Research on Dynamic Positioning of Competitive Skiing Based on UWB

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Abstract: Dynamic positioning algorithm of skiers based on Ultra Wide Band (UWB) is discussed in this paper. Firstly, a Non-Line of Sight (NLOS) base station screening method combining with Geometric Dilution Precision (GDOP) is proposed to suppress the degradation of positioning accuracy caused by athletes' body occlusion. Secondly, the CTRUM (constant turn rate and Uniform motion) model is constructed according to the skiing state of athletes; then, the Unscented Kalman Filter (UKF) is used to fuse the UWB positioning information and the angular velocity and acceleration of the Inertial Measurement Unit (IMU). According to the information of the fusion, the CTRUM model is dynamically updated to improve the positioning deviation of the skiers during the curve skiing. Finally, the algorithm is deployed in the upper computer system and experiments are carried out to verify that the method can screen out the NLOS base station and improve positioning accuracy of the athletes' curve movement.

Keywords: Ultra Wide Band, Positioning Algorithm, Geometric Dilution Precision, Non-Line of Sight, Signal Processing

1. INTRODUCTION

In recent years, with the continuous development of wireless communication and wireless sensor networks, wireless positioning technology has attracted more and more people's attention, and has been widely used in disaster emergency, target tracking, car navigation, pedestrian navigation, athlete-assisted training and other fields [1]. In the outdoor environment, the combined positioning system composed of the global satellite navigation system and the inertial navigation system can provide reliable positioning on the plane map; however, due to the slow acceptance rate of the satellite signal, the accuracy is not enough to meet the high-precision positioning requirements of the skier at high speed. Common positioning technologies include Radio Frequency (RF), UWB, Light Detection and Ranging (LiDAR) and Industrial Cameras [2].

Compared to other technologies, UWB has the advantages of low power consumption, strong penetrating power, high time resolution and high transmission data rate [3-4], and can provide large coverage, in line-of-sight (LOS) it can reach centimeter or even millimeter-scale ranging and positioning accuracy [5-6]. Based on the improvement of the location update rate, this paper proposes a non-line-of-sight base station screening algorithm that utilizes redundancy information of multiple base station and combines GDOP precision factors. The algorithm calculates the combination of each base station sequence and performs each base station combination, and screen out the NLOS base station by determining whether the standard deviation of the base station combination is less than the threshold. After the NLOS base station is excluded, the group with the highest accuracy is selected according to the GDOP factor score of each group of base stations.

Ski racing is a kind of non-uniform curve sport, since the acceleration changes greatly during motion. Traditional positioning methods usually use Kalman filtering (KF) to improve the positioning accuracy. KF can predict the position of the next moment according to the position of the athlete at present to assist the positioning. However, it is found that the KF can not fit the non-uniform curve motion well during the experiment. Therefore, this paper adopts a fusion positioning algorithm that uses UKF composing UWB locating information, IMU angular velocity and acceleration information, which applies the short-time and high-precision characteristics of the IMU to assist the UWB in positioning.

2. HIGH-PRECISION BASE STATION GROUP FILTERING ALGORITHM USING MULTI-BASE STATION REDUNDANCY INFORMATION

2.1. Positioning Principle and Error Analysis

UWB based on DS (double-sided two-way Ranging) ranging is indirectly determined by calculating the UWB pulse signal twice from the total time of returning the tag after the tag is sent to the base station. The time of two communication during transmission can compensate for the error caused by the clock offset of the base station and the tag. The pulse signal flight time is as shown in (1):

$$T_{prop} = \frac{T_{round1}T_{round2} - T_{reply1}T_{reply2}}{T_{round1} + T_{round2} + T_{reply1} + T_{reply2}} \quad (1)$$

T_{prop} is the pulse signal flight time, T_{round1} is the interval between the first transmission of the signal and the first reception signal, and T_{round2} is the interval between the first reception of the signal and the second transmission of the signal. T_{reply1} is the interval at which the base station receives the first transmission signal for the first time, and T_{reply2} is the interval between the first transmission of the base station and the second reception signal. Therefore, in the LOS environment, the error of the system is only determined by the accuracy of the clock. The error formula is as shown in (2):

$$Error = T_{prop} \times (1 - \frac{K_a + K_b}{2}) \quad (2)$$

According to the error formula, it can be assumed that the base station and the tag are both at a clock precision of 20 ppm, the ranging distance is 100 meters, the T_{prop} is 333 ns, the error is calculated to be 2.2 mm, which can be negligible. Therefore, the hardware does not cause ranging error in positioning, and the error is generally caused by NLOS pulse signal propagation, influence of environmental factor and multipath effect.

