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Conference Paper · July 2018

DOI: 10.23919/ChiCC.2018.8483323

Proceedings of the 37th Chinese Control Conference
July 25-27, 2018, Wuhan, China

UWB and IMU System Fusion for Indoor Navigation

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Abstract: Ultra-wideband (UWB) localization is used for the indoor navigation, but the positioning accuracy will be affected by non-line-of-sight (NLOS) environment. And this error is difficult to accept for the indoor navigation. In this work, we mainly study the UWB\Inertial Measurement Unit (IMU) fusion algorithms based on the extend Kalman filter (EKF) and unscented Kalman filter (UKF). And we put forward an errors complementary extend Kalman filter algorithm for indoor navigation on the NLOS environment. Then, we carry out the experiments with the omnidirectional robot. Through the experiment, we find that the new algorithm is also good for NLOS navigation. Compared with the other two algorithms, the new algorithm reduces the computational complexity.

Key Words: UWB/IMU, EKF, UKF, Errors Complementary

1 Introduction

Nowadays, many applications require reliable and accurate indoor positioning, such as warehouse management, personnel monitoring and positioning in hospital or prison and so on[1-2]. However, due to the accuracy of the global navigation satellite system and the signal attenuation and reflection in the building, this type of positioning system can't be used for indoor positioning. Therefore, there is an urgent need for an indoor positioning system.

Most indoor location systems make use of radio technologies, such as WiFi, Zigbee, UWB and so on[3]. In this paper, the UWB positioning system is mainly selected, which has the obvious advantages of good anti-multipath interference effect, low energy consumption, low cost and high accuracy. And it mainly uses ranging based on round trip time (RTT)[4].

In order to maintain the accuracy of RTT measurement, we need to consider some factors such as time delay, signal reflection, environmental impact and so on. Therefore, we need to calibrate the system accurately before installing the anchors, which can ensure the accuracy of the system. Despite accurate calibration, however, positioning may still having large errors when the tagged object moves to NLOS conditions or the experimental ambient noise is excessive [5]. So, the positioning accuracy can be improved by combining the UWB system with the inertial navigation system (INS)[6-8]. The system can have better positioning accuracy than using either system alone.

This paper studied the different filtering algorithms for the indoor omnidirectional robots navigation with UWB system and INS system. And put forward the errors complementary extend Kalman filter algorithm that using the extend Kalman filter to estimate the errors and correcting the navigations states.

The remainder of this paper is organized as follows. In the second section, the principle and calibration of UWB are mainly carried out, and the conversion of IMU coordinates is also included. The third section introduces the various algorithms for IMU and UWB fusion. The fourth section mainly carried out the experiments of various methods under the indoor environment and carried out a comparative evaluation. The fifth section mainly summarizes the work of the article.

2 UWB and IMU

2.1 The principle of distance measurement

The UWB module is based on the DWM1000 chip of DecaWave company. And the DWM1000 module location method is mainly the arrival time method. In this paper, the Symmetric-double-sided Two-way Ranging (SDS-TWR) symmetric bilateral ranging method is selected. Compared with the Two-way time-of-flight ranging (TW-TOF) bilateral ranging method, the SDS-TWR ranging method mainly adds an extra communication, so that the time of the two communication can make up for the error by the clock offset, and eliminate the time difference between the two devices. The principle is shown in Figure 1.

The Device A represents the anchor, and the Device B represents the tag. First, the anchors send the packets to the label, meanwhile recording the sending timestamp and the receiving timestamp. The $T_{\mathrm{round}1}, T_{reply1}, T_{round2}, \mathrm{T}_{reply2}$ can be calculated by time stamps. The propagation time of electromagnetic wave in the air is T_{prop}, so the derivation formula is as

*This work is supported by National Nature Science Foundation under Grant (61663014)

