Multi-sensor data fusion for indoor drone positioning

Yufeng Chen [1], Jintao Ding [2,*],
[1] Chengdu Technological University, Chengdu, Sichuan Province, China
[2] Chengdu Technological University, Chengdu, Sichuan Province, China
[*] ysrobot@163.com

Abstract

The positioning of indoor mobile machines cannot be solved by a single sensor. A positioning system based on multi-sensor data fusion is designed. The system combines the positioning results of UWB with the positioning results of low-cost MEMS inertial measurement elements to improve the positioning accuracy of the system. The system includes two Kalman filters. The primary Kalman filter is used to fuse the angular velocity information of gyroscope and the angular value of magnetometer, so as to obtain more accurate heading angle. The secondary Kalman filter combines the IMU track estimation results with the UWB positioning results to obtain accurate positioning results. The final experimental results show that the method is effective.

Keywords- UWB；Multi-sensor data fusion； Kalman filter；indoor position

1. Introduction

Due to the improvement of chip performance and the development of artificial intelligence technology, more and more intelligent mobile terminal devices have emerged, such as storage and transportation carts, factory workshop logistics carts, and so on. A crucial engineering technical issue in the use of these devices is positioning and autonomous navigation. Outdoor, these mobile terminals can use global navigation satellite systems (GNSS) such as Bei-Dou positioning, which have been widely used and have advantages in system reliability and cost of use. However, for example, storage and transportation cars or home service robots work in indoor environments, due to the obstruction effect of buildings, satellite signals are too weak to be used.

This makes how to achieve reliable positioning and path planning for an indoor mobile terminal an application obstacle for indoor intelligent mobile terminals, which is a key research direction in the field of mobile robots. Many scholars have explored and studied this and achieved certain results. Overall, there are several technologies for indoor positioning of mobile robots currently available:

1.1 Based on triangulation positioning

Triangle positioning technology is mainly represented by pseudo star positioning [1], Bluetooth [2], Zigbee [3], UWB [4], etc. The basic principle is to obtain the distance between the target to be located and several pre established reference points, which are generally more than three, and then apply a triangular positioning algorithm to obtain the relative position. The positioning accuracy of such technologies depends on the measurement of distance, which is generally obtained through wireless signal time-of-flight method or signal strength estimation. However, due to the presence of a large number of fixed or mobile equipment indoors and the movement of on-site personnel, electromagnetic waves may have blind spots or reflect, refract, or scatter signals, The propagation path of the wireless signal to the receiver is not straight and there is randomness, which makes the distance between the target and the reference point uncertain, resulting in poor positioning accuracy of the system and inability to achieve practical value.

1.2 Based on Inertial Measurement

Inertial positioning is to obtain the three-axis acceleration and angular acceleration of the positioning target in the space coordinate system by installing an IMU (inertial measurement unit) on the positioning target, and then calculate the relative position of the target using the dead reckoning algorithm. Thanks to the development of electronic technology and MEMS technology, IMUs now have enormous advantages in size, cost, and power consumption, and are very easy to digitize and intelligentize. However, the trajectory estimation algorithm has a major flaw, which is that it accumulates the errors of each measurement. Therefore, over time, the errors of IMU continue to accumulate, leading to an increase in the error of target attitude estimation. This makes IMU based inertial measurement elements only able to ensure short-term positioning accuracy.

3rd International Conference on Artificial Intelligence, Automation, and High-Performance Computing
(AIAHPC 2023), edited by Simon X. Yang, Dimitrios A. Karras, Proc. of SPIE Vol. 12717,
1271709 · © 2023 SPIE · 0277-786X · doi: 10.1117/12.2687168

The above technologies have their own advantages and disadvantages, so it is difficult to achieve a relatively high-precision positioning effect if only a single method is used. Therefore, utilizing the rapidly developing multi-sensor fusion algorithms in recent years to combine the above technologies is a good research direction [5]. Reference [6] combines UWB with LiDAR technology, achieving good results. However, due to the susceptibility of LiDAR to sudden interference such as personnel movement, the use of this application has certain limitations; Reference [7] combines IMU with indoor Wi-Fi signals, although it has the characteristic of low cost for the entire positioning system. However, due to the low ranging accuracy of Wi-Fi based on signal strength, and the fact that most Wi-Fi hotspots are private, access is limited; Reference [8] combines UWB with wheel odometers, but wheel odometers may experience significant nonlinear errors in the positioning system during operation due to factors such as unevenness of the running surface, sliding between the wheels and the running surface, and deformation of the wheels due to the weight of the positioning target itself.

