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A location method based on UWB for ward scene application

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Abstract—Epidemic prevention robots(EPRs) play an extremely important role in the period of an influenza outbreak. Most of the used scenes of EPR are indoor scenes such as ward and consulting room. The cost of the existing indoor positioning system based on vision is too high, but the positioning accuracy based on wireless technology is not enough, which restricts the development of EPR. In this paper, a positioning system based on UWB is proposed to provide a positioning service for EPR. A particle filter with adaptive particle redistribution is used to fuse the odometer and UWB. The incremental data of the odometer is used to predict the motion of EPR, and UWB data is used as the observation value to realize the pose estimation of EPR. The experimental results in the ward scene show that the method has good tracking performance and the positioning error is 3~7cm, providing robust and precise localization estimation for EPR applications.

Index Terms—EPR, indoor positioning system, UWB, adaptive particle redistribution

I. INTRODUCTION

With the rapid development of Epidemic prevention robots (EPRs) in recent years, the working environment of EPR has become more and more diverse, and the navigation application of robots in a complex environment has become particularly important. The accurate estimation of robot position is the key to its navigation effect. Nowadays, outdoor location system has developed very maturely, such as global position system (GPS) of the United States [1]. These localization systems have more accurate positioning performance in the outdoor environment, but they can not complete the positioning in the indoor environment. At present, several indoor positioning schemes have been proposed. For example, Wang et al. [2] applied WiFi Positioning Technology to the complex indoor environment; Bai et al. [3] implemented indoor positioning function with Bluetooth module. These radio-based technologies can only achieve meter-level accuracy. Although the location system based on lidar [4], QR code [5] [6] and lidar and vision fusion [7] can achieve centimeter-level accuracy, which the energy consumption and cost are significantly improved. Moreover, there is a non-line-of-sight situation in the ward environment, which will make it impossible to realize the positioning of the EPR.

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To obtain higher location accuracy and lower power consumption, researchers focus on ultra wide band (UWB) technology. UWB signal has a wide band range of 3.1~10.6GHz. The wide band performance makes it have a very narrow pulse, high time resolution, and strong penetration, which is suitable for indoor environment positioning. However, in the actual location process, the positioning accuracy of the object is not only affected by the device itself but also the occlusion of the wireless signal in the complex environment will increase the positioning error. Therefore, the single UWB location and navigation technology [8] [9] has been unable to meet the growing production and living needs of people. To get more accurate location data, researchers proposed a multi-sensor data fusion scheme and different fusion algorithms. The main algorithms based on the Kalman filter are as follows: Li et al. [10] proposed a multi-sensor data fusion algorithm based on fuzzy adaptive KF filter for multi-sensor dynamic system whose covariance of observation noise can not be accurately known or constantly changing. Feng et al. [11] propose an integrated indoor positioning system combining IMU and UWB through the extended Kalman filter (EKF) and unscented Kalman filter (UKF). Li et al. [12] used error state Kalman filter (ESKF) to fuse the measurement results of IMU with UWB. Because the motion state of the mobile robot can not be accurately predicted in most cases, particle filter algorithm for nonlinear system [13] has been gradually applied to robot location system. Wang et al. [14] used a particle filter algorithm to fuse lidar and UWB and achieved robot relocation in the scene with fewer features. Tian et al. [15] proposed an INS and UWB fusion system using particle filter (PF) for pedestrian tracking. To better achieve the tracking effect of the robot, most positioning schemes choose to use radar or IMU sensors to fuse with UWB or GPS, which has a high cost and power consumption.

Aiming at the shortcomings of the traditional positioning scheme, this paper proposes a fusion of UWB and odometer positioning systems based on particle filters. It achieves higher positioning accuracy and lower positioning cost. The main contributions of this paper are as follows:

(1)For the nonlinear motion of the EPR, the algorithm uses the mileage increment data of the odometer to predict the next moment of the robot's motion, and evaluates the predicted particles through the UWB data, retains the particles with higher weight and some particles with lower weight, and then circulates the filtering process to realize the positioning function of the anti epidemic robot.

(2)In order to improve the tracking effect of epidemic prevention robot, we propose a filtering algorithm with adaptive particle weight distribution, which adjusts the distribution of predicted particles according to the angle data of odometer to enhance the tracking effect.