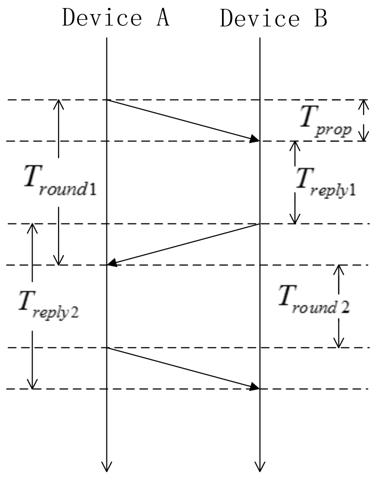

Fig 1. The principle of SDS-TWR distance measurement

$$\begin{cases} T_{round1,2} = T_{reply1,2} + 2T_{prop} \\ T_{prop} = \dfrac{T_{round1} * T_{round2} - T_{reply1} * T_{reply2}}{T_{round1} + T_{round2} + T_{reply1} + T_{reply2}} \end{cases} \quad (1)$$

and the distance between the anchor and tag is

$$\mathrm{D} = \mathrm{C} * T_{prop} \quad (2)$$

where $C \approx 3 \times 10^8 m/s$ is the speed of electromagnetic wave propagation in the air.

2.2 Range measurement calibration

Using the SDS-TWR method, the clock offset error between the two devices is eliminated effectively. However, in the actual situation, there is still a certain time error due to the problem of the clock precision of each device itself. In addition, a series of external factors, such as temperature change caused by external environment, signal attenuation in electromagnetic wave transmission, and environmental reflection, will also cause some errors.

In order to obtain more accurate ranging information, it is necessary to calibrate the tags and anchors one by one. On the assumption that the ambient noise is constant in a complete LOS environment. The tag and anchor have multiple measured on a fixed distance, then we take the average values to do linear fitting. The experiment will be in the fourth section.

2.3 IMU coordinate transformation

IMU mainly uses the data of accelerometers and gyroscopes. In the system, IMU is installed on the body. Therefore, the relevant data of IMU measurement is suitable for body coordinate system, so we must use the rotation matrix to transform the measured data to the navigation coordinate system.

Paper [10] gives the 3D rotation matrix of the body coordinate system in the general state to the navigation coordinate system.

$$R_n^b = \begin{bmatrix} c\theta c\varphi & -c\theta s\varphi + s\phi s\theta c\varphi & s\phi s\varphi + c\phi s\theta c\varphi \\ c\theta s\varphi & c\theta c\varphi + s\phi s\theta s\varphi & -s\phi c\varphi + c\phi s\theta s\varphi \\ -s\theta & s\phi c\theta & c\phi c\theta \end{bmatrix} \quad (3)$$

In this rotation matrix, the s, c means $\sin$ and $\cos$. And ϕ indicates the roll angle, θ indicates the pitch angle, and φ indicates the yaw angle. Since the main work of this paper is on the 2D and X-Y planes, the roll and pitch angles are zero. The matrix can be simplified as follows:

$$R_n^b = T_n^b = \begin{bmatrix} c\varphi & -s\varphi \\ s\varphi & c\varphi \end{bmatrix} \quad (4)$$

3 Algorithm for fusion

The frequency range of the UWB system is lower than that of the IMU, and it can't provide the attitude information and can only give the position. Although the IMU is highly dynamic, its error is not bounded and will accumulate over time. So the fusion of these two systems makes up for the shortcomings of the two systems, and the new system performance better.

3.1 EKF

The UWB coordinate system is mainly used as the navigation coordinate system. And what we use are angular rate and acceleration information, so the model is as follows:

$$\begin{cases} p_{k+1}^n = p_k^n + \Delta T v_k^n + \dfrac{\Delta T}{2} a_k^n \\ V_{k+1}^n = V_k^n + \Delta T a_k^n \end{cases} \quad (5)$$

where ΔT is the sampling time from k to $k+1$, $p^n = \begin{bmatrix} x & y \end{bmatrix}^T$ is the position in the navigation coordinate system as well as $V^n = \begin{bmatrix} V^x & V^y \end{bmatrix}$ is the speed and $a^n = \begin{bmatrix} a^x & a^y \end{bmatrix}$ is the acceleration. So, state equation is

