P_{k,k-1}H_k^T(H_kP_{k,k-1}H_k^T + R_k)^{-1} \\ \hat{X}_k = \hat{X}_{k,k-1} + K_k\left(Z_k - H_k\hat{X}_{k,k-1}\right) \\ P_k = (I - K_kH_k)P_{k,k-1} \end{cases} \tag{14}$$

where, $\hat{X}_{k,k-1}$ is the state prediction vector; $P_{k,k-1}$ is the covariance matrix of the predicted state; K_k is the gain matrix; $\hat{X}_k$ is the estimated state vector at time of k; P_k is the estimated state covariance matrix at time of k; I is the identity matrix.

Define the new information vector:

$$\xi_k = Z_k - H_k\hat{X}_{k,k-1} \tag{15}$$

When LOS is between the base station and the tag, ξ follows a Gaussian distribution with an average of zero.When there is an NLOS environment between the base station and the tag, there is an NLOS ranging error, and ξ can be considered to obey a Gau-ssian distribution with an average value of $\tilde{Z}_k - \hat{Z}_k$.

$$\begin{cases} \xi \sim N(0,\ D_k), \quad LOS \\ \xi \sim N\left(\tilde{Z}_k - \hat{Z}_k,\ D_k\right),\ NLOS \end{cases} \tag{16}$$

where, $\tilde{Z}_k$ is the actual measurement information in the NLOS environment; $\hat{Z}_k$ is the real measurement information in the NLOS environment; D_k is the covariance matrix of the new vector,and $D_k = HP_{k,k-1}H^T$. Let c be a constant and define the check information as $\Delta\xi_k = \xi^T D_k^{-1}\xi$ .When $\Delta\xi_k \leqslant c$, it can be considered that there is an NLOS environment between the base station and the tag, and there is an NLOS error in the ranging information[11].

In LOS/NLOS mixed environment, there are both good ranging information values a-nd range outliers with NLOS ranging error. In order to make full use of good ranging information values, a single new value is used to check the new information:

$$\Delta\xi_{k,i} = \xi_{k,i}(D_k^{-1})_{i,i}\xi_{k,i} \tag{17}$$

When A contains abnormal measurement information caused by NLOS ranging error, $|\Delta\xi_{k,i}| > c$. When $V_{k,i}$ is the measurement information in the LOS environment bet-ween the base station and the label, $|\Delta\xi_{k,i}| \leqslant c$ .By using $\Delta\xi_{k,i}$ and Huber function to construct the anti-difference factor[12]:

$$\lambda_i = \begin{cases} 1, \quad |\Delta\xi_{k.i}| \leqslant c \\ \dfrac{|\Delta\xi_{k,i}|}{c},\ |\Delta\xi_{k,i}| > c \end{cases} \tag{18}$$

Making $\Lambda = \mathrm{diag}[\,\lambda_1 \quad \lambda_2 \quad \lambda_3 \quad \lambda_4\,]$,so that the anti-difference covariance matrix of the measured information is $\overline{R}_k = \Lambda R_k$ ， The updating process of the improved Kalman filter is:

$$\begin{cases} \bar{K} = P_{k,k-1} H^T \left(H P_{k,k-1} H^T + \bar{R}_k \right)^{-1} \\ P_k = \left(I - \bar{K}_k H \right) P_{k,k-1} \\ \hat{X}_k = \hat{X}_{k,k-1} + \bar{K}_k \xi_k \end{cases} \tag{19}$$

Formula (19) is used to improve the standard Kalman filter algorithm, and a single ne-w information value is used to detect and judge whether the measurement information contains NLOS error. According to Formula (19), the covariance matrix of measurem-ent noise is estimated and corrected in real time, so as to improve the anti-difference performance of UWB indoor positioning system.