Due to the fact that UWB technology is based on the time-of-flight method for positioning, it has high positioning accuracy but is susceptible to interference; The IMU based trajectory prediction has the characteristics of strong anti-interference but long-term error accumulation. The characteristics of the two can complement each other, so this article uses data fusion algorithms to complement each other to achieve high indoor positioning accuracy.

2. Data Fusion Based on Kalman Filter

Kalman filtering is an efficient autoregressive estimator that can make optimal estimates of the state values of dynamic systems in the presence of combined information with many uncertainties, as shown in Figure 1, first use a magnetic intensity meter to obtain the angle information of the robot θ_1. Simultaneously, by integrating angular velocity ω from IMU we can obtain the angle information of a robot θ_2. Then, accurate heading angles θ are generated through Angle Kalman filter. the acceleration value output by the IMU accelerometer in the robot coordinate system is double integrated to obtain the robot position P. And through the UWB positioning system, we have a measurement position P-UWB. Perform position Kalman fusion of the two to obtain accurate position information.

2.1 Angle fusion

The angle fusion uses two sensors, gyroscope and magnetometer, in which the magnetometer outputs the angle value. The gyroscope measures the instantaneous angular velocity, which is the angular value after integration.

First, model the angle obtained by the gyroscope, select the angle and zero deviation as the system state variables, then the following equation can be listed.[9]

$$\begin{cases} \dot{angle} = (Gyro - bias) \\ \dot{bias} = 0 \end{cases} \tag{1}$$

$angle$: The angle of the gyroscope output

$Gyro$: The instantaneous angle speed measured by the gyroscope

$bias$: The instantaneous zero bias of the gyroscope

Discrete the above equations to obtain the state transfer equations:

$$\begin{pmatrix} angle \\ bias \end{pmatrix} = \begin{pmatrix} 1 & -dt \\ 0 & 1 \end{pmatrix} \begin{pmatrix} angle \\ bias \end{pmatrix} + \begin{pmatrix} dt \\ 0 \end{pmatrix} \text{Gyro} \tag{2}$$

Gyroscope output equation:

$$\text{angle} = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} angle \\ bias \end{pmatrix} \tag{3}$$

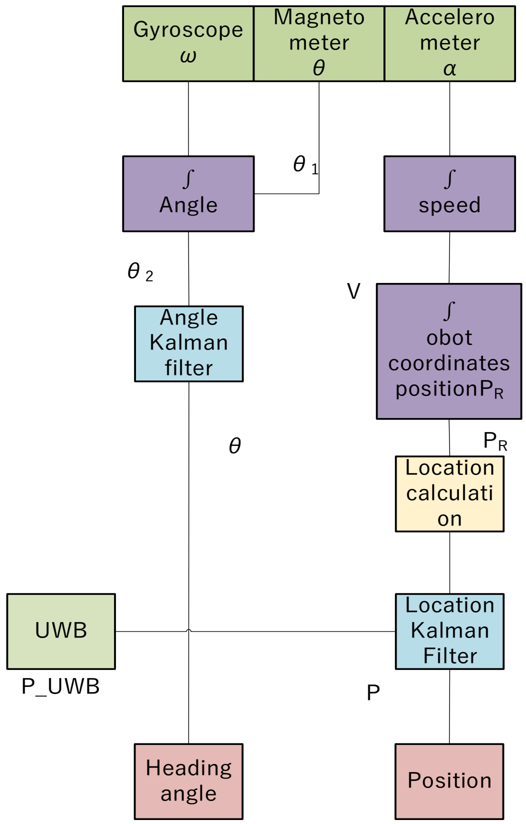

Fig. 1. Data fusion algorithm block diagram

With the state equation of the gyroscope and the angle value of the magnetometer, the Kalman filter[10] can now be used for data fusion to calculate the robot's heading angle. The specific algorithm is as follows:

Initial P_k, Q_k, R_k

Algorithm alman filter $(P_{k-1}, X_{k-1}, u_k, Z_k)$ **:**

Prediction: $X_k = F_k X_{k-1} + B_k u_k$

$$P_k = F_k P_{k-1} F_k^T + Q_k$$

Update: $K_k = \frac{P_k H_k^T}{H_k P_k H_k^T + R_k}$

$$X_k = X_k + K_k (Z_k - H_k X_k)$$

$$P_k = (I - K_k H_k) P_k$$

return X_k, P_k

Z_k: The angle value measured for the magnetometer

Angle fusion effect:

Figure 2 shows the angular velocity value of L3G4200DTR output in 1 minute under static condition

Fig. 2. The stationary gyroscope output

Figure 3 shows the angle values obtained by integrating the above angular velocities. Since there is no rotation, the angle value should be zero. However, as can be seen from the graph, the error of the angle data increases over time. Therefore, if other correction methods are not used, using this angle value cannot be used for trajectory prediction to obtain accurate positions.

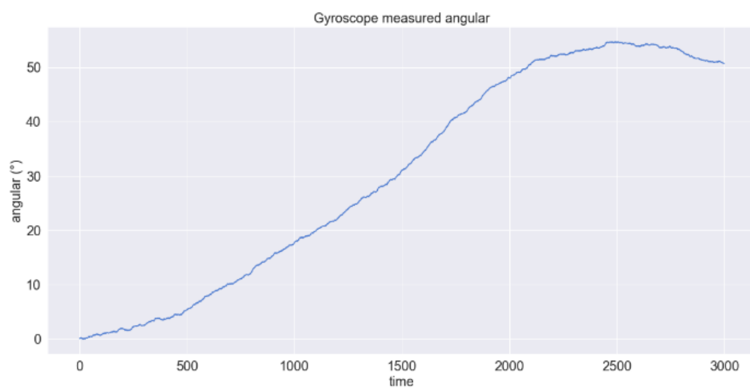

Fig. 3. The angle value calculated at stationary

Figure 4 shows the angle values measured by a magnetometer, but although the signal error does not increase over time, the noise is large, resulting in a large variance of the angle values and a large positioning error.

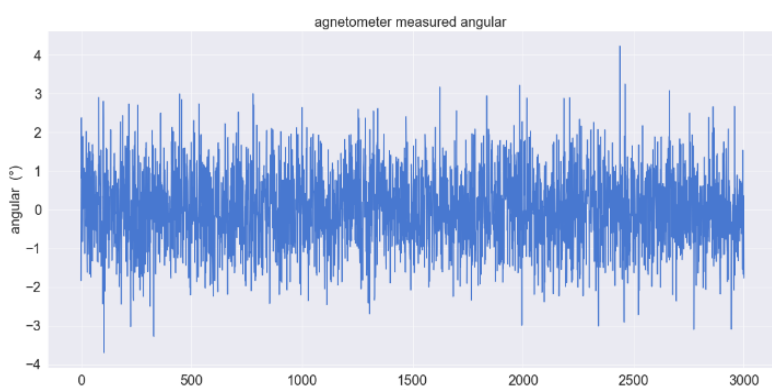

Fig. 4. The output value of the magnetometer at stationary

Figure 5 shows the angle values obtained from the magnetometer and gyroscope after data fusion using a Kalman filter. It can be seen that the variance of this angle value is small and the error does not increase over time.

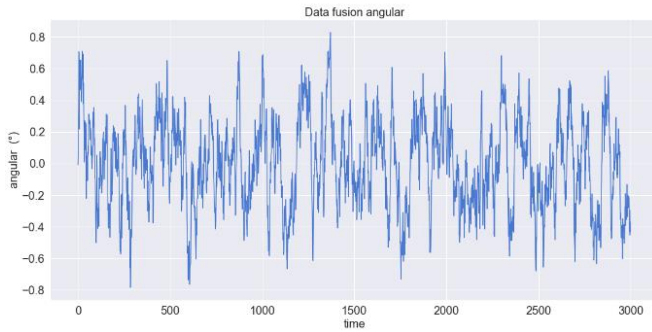

Fig. 5. The angle value after data fusion

2.2Position fusion

After the robot's heading angle is obtained in the previous step, the acceleration output from the accelerometer can be used to calculate the position. However, because the accelerometer also has noise and zero drift problems, the position information calculated solely from the IMU will become more and more error over time. Therefore, the output of UWB is required. UWB can provide a position value with large error, but its error size is constant. The optimal estimation can be obtained by Kalman data fusion.