(3)Both simulation and practical experiments have been conducted. A large number of field tests are carried out in the ward environment, and the results show that the method has high positioning accuracy and robustness, which is suitable for the application of EPR in the ward and clinic.

II. UWB LOCATION

The principle of UWB ranging is to calculate the product of a time of flight (TOF) and electromagnetic wave propagation speed, so the main working mechanism of the module is to record the time of information transmission and arrival through information exchange, and calculate the flight time according to the relationship between these times, so as to calculate the distance between the base station and the tag.

A. Double-sided Two-way Ranging

This design uses a Double-sided Two-way ranging method based on the time of flight (TOF) method. After the tag initiates the ranging request (Poll), it changes to the receiving state. The anchor in the receiving state returns the response message (Resp) after receiving the request message, and the tag returns the final message (Final) after receiving the response message. In the whole process, three packets are sent between the two devices, three ranging are carried out, and four-time intervals are generated. The time interval between the tag sending the 'Poll' message and receiving the 'Resp' message is T_{round1} , and the time interval from receiving the 'Resp' message to sending the 'Final' message is T_{round2} . The time interval between the anchor receiving the 'Poll' message and sending the 'Resp' message is T_{reply1} , and the time interval from sending the 'Resp' message to receiving the 'Final' message is T_{reply2} . Consequently, The distance between the tag and the anchor should be:

$$T_{porp} = \left(\frac{T_{round1} \times T_{round2} - T_{reply1} \times T_{reply2}}{T_{round1} + T_{round2} + T_{reply1} + T_{reply2}} \right) \quad (1)$$

In order to achieve two-dimensional positioning, a mobile tag needs to measure the distance to at least three fixed anchors, and then combine the three distances in an infrastructure-based solver to calculate the coordinates. Using conventional two-sided two-way ranging, each distance measurement needs to transmit 3 messages, meaning that the label needs to send 6 messages and receive 3 messages, for a total of 9 transmissions to locate the label position. In the asymmetric ranging scheme, the tag sends the Poll message, and the three anchors delay sending the Resp message after receiving the Poll message. The tag records the time stamp of the Resp message returned by the three anchor nodes in turn, and then packages and sends the Final message. The anchor read the corresponding time stamp information, which makes the tag be located after sending two messages and receiving three messages. This scheme is illustrated in Fig. 1. This represents a substantial saving in message traffic thereby saving battery power and air-time.

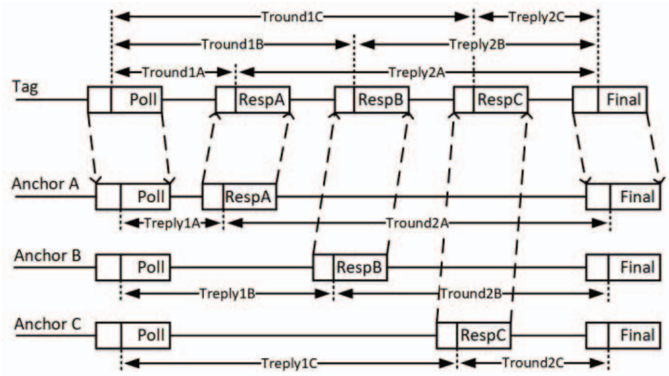

Fig. 1. UWB positioning scheme.

B. Calibration of UWB

The existing UWB positioning system does not have an accurate error model, so it is necessary to calibrate the UWB ranging error model in the actual environment. Firstly, the location of the anchor is fixed, and then place the tag on 16 random positions from 1.5m to 12m, then sample 100 groups of distance data at each position, and finally process and analyze the collected data through MATLAB.