3. Experiment and analysis

In order to verify the validity and reliability of the proposed algorithm, static and dynamic experiments are carried out respectively.In the experiment, four UWB base stations were placed in fixed positions, their coordinates were (250,-133,70)cm, (170,115,70)cm, (-240,122,70)cm, (-240,-165,70)cm, and the UWB tag was fixed on the mobile robot. To add NLOS errors, the experimenter walked between the base station and the tag during the experiment.

In the static experiment, the coordinates of UWB tags were fixed as (38,-25,16)cm, so the real distances between the tags and the four base stations were 237.9cm, 192.4cm, 314.4cm, 311.3cm, respectively.The measured distance information is shown in Figure 3. Figure 4(a) shows the position calculation results based on standard Kalman filter and improved Kalman filter respectively, and Figure 4(b) shows the x and Y coordinates corresponding to the two methods respectively.It can be seen from Figure 4 that when the robot is disturbed by NLOS when it is static, the position solved by KF will fluctuate greatly. Although the position solved by IKF also fluctuates, it is obviously smaller than that by KF, and has a certain tolerance.

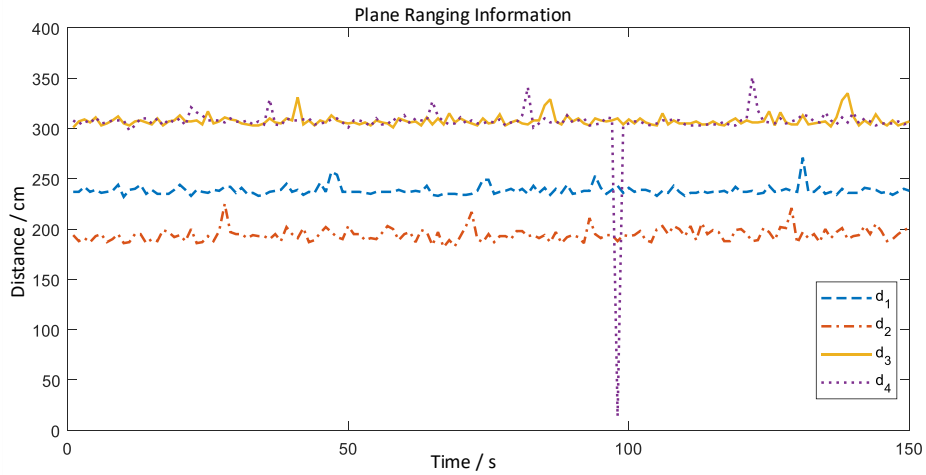
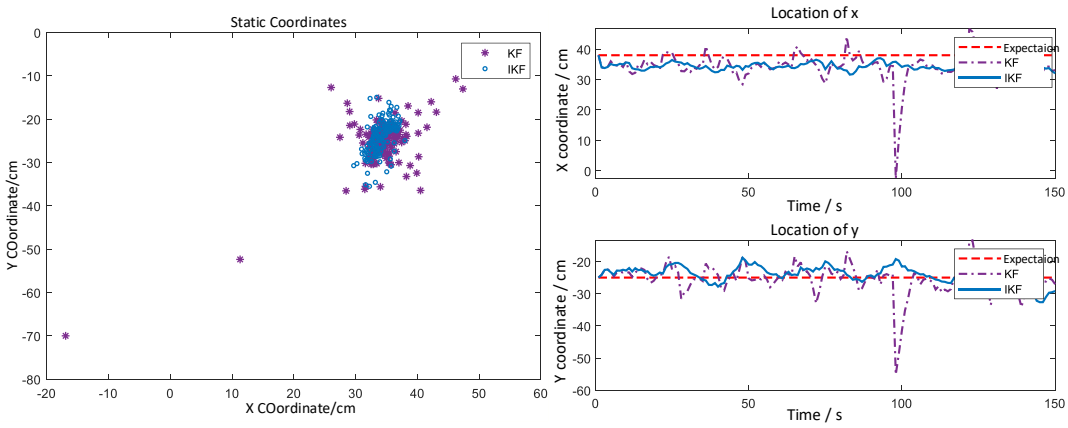


Figure 3: Static ranging information

Static positioning error of UWB positioning is shown in figure 5. It can be seen that kF-based position estimation has a large error and large fluctuation, while ikF-based position estimation has a smaller error than KF, and the error curve is relatively flat.It indicates that in the static experiment, when the UWB positioning process is disturbed by NLOS, the standard Kalman filter cannot effectively eliminate the error, but the improved Kalman filter can eliminate the error caused by NLOS to a certain extent.