$$x_{k+1} = Ax_k + Bu_k + w_k \quad (6)$$

and where the $x_k = \begin{bmatrix} x_k & y_k & V_k^x & V_k^y \end{bmatrix}^T$

$A = \begin{bmatrix} I_{2\times2} & \Delta T I_{2\times2} \\ 0_{2\times2} & I_{2\times2} \end{bmatrix}$ $B = \begin{bmatrix} \dfrac{\Delta T^2}{2} I_{2\times2} \\ T I_{2\times2} \end{bmatrix}$, the vector u combines acceleration and angular velocity measurements

$$u = a^n = \begin{bmatrix} a^x \\ a^y \end{bmatrix} = T_n^b a^b,\ w_k \sim N(0,\ Q).$$

Due to the measurement of the IMU is used as an input, so the distance measurements of the UWB are only used in the correction phase of the EKF and they are in the measurement vector z_k. And according to measurement we can get the measurement estimation $h\left(\hat{x}_k^-\right)$.

$$z_k = \begin{bmatrix} d_k^1 \\ \vdots \\ d_k^n \end{bmatrix} \quad (7)$$

$$h(\hat{x}_k^-)=\begin{bmatrix}\sqrt{(\hat{x}_k^- - A_{x,1})^2+(\hat{y}_k^- - A_{y,1})^2}\\ \vdots \\ \sqrt{(\hat{x}_k^- - A_{x,n})^2+(\hat{y}_k^- - A_{y,n})^2}\end{bmatrix} \tag{8}$$

In the (7) d_k^n means the distance measurement with anchor n at k time. And the (8) $\begin{bmatrix}A_{x,n} & A_{y,n}\end{bmatrix}$ means the position of the anchor n in the navigation coordinate system. Now, the Jacobian matrix can be calculated as

$$H_k=\begin{bmatrix}\frac{\left(\hat{x}_k^- - A_{x,1}\right)}{\left\|A_{x,1}-p_k^n\right\|} & \frac{\left(\hat{y}_k^- - A_{y,1}\right)}{\left\|A_{x,1}-p_k^n\right\|}\\ \vdots & \vdots \\ \frac{\left(\hat{x}_k^- - A_{x,n}\right)}{\left\|A_{x,n}-p_k^n\right\|} & \frac{\left(\hat{y}_k^- - A_{x,n}\right)}{\left\|A_{x,n}-p_k^n\right\|}\end{bmatrix} \tag{9}$$

$\|\bullet\|$ means the Euclidean distance, then according to the formula (7-9), the measurement equation is

$$z_k = H_k x_k + v_k \tag{10}$$

and $v_k \sim N(0,\mathrm{R})$.

The covariance of the UWB range measurements was set as $Var(\mathrm{R})=0.0514^2$. Now, we can get the position by EKF predict and update formulas.

3.2 UKF

In this paper UKF model and EKF model are roughly the same, the main change is the measurement equation does not require Jacobian matrix.

$$z_k = h(x_k)+v_k \tag{11}$$

The algorithm is based on the UT transform and uses the Kalman filter as the framework. So, at first calculating the Sigma points $S_i=\{\chi_i \quad W_i\}$.

System initialization state estimation:

$$\begin{cases}\hat{x}_0 = E\left[x_0\right]\\ P_0 = E\left[(x-\hat{x}_0)(x-x_0)^T\right]\end{cases} \tag{12}$$

State estimation:

$$\begin{cases}\chi_k^0 = \hat{x}_k\\ \chi_k^i = \hat{x}_k + (\sqrt{(n+\lambda)\mathrm{P}_k})_i, i=1,2,\cdots,n\\ \chi_k^{i+n} = \hat{x}_k - (\sqrt{(n+\lambda)\mathrm{P}_k})_i, i=n+1,\cdots,2n\end{cases} \tag{13}$$

Weight:

$$\begin{cases}W_0^m = \dfrac{\lambda}{n+\lambda}\\ W_0^c = \dfrac{\lambda}{n+\lambda}+1-\alpha^2+\beta\\ W_i^m = W_i^c = \dfrac{1}{2(n+\lambda)}, i=1,\cdots,2n\end{cases} \tag{14}$$

The n is a state dimension. So there is a total of three constants α,β,λ which needs to be determined. According to paper [11], we select α=$0.01,\beta=2,\lambda=-1$. And now we can use UKF formulas to get position.