Average 100 groups of data collected at each position as the measurement value of the position. The result of system error is the difference between the average value at each position and the corresponding true value, as shown in Fig. 2. It can be seen from the figure that the error presents a stable trend with the increase of ranging distance. After fitting, the curve equation is as follows:

$$f(x) = 5.8e^{-0.8} \cdot x^3 - 1.4e^{-0.4} \cdot x^2 + 0.1 \cdot x - 20.2 \quad (2)$$

C. UWB Coordinate Calculation

The anchor should be selected in the peripheral and as high as possible position of the EPR movement area. According to the indoor environment, the anchor are arranged on the three equal points of the circumscribed circle of the moving area as far as possible to ensure that

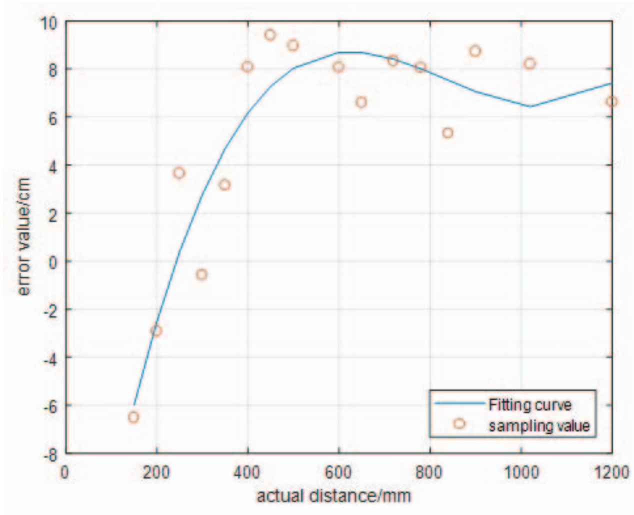

Fig. 2. Fitting curve of UWB ranging.

the distance difference between the tag and each anchor is small and reduce the system error caused by UWB. The error caused by NLOS can be avoided by placing the anchor in a higher place.

Suppose that the coordinates of the anchor are $A_1(X_1, Y_1, Z_1)$, $A_2(X_2, Y_2, Z_2)$,$A_3(X_3, Y_3, Z_3)$, and the coordinates of anchor A_1, A_2 and A_3 are known when they are installed and deployed. And the coordinates of the tag are $T_0(X_0, Y_0, Z_0)$.Set D_1,D_2, and D_3 as the relative distances calculated by the time of flight between the three anchor stations and the tag, and each anchor draws a circular track with the relative distance as the radius. The intersection of the three circular equations is the coordinate of the tag. The distance from the tag to the i-th anchor can be expressed as:

$$(x_i - x)^2 + (y_i - y)^2 = d_i^2, i \in (1, 2, 3) \tag{3}$$

Because there are two unknowns X and Y, and there are three equations, to calculate the coordinates of the tag, the least square method is usually used to solve the contradictory equation.Firstly, the equation is transformed into matrix form:

$$A \begin{bmatrix} x \\ y \end{bmatrix} = B \tag{4}$$

$$A = \begin{bmatrix} x_1 - x_2 & y_1 - y_2 \\ x_1 - x_3 & y_1 - y_3 \\ x_2 - x_3 & y_2 - y_3 \end{bmatrix} B = \begin{bmatrix} \frac{d_2^2 - d_1^2 + x_1^2 - x_2^2 + y_1^2 - y_2^2}{2} \\ \frac{d_3^2 - d_1^2 + x_1^2 - x_3^2 + y_1^2 - y_3^2}{2} \\ \frac{d_3^2 - d_2^2 + x_2^2 - x_3^2 + y_2^2 - y_3^2}{2} \end{bmatrix} \tag{5}$$

The coordinates of the tag are obtained by the least square method:

$$\begin{bmatrix} x \\ y \end{bmatrix} = (A^T A)^{-1} A^T B \tag{6}$$

III. FUSION OF UWB AND ODOMETER DATA BASED ON PARTICLE FILTER

Because the motion state of the EPR is usually unknown, the state equation of the robot motion can not be given, which Kalman filter can not be used to estimate the pose of the robot. For the nonlinear motion of EPR, a particle filter is usually used to estimate the trajectory of the robot.