During the dynamic experiment, the height of UWB tag remained unchanged, and the open-loop control mobile robot moved according to the given speed, and the dynamic ranging results were obtained as shown in Figure 6. Dynamic positioning results are shown in Figure 8, Figure 8(a) is the solution result of position coordinates, and Figure 8(b) is the position in the X direction

and y direction. In the dynamic experiment, the error results of position calculation are shown in Figure 9.It can be seen from the dynamic positioning results that in dynamic positioning, when affected by NLOS, the position estimation error based on KF is large, and the maximum position offset can



(a) Position calculating (b) Coordinate information of X and Y

Figure 4: Static location result

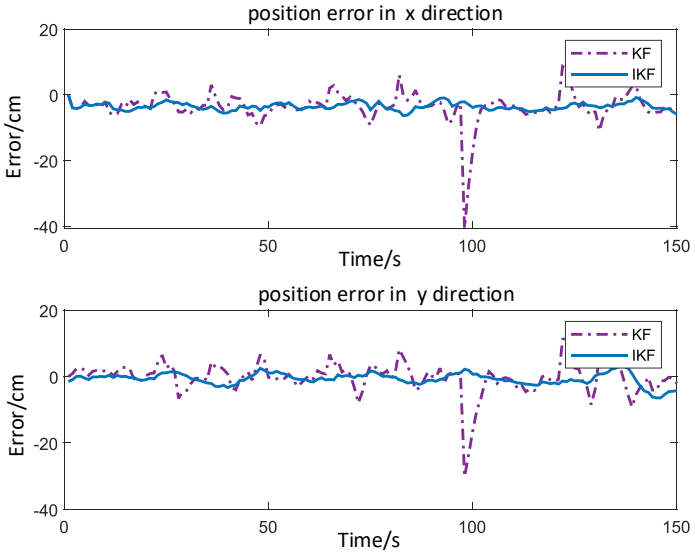


Figure 5: Static position error in x and y directions

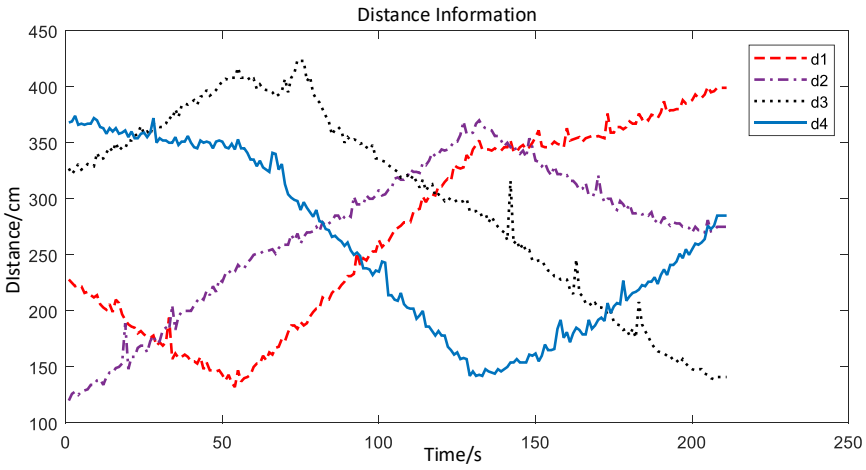
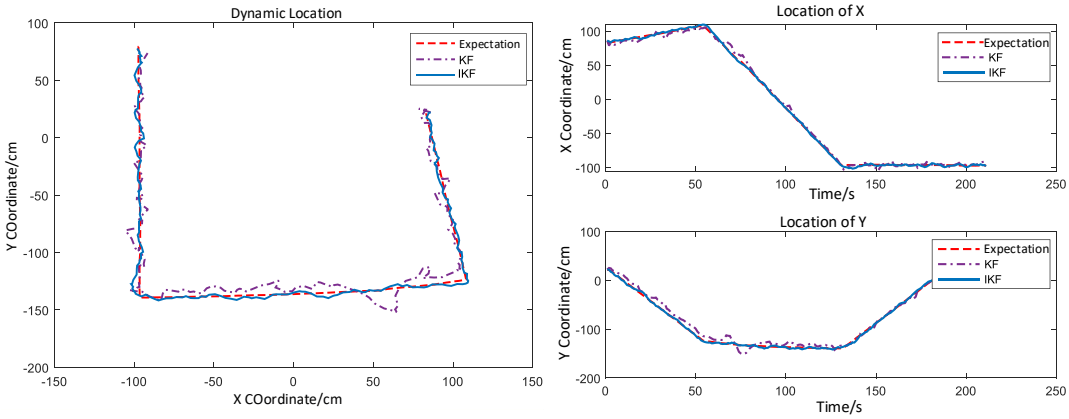