According to the robot motion process modeling, select the state vector as $\{\mathrm{P_x}, \mathrm{P_y}, \mathrm{v_y}, \mathrm{v_x}, \mathrm{bias_y}, \mathrm{bias_x}\}$ where:$\mathrm{P_x}, \mathrm{P_y}$:Is the coordinates of the y and x axes of the robot in the world coordinate system

$\mathrm{v_y}, \mathrm{v_x}$:Is the velocity vector of the robot's y-axis and x-axis in the world coordinate system

$\mathrm{bias_y}, \mathrm{bias_x}$:Is the zero offset of the accelerometer

Then the following equation of state can be established according to kinematics:

$$\dot{P_y} = v_y$$

$$\dot{P_x} = v_x$$

$$\dot{v_y} = \cos\theta \cdot \left(\alpha_{cy} - bias_y\right) - \sin\theta \cdot (\alpha_{cx} - bias_x)$$

$$\dot{v_x} = \sin\theta \cdot \left(\alpha_{cy} - bias_y\right) + \cos\theta \cdot (\alpha_{cx} - bias_x)$$

$$\dot{bias_y} = 0$$

$$\dot{bias_x} = 0$$

The matrix form is as follows:

$$\begin{pmatrix} \dot{P_y} \\ \dot{P_x} \\ \dot{v_y} \\ \dot{v_x} \\ \dot{bias_y} \\ \dot{bias_x} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -cos\theta & sin\theta \\ 0 & 0 & 0 & 0 & -sin\theta & -cos\theta \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} P_y \\ P_x \\ v_y \\ v_x \\ bias_y \\ bias_x \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ cos\theta & -sin\theta \\ sin\theta & cos\theta \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \alpha_{cy} \\ \alpha_{cx} \end{pmatrix} \tag{4}$$

Due to heading angle θ It changes at any time, not a fixed value, so the system is a linear time-varying continuous state equation. For a linear time-varying system:

$$\begin{cases} \dot{x} = A(t)x + B(t)u \\ y = C(t) + D(t)u \end{cases} \tag{5}$$

When the sampling period T is small, generally when it is about 1/10 of the minimum time constant of the system, the discrete shape equation can be approximately expressed as:

$$\begin{cases} x\big((k+1)\big) \approx (TA + I)x(kT) + TBu(kT) \\ y(kT) = Cx(kt) + Du(kT) \end{cases} \tag{6}$$

Therefor the discrete state transition equation is:

$$\begin{pmatrix} P_y \\ P_x \\ v_y \\ v_x \\ bias_y \\ bias_x \end{pmatrix} = \begin{pmatrix} 1 & 0 & \Delta T & 0 & 0 & 0 \\ 0 & 1 & 0 & \Delta T & 0 & 0 \\ 0 & 0 & 1 & 0 & -cos\theta \cdot \Delta T & sin\theta \cdot \Delta T \\ 0 & 0 & 0 & 0 & -sin\theta \cdot \Delta T & -cos\theta \cdot \Delta T \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} P_y \\ P_x \\ v_y \\ v_x \\ bias_y \\ bias_x \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ cos\theta \cdot \Delta T & -sin\theta \cdot \Delta T \\ sin\theta \cdot \Delta T & cos\theta \cdot \Delta T \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \alpha_{cy} \\ \alpha_{cx} \end{pmatrix} \tag{7}$$

Output equation:

$$\begin{pmatrix} Py \\ px \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} P_y \\ P_x \\ v_y \\ v_x \\ bias_y \\ bias_x \end{pmatrix} \tag{8}$$

With the state equation of track calculation and the position information of UWB, the Kalman filter can now be used for data fusion to find the standard position value of the robot. The specific algorithm is as follows:

Initial $\boldsymbol{P_k}$, $\boldsymbol{Q_k}$, $\boldsymbol{R_k}$

Algorithm Kalman filter ($\boldsymbol{P_{k-1}}, \theta_k, \boldsymbol{X_{k-1}}, \boldsymbol{u_k}, \boldsymbol{Z_k}$)

Prediction:

Update $\boldsymbol{F_k}$ according to $\boldsymbol{\theta_k}$

$\boldsymbol{X_k = F_k X_{k-1} + B_k u_k}$

$\boldsymbol{P_k = F_k P_{k-1} F_k^T + Q_k}$

update: $\boldsymbol{K_k = \frac{P_k H_k^T}{H_k P_k H_k^T + R_k}}$

$\boldsymbol{X_k = X_k + K_k(Z_k - H_k X_k)}$

$\boldsymbol{P_k = (I - K_k H_k) P_k}$

return $\boldsymbol{X_k}$, $\boldsymbol{P_k}$

$\boldsymbol{Z_k}$: Location information measured for the UWB

3.Experimental data

To verify the positioning effect, we control the robot to start from the bottom left origin on a square with a side length of 900cm * 900cm, and the robot's path is clockwise. We tested the positioning accuracy of using only IMU heading calculation method for positioning, using only UWB triangulation for positioning, and the proposed fusion of IMU and UWB data in this paper.

From Figure 6, it can be seen that the IMU positioning results showed good performance in the initial stage of the experiment, with relatively small variance in the positioning data. However, as time went on, the accumulated IMU measurement errors increased, resulting in larger positioning errors, ultimately causing the measured robot trajectory to gradually deviate from the actual motion path.

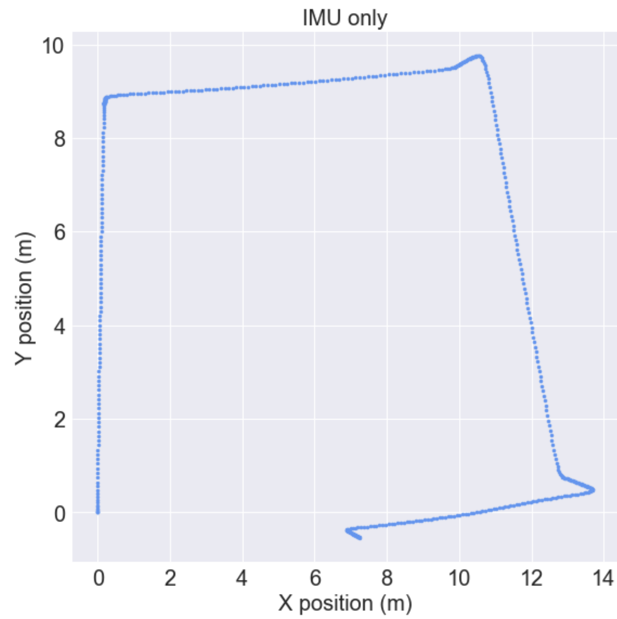

Fig. 6. IMU positioning

It can be seen from Figure 7 that the variance of UWB noise is relatively large, but its variance will not increase with time, and will always remain within a certain range, and will not deviate too much from the actual track.

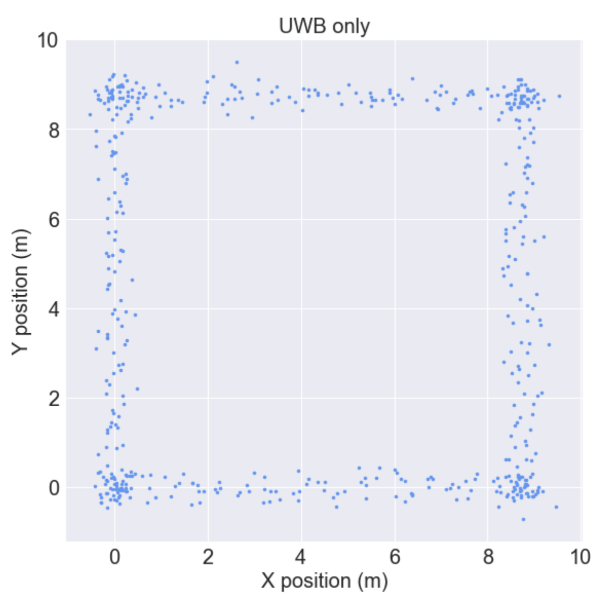

Fig. 7. UWB positioning

As can be seen from Figure 8, the location result obtained by IMU and UWB data fusion is superior to any single location result. The track did not deviate too much, and the variance of the overall noise also decreased.