A. Position Prediction by Odometer

In this paper, the incremental data of the odometer is used to predict the motion state of the robot, and the influence of the cumulative error of the odometer on the positioning accuracy of the robot is eliminated. The main idea is to assume that the robot maintains the same motion state in the four sampling times of the odometer, and predict the pose of the fourth odometer according to the data of the first three odometers. Because only the difference of odometer data is used in each prediction process, the influence of odometer cumulative error is avoided. The incremental model of the x-axis component (y-axis components are similar) is expressed as follows:

$$\begin{cases} \Delta x = [(x(t-1) - x(t-2)) - (x(t-2) - x(t-3))] \\ \Delta \widetilde{x} = x(t-1) - x(t-2) \end{cases} \tag{7}$$

The prediction model can be expressed as follows:

$$\begin{cases} z_x(t-1) + [\Delta x + x(t-1) - x(t-2)] & |\Delta x| > 0.1 \\ z_x(t-1) + [+x(t-1) - x(t-2)] & |\Delta x| \leqslant 0.1 \\ z_x(t-1) & |\Delta \widetilde{x}| < 0.1 \end{cases} \tag{8}$$

When the EPR is turning, it can't predict the position of the robot at the next moment through the distance data of the odometer, resulting in no particles to match near the coordinates after turning, which makes the filtered data drift greatly. So we need to judge whether the robot is turning or not through the angle data. When the robot stops turning, the particles are randomly redistributed in a certain range of the current coordinates of the robot to ensure that there are enough particles for the robot to match after the robot turns. The particle redistribution model is as follows:

$$particle(i) = \begin{bmatrix} z_x(t) + a \\ z_y(t) + b \end{bmatrix} \quad a, b \in (-1, 1), i \in (1, 1000) \tag{9}$$

B. Fusion of UWB and Odometert Data

The particle filter is based on the Bayesian principle and importance sampling. Its essential idea is to use a group of samples or particles to approximate the posterior distribution of the system, and then use approximate estimation to approximate the state of the nonlinear system. The core of the whole process is an iterative process of "prediction-correction". The specific process is as follows:

- Initialization: N particles are randomly distributed in the whole map, the initial pose of the robot is given by the stabilized UWB coordinate data, and the initialization data of the odometer is the UWB coordinate data.

- Prediction: According to the odometer prediction model given above, each particle is brought into the same state transition equation to make the same prediction for each particle.
- Correction: The UWB coordinate data at t is compared with the predicted particle coordinate data, and the predicted particle coordinate is evaluated. Then we calculate and normalize the weight of each particle.
- Resampling: The particles with small weight are eliminated, and the particles with large weight are copied to meet the needs of particle number and save computing time. Reselect the original particle set $\{z_t^{(i)}, \omega_t^{(i)}\}$, and form a new particle set. The new particle set is used as the prior knowledge to predict the robot position at t + 1.

IV. THE RESULTS OF EXPERIMENTS

A. Layout Experimental System

The robot used in this experiment is AIMIBOT EPR. The main body of EPR is mainly composed of the aluminum roof and carbon steel. The body contains a balanced driving system (with two universal wheels and two direct driving wheels), reversible DC motor, motor control and driving electronic equipment, high-resolution motion encoder and battery power supply, as well as ultrasonic and anti-drop sensors The digital attitude sensor is directly mounted on the NUC airborne computer. The particle filter process and experimental scene are shown in Fig. 3.

B. Data Acquisition and Analysis

The results of the static state positioning experiment are shown in Fig. 4, and the positioning error is shown in Table I. After 100 sets of coordinate data are calculated by UWB solution, the average coordinate is taken as the test coordinate point. When the tag is still, the maximum positioning error is 4cm, and the average positioning error is 3.8cm. Due to the multipath effect in UWB data transmission, data fluctuation will occur in UWB ranging, resulting in a centimeter-level error in the coordinates.

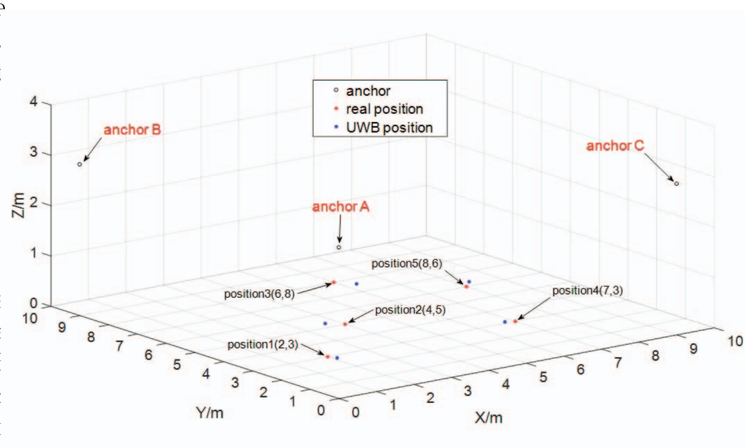

Fig. 4. Experimental results of UWB static point positioning.