Figure 6: Dynamic ranging information



(a) Position trajectory (b) Coordinate information of X and Y

Figure 7: Dynamic location result

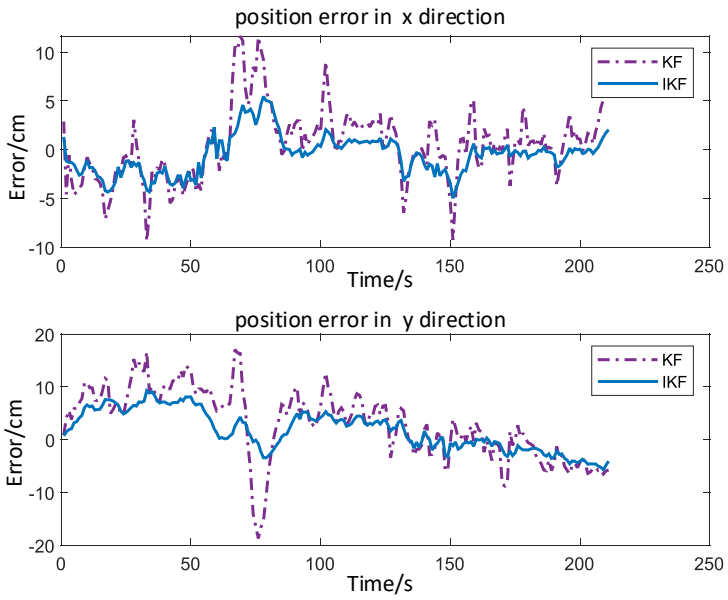


Figure 8: Dynamic position error in x and y directions

reach 20cm.Ikf-based position estimation can reduce the error to a certain extent, and the maximum position deviation is about 6 cm. However, due to the difficulty of eliminating LOS error in the ranging process, the error fluctuation of its position solution is large, and the stability of positioning needs to be improved.

4. Conclusion

The accuracy and reliability of UWB indoor positioning system are reduced due to the influence of NLOS ranging error. In this paper, an improved Kalman filter theory is proposed. LOS environment and NLOS environment are determined by setting error check vector, and anti-error is achieved by updating the covariance matrix of measurement equation. In the experiment, NLOS ranging error is added to form the anomaly of measurement information, and the comparison and analysis of the standard Kalaman filter and the improved Kalman filter verify the effectiveness and reliability of the improved algorithm. This shows that this method can effectively eliminate the influence of NLOS ranging error on location calculation and improve the accuracy and reliability of indoor positioning.

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