3.3 Errors Complementary EKF with Moving Average

This algorithm use EKF equations for estimating the errors in the navigations states and use errors to calibrate the navigation. On the other hand combine with moving average to get stable and accurate distance data.

First of all, creating error state vector

$$\Delta x_k = \begin{bmatrix}\Delta p_k^n\\ \Delta v_k^n\end{bmatrix} \tag{15}$$

Then

$$\Delta\hat{x}_{k+1}^- = E_{k+1}\Delta\hat{x}_k + \mathrm{B}_e\Delta u + w_k \tag{16}$$

where the $E_k=\begin{bmatrix}I_{2\times2} & \Delta T I_{2\times2}\\ 0_{2\times2} & I_{2\times2}\end{bmatrix}$, $B_e=\begin{bmatrix}\frac{\Delta T^2}{2}I_{2\times2}\\ TI_{2\times2}\end{bmatrix}$,

and Δu means the errors of acceleration in the navigation coordinate system. To use the EKF, the range measurements have to related to the error states. We know the anchors position, and the position provide by IMU measurements, so the range can be calculated. To related errors we adjust the measurement function $h(\Delta\hat{x}_k^-)$ for taking the errors into it.

$$h(\Delta\hat{x}_k^-)=\begin{bmatrix}\left\|A_1-(\hat{x}_k+\Delta\hat{p}_k)\right\|-\left\|A_1-\hat{x}_k\right\|\\ \vdots \\ \left\|A_n-(\hat{x}_k+\Delta\hat{p}_k)\right\|-\left\|A_n-\hat{x}_k\right\|\end{bmatrix} \tag{17}$$

So $\Delta\hat{p}_k^- = \begin{bmatrix}\Delta\hat{x}_k^- & \Delta\hat{y}_k^-\end{bmatrix}$ And the Jacobian H_k will be as

$$H_k=\begin{bmatrix}\frac{A_{x,1}-(\hat{x}_k+\Delta\hat{x}_k^-)}{\left\|A_1-(\hat{x}_k+\Delta\hat{p}_k)\right\|} & \frac{A_{y,1}-(\hat{x}_y+\Delta\hat{x}_y^-)}{\left\|A_1-(\hat{x}_k+\Delta\hat{p}_k)\right\|}\\ \vdots & \vdots \\ \frac{A_{x,n}-(\hat{x}_k+\Delta\hat{x}_k^-)}{\left\|A_n-(\hat{x}_k+\Delta\hat{p}_k)\right\|} & \frac{A_{y,n}-(\hat{x}_y+\Delta\hat{x}_y^-)}{\left\|A_n-(\hat{x}_k+\Delta\hat{p}_k)\right\|}\end{bmatrix} \tag{18}$$

The vector Δz_k is the difference between the UWB range measurements and the predicted ranges that provide by IMU measurements and anchors position. And now, we can get the errors by EKF predict and update formulas. When we get the errors, we put them into navigation equations to correct the position. And the navigation equations is formula (5). So putting the estimated errors in the navigation equations, which make the EKF's prediction and correction phases simplify. When the errors are inserted, now we assumed that the states are correct and no errors. Then $\Delta\hat{x}_{k+1}^-$ is zero, and the measurement function $h(\Delta\hat{x}_k^-)$ is also zero. So only the Kalman gain and Δz_k are used for errors estimate. On the other hand, we have simplified the complexity of the algorithm.

In order to cope with the noise of measurement information and the interference of the NLOS environment, the moving average method is introduced to strengthen the stability of the system. Because of the relatively high frequency of measurement information, the moving average method is mainly used for the acquisition of measurement information, so that the measurement information of the system is more optimized. So Fig. 2 is the architecture of the algorithm.