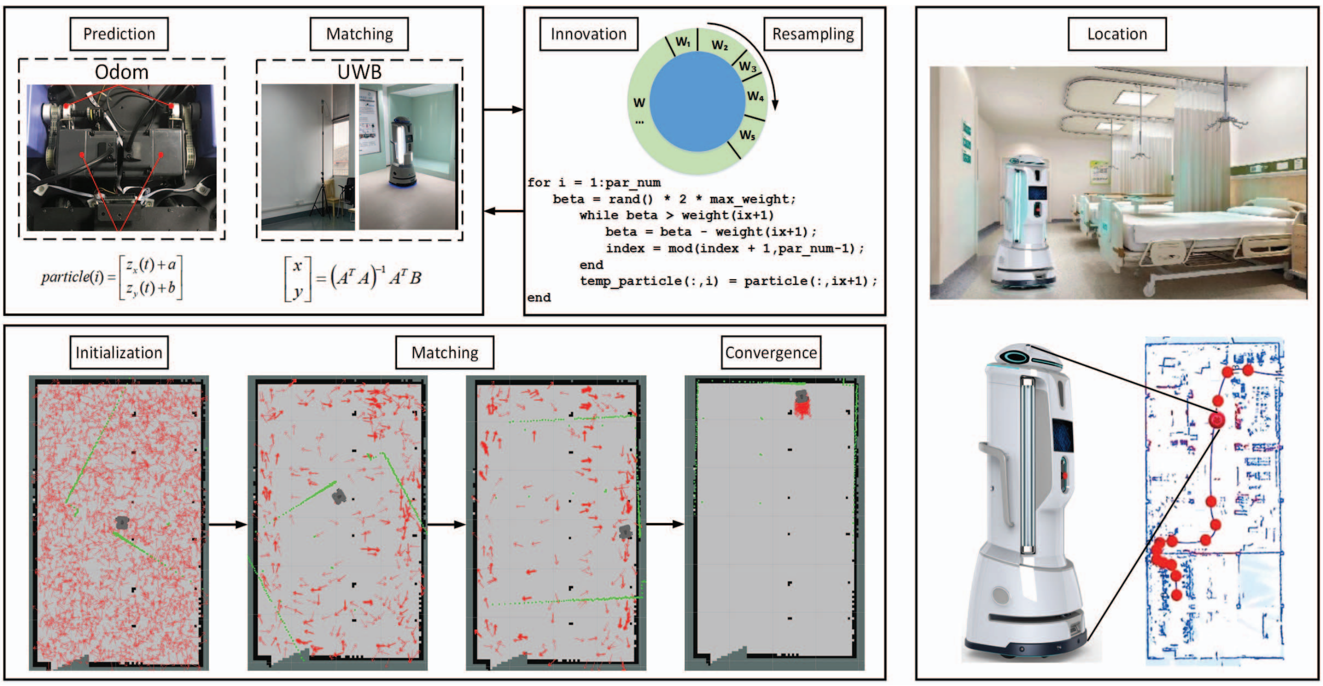

Fig. 3. Particle filter process and experimental scene.

TABLE I
UWB positioning error

Position	World Coordinates	Results of UWB	Average Error
1	(2.0,3.0)	(2.03,2.95)	0.04
2	(4.0,5.0)	(3.93,5.03)	0.05
3	(6.0,8.0)	(6.03,7.96)	0.035
4	(7.0,3.0)	(6.96,3.03)	0.035
5	(8.0,6.0)	(8.03,6.03)	0.03

In a 6m×4m open room, let the EPR move along a 4m × 2m rectangular trajectory. The odometer trajectory, UWB trajectory, and particle trajectory are shown in Fig. 5. Because the EPR is in motion, the UWB coordinate calculation has calculation time, which makes the sensor data lag behind, leading to the increase of coordinate error. The maximum error of the UWB coordinate is 23cm.