Perform the above experiments for 10 times and calculate the variance under various methods, as shown in Table 1:

Table 1 Variance of each method

	IMU	*UWB*	*FUSION*
variance	5.023	0.89	0.34

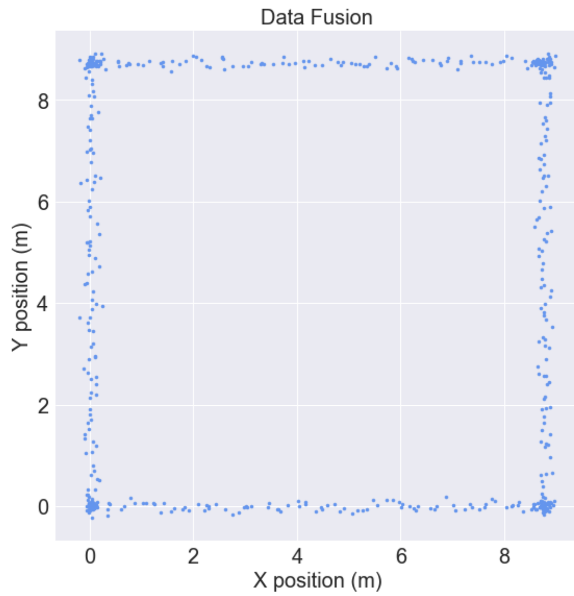

Fig. 8. Data Fusion positioning

4. Conclusion

Aiming at the problem of indoor positioning of mobile robots, this paper designs a system that integrates multiple sensors. The system makes full use of the advantages of both communication and positioning of UWB. In view of the NLOS problem caused by the influence of the surrounding environment and mobile personnel, this paper chooses to integrate the positioning results of UWB with the positioning results of low-cost MEMS inertial measurement elements. Firstly, an angle value fusion algorithm based on gyro angular velocity information and magnetometer angle is designed, and more accurate heading angle is obtained through Kalman filter, which provides a basis for later positioning. Secondly, on the basis of IMU track estimation algorithm, Kalman filter is used again to realize the fusion of UWB and IMU. The final experimental results show that the method is effective and can give more accurate positioning.

References

[1] Yang Guang Research on GPS and Pseudosatellite Combined Positioning Technology and Its Application in Deformation Monitoring. Journal of Surveying and Mapping 35.4 (2006): 410-410.

[2] Li Juanjuan et al Fuzzy Fingerprint Localization Algorithm under Bluetooth 4.0 Standard Specification. Journal of Shanghai University: Natural Science Edition 2 (2013): 6

[3] Wang Yuan, and Lin Jinguo Discussion on Several Commonly Used Indoor Positioning Techniques. "Chinese Instruments 2 (2011): 4.

[4] Ding Rui et al A UWB localization method based on joint estimation of TOA and DOA. Journal of Electronics and Information Technology 32.2 (2010): 313-317

[5] He You, Guan Xin, and Wang Guohong Progress and Prospects of Multi sensor Information Fusion Research. Journal of Astronautics 26.4 (2005): 7

[6] Chen Zhijian et al Indoor UWB/LiDAR Combined Localization Algorithm. Journal of Navigation and Localization 7.1 (2019): 6.

[7] Lei Yuwei et al The Application of WiFi and MEMS-IMU Fusion Localization Method in Indoor Localization. Journal of Navigation and Localization 4.4 (2016): 7.
[8] Xu Qingkun, Wang Tianhao, and Song Zhongyue Design of Indoor Mobile Robot Positioning Based on the Integration of UWB and Odometer. Mechanical Design and Manufacturing (2021)
[9] Zhang Haipeng, Fang Jiancheng Experimental study on short-time drift characteristics of MEMS gyroscope [J] Chinese Journal of Inertial Technology, 2007, 15 (1): 5
[10] Fu Mengyin, Deng Zhihong, and Zhang Jiwei Kalman filtering theory and its role in navigation systems Science Press, 2003