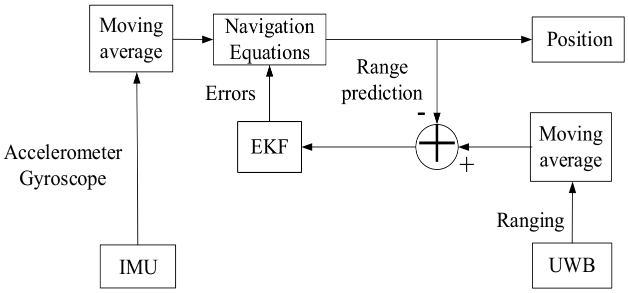

Fig 2. The architecture of the algorithm

4 Experiment

The single tag or anchor point of the UWB system is mainly used by the DWM1000 chip. The single range measurement is about 4ms, and the data is output through the serial port. This experiment uses 1 Tags and 6 anchors so that it can provide about the 40Hz location frequency. The carrier used in the experiment is a three wheeled omnidirectional robot, which controls the encoder motor by using the Raspberry 3 to control the STM32 drive board through the serial port. The IMU inertial measurement unit is a MPU9250 inertial measurement unit, which use the STM32 chip reads the data from the IIC and to output the data through the serial port. So the UWB ranging and IMU measurements are fusion in the Raspberry 3. And the experimental area is about 4m × 3m in the laboratory.

4.1 Ranging Calibration

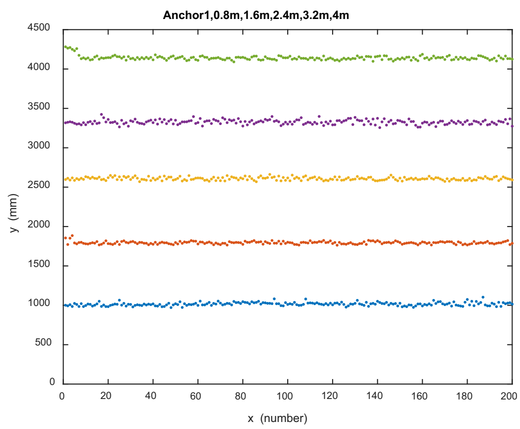

Fig 3. Tag and Anchor1 distance measurement

We choose one anchor to rang distance with tag. And the scene is completely under the condition of LOS. The scene is completely under the condition of LOS, UWB tag and anchors are placed on a fixed distance. According to the distance of 0 ~ 4m were divided into 5 groups, each interval of 0.8m. Each distance ranging 200 times, the average distance information as the current value of the distance. Figure 3 is the distance measurement between tag and anchor 1. And Fig. 4 is the three order linear fitting for anchor1 and tag. And the other 5 anchors do the same step to calibrate.

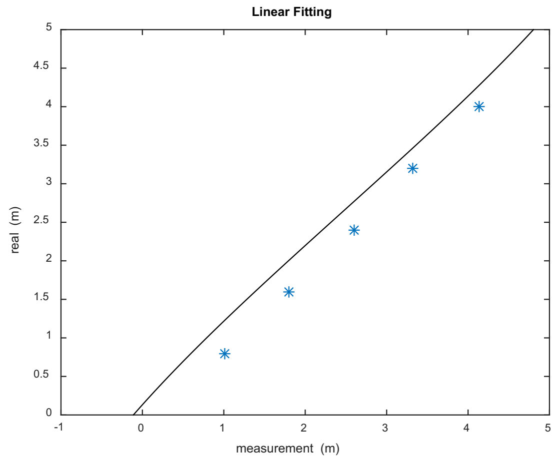

Fig 4. Three order Linear Fitting

4.2 Indoor IMU/UWB Experiment

The experiment is divided into three groups, which correspond to three algorithms. Each group conducts experiments under LOS environment and NLOS environment. Due to the small car, we use the desk and chairs to keep out the signals. Figure 5, 6, 7 is EKF, UKF and Errors Complementary EKF, respectively.