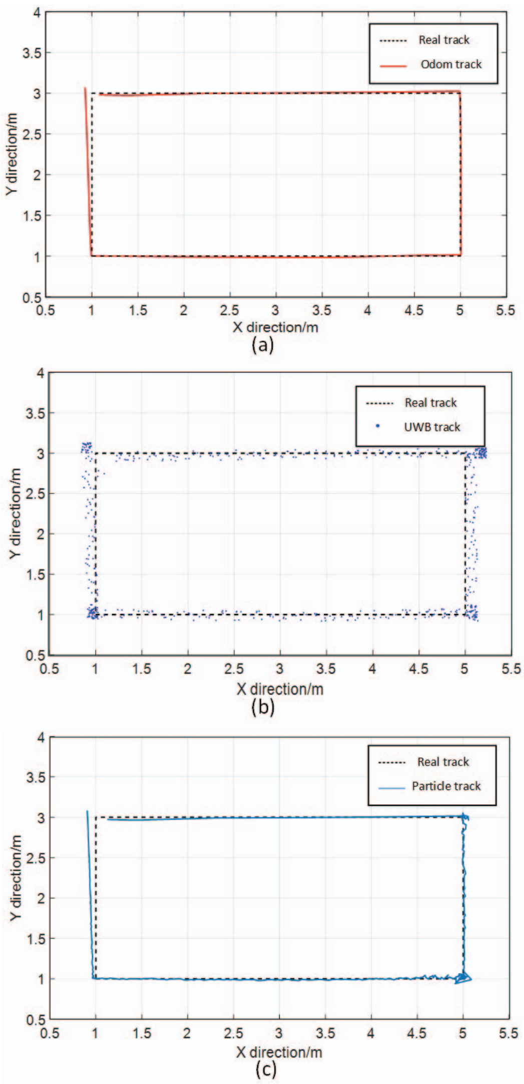

Fig. 5. (a) Comparison between odometer track and real track. (b) Comparison between UWB track and real track. (c) Comparison between particle track and real track.

The odometer trajectory, UWB trajectory and real trajectory in the process of EPR rectangular motion are shown in Fig. 6(a), and the errors in X and Y directions are shown in Fig. 6(b).The particle filter algorithm redistributes the particles at the turning point. The experimental results are shown in Fig. 6(c). When the EPR turns, the positioning error increases significantly. The reason is that the particles are redistributed at this time, and the distribution particles are reinitialized within a certain range of the coordinate so that the error increases. The maximum error of the x-axis is 8.1cm, and the maximum error of the y-axis is 12.5cm.

The experimental results of the EPR in the ward are shown in Fig. 7. The EPR patrols three hospital beds in turn. Because of the existence of a non-line of sight (NLOS) in the ward, the UWB positioning error increases, and the singular value of positioning error appears. After the particle filter algorithm, the error of coordinate data with the real trajectory decreases but compared with the test results in an open room, the error increases.

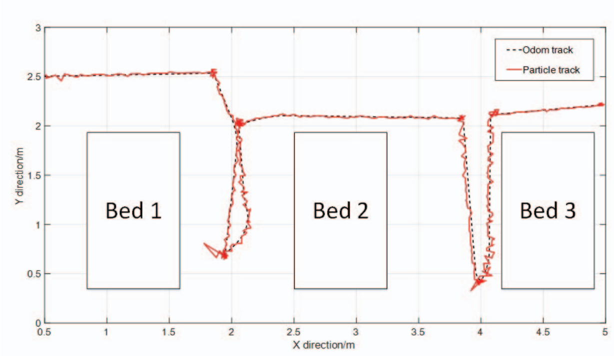

Fig. 7. The track of inspection.

The positioning error of the EPR in the ward is shown in Fig. 8. The maximum error is 16.2cm, and the average error is 6.8cm.