2.2. NLOS Base Station Screening Algorithm

Since the application scenario of the algorithm is the outdoor sports player positioning, where is no complicated environmental factor, so the error caused by the multipath effect can be neglected and we only need to consider the NLOS error caused by the moving body blocking the base station. The algorithm selects the NLOS base station according to dispersion degree of every base station group's positioning estimates, and the algorithm principle and flowchart are as follows.

Suppose that there a total of N (N≥5) base stations are searched by the tag, and the base station is divided into N-1 base station groups and there are N types of base station combinations. Each base station combination continues to divide the base station into 3 sets to calculate positioning estimates to count the standard deviation of this base station combination. When N base stations are not occluded, the positioning coordinates values calculated by each base station group are true, and their standard deviations are close to 0. If one of the base stations is occluded, only the base station combined with one group of base stations will not be affected by the NLOS signal, and the estimated values calculated by other base station combinations including the occluded base station will have a random deviation, while the positioning evaluation standard deviation of the base station combination is not zero.

According to the above principle, when the number of base stations searched by the tag is N≥5, the standard deviation of the label positioning of each group of N-1 base stations is counted, if the standard deviation of each packet is less than a preset threshold (measured when the base station is not occluded), then no base station is blocked by the positioning; otherwise, only one combination of the N groups of base stations does not include the occluded base station, that is, the group with the smallest standard deviation of the positioning estimates, and the NLOS base station can be selected by searching for the base stations not included in the group of base stations.

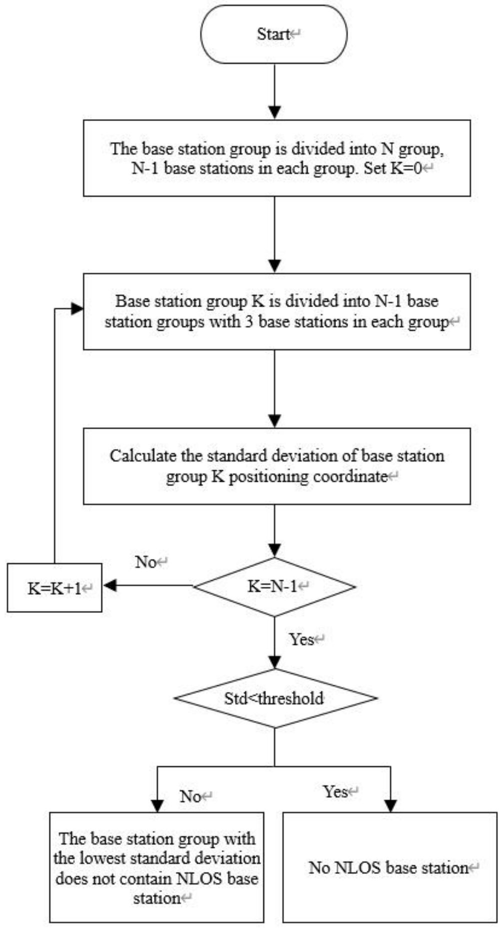

Fig.1 NLOS base station screening algorithm flow chart

2.3. GDOP based Base Station Screening

In UWB positioning, GDOP is usually used to measure the influence of the geometrical distribution of the base station on the positioning accuracy. GDOP is a parameter that characterizes the relative influence of the media of each part of the space on the measurement results. It characterizes the degree of geometric distribution of labels and searchable base stations in space. The size of the GDOP value is proportional to the error of the UWB positioning. The larger the GDOP value, the larger the positioning error and the lower the positioning accuracy. GDOP includes Position Dilution of Precision (PDOP), horizontal dilution of precision (HDOP), vertical dilution of precision (VDOP) and time dilution of precision (TDOP).

PDOP usually refers to the degree of accuracy and intensity, which directly reflects the distribution of UWB base stations. When the PDOP value is large, the searched base stations are not ideally distributed. They form a geometric perimeter that is too short and has low positioning accuracy, and vice versa. PDOP is usually calculated by HDOP and VDOP, and the simple relationship between them is shown by (3) :

$$PDOP^2 = HDOP^2 + VDOP^2 \tag{3}$$

The GDOP actually characterizes the degree of the volume outlined by the base station and the tag in the space. The larger the value of GDOP, the smaller the unit vector volume represented by the unit, which means that the angle of the tag to each base station is very similar. At this time, the GDOP will cause the deteriorated positioning accuracy. When the GDOP value is small, which represents a large unit vector volume, it indicates that the positioning accuracy is high at this time. A good GDOP actually means that the base station is not spatially distributed in one area