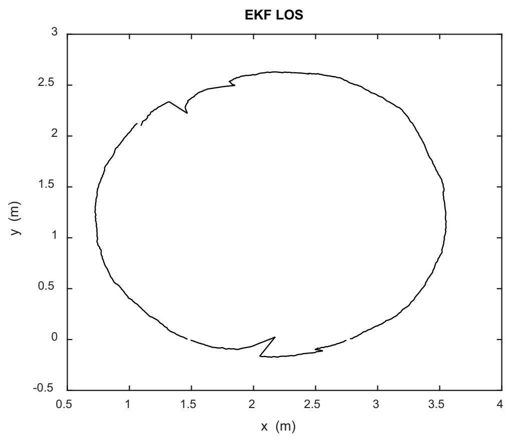

Fig 5(a). EKF LOS Measurement

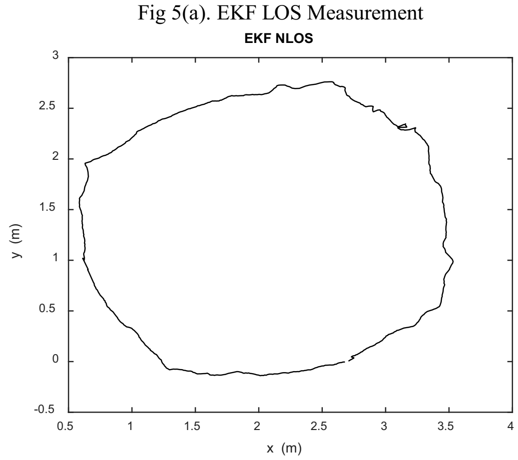

Fig 5(b). EKF NLOS Measurement

Fig 5. EKF Measurement

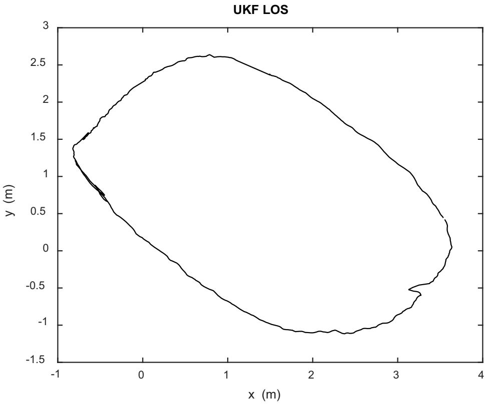

Fig 6(a). UKF LOS Measurement

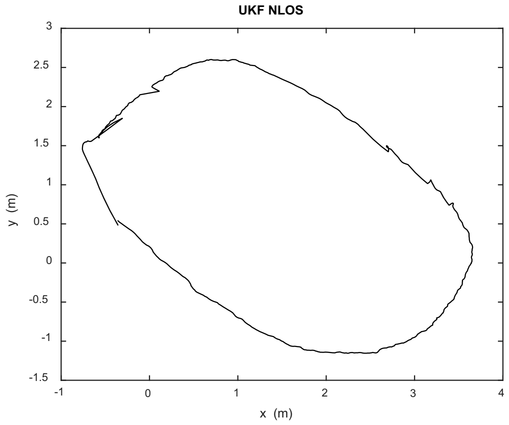

Fig 6(b). UKF NLOS Measurement

Fig 6. UKF Measurement

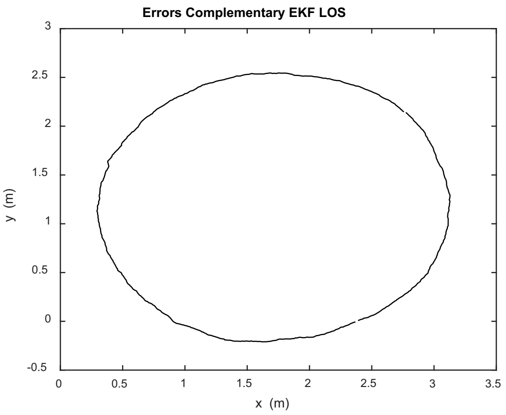

Fig 7(a). Complementary EKF LOS Measurement

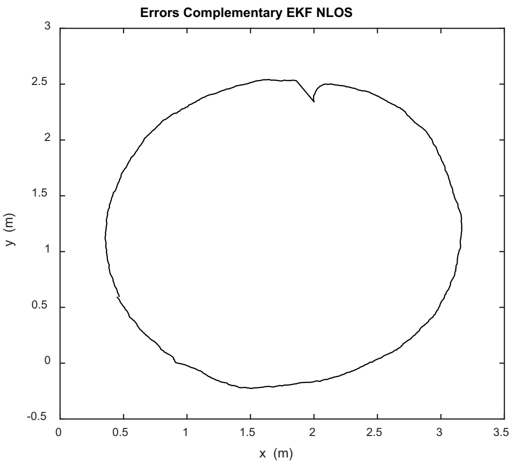

Fig 7(b). Complementary EKF NLOS Measurement

Fig 7. Complementary EKF Measurement

Table1. The error of NLOS relative to LOS

Error	x(m)		y(m)	
	mean	max	mean	max
EKF	0.911	0.2124	0.0791	0.1137
UKF	0.0623	0.1524	0.0319	0.1436
CEKF	0.0744	0.1711	0.5174	0.1091

From the error results, it can be seen that in the NLOS environment, all kinds of fusion algorithms can achieve relatively accurate positioning accuracy.

5 Summary

In indoor environment, in order to deal with the failure of GNSS location, we need to adopt other indoor location system instead of GNSS, and because of the advantages of UWB location, UWB is a good choice. In this paper, the three order polynomial fitting method is used to compensate the error of the range error that still exists in SDS-TWR. At the same time, errors complementary fusion algorithm is proposed. We can get the UWB/IMU state and measurement equations, the position is finally obtained by predict and update. The experiments are used to compare the above three algorithms, and it is proved that the new algorithm is also good for NLOS navigation. And due to its low computer cost, the next step we will use the new algorithm to the quadcopter navigation in the indoor environment.