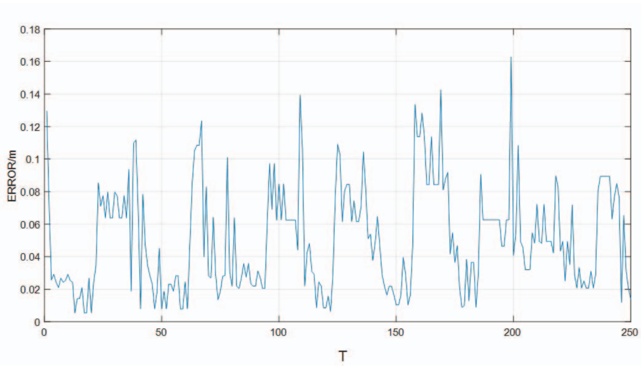

Fig. 8. Experimental results of UWB static point positioning.

V. CONCLUSIONS

In this paper, a positioning system based on the fusion of UWB and an odometer based on particle filter is proposed.

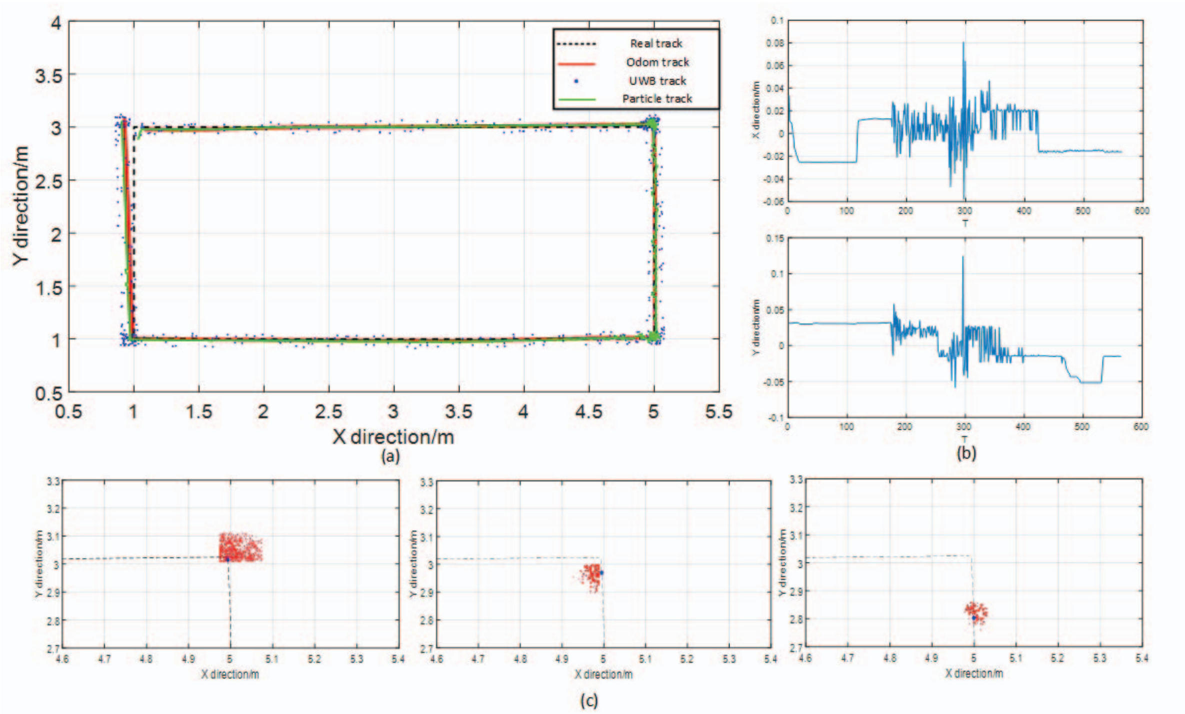

Fig. 6. (a) The aligned trajectories of different approaches. (b) Error of x-axis and y-axis. (c) Particle redistribution during turning.

Through this system, the positioning and path tracking of EPR can be realized, and high-precision positioning can be achieved without expensive equipment such as lidar, camera, or IMU. The experimental results show that the positioning error is reduced to centimeter-level after fusion, and the average error is 3.8cm in the open room and 6.8cm in the non-line of sight situation. Compared with the traditional fusion method based on Kalman filter and particle filter, because the accumulated error of odometer can not be eliminated, the positioning error is about 10 cm. And with the increase of movement time, the error increases gradually.It has good robustness to the nonlinear motion of EPR which can not describe the state equation.

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