References

[1] Borràs Sillero J. Sensor fusion methods for indoor navigation using UWB radio aided INS/DR[J]. 2012.

[2] Benini A. Localization and Navigation of Autonomous Systems in Complex Scenarios[J]. 2014.

[3] Yang zhou. Study on High Precision Indoor Positioning Technology Based on UWB/MEMS[D]. China University of Mining and Technology, 2015. (In Chinese)

[4] Sahinoglu Z. Ultra-Wideband Positioning Systems[M]. Cambridge University Press, 2008.

[5] Tao Cai. Research on Optimization of SDS-TWR and Fusion of Location Algorithm in Indoor Position Based on UWB[D]. Central China Normal University, 2016. (In Chinese)

[6] XU Aigong, LIU Tao, SUI Xin, et al, Indoor positioning and attitude determination method based on UWB/INS tightly coupled [J]. Journal of Navigation and Positioning, 2017, 5(2):14-19. (In Chinese)

[7] Mueller M W, Hamer M, D'Andrea R. Fusing ultra-wideband range measurements with accelerometers and rate gyroscopes for quadrocopter state estimation[C]// IEEE International Conference on Robotics and Automation. IEEE, 2015:1730-1736.

[8] Guo K, Qiu Z, Miao C, et al. Ultra-Wideband-Based Localization for Quadcopter Navigation[J]. Unmanned Systems, 2016, 04(01):23-34.

[9] Simo. Särkkä. Recursive Bayesian inference on stochastic differential equations /[J]. Helsinki University of Technology, 2006.

[10] Noureldin A, Karamat T B, Georgy J. Inertial Navigation System[M]// Fundamentals of Inertial Navigation, Satellite-based Positioning and their Integration. Springer Berlin Heidelberg, 2013:125-166

[11] Merwe R V D. Sigma-point kalman filters for probabilistic inference in dynamic state-space models[M]. Oregon Health & Science University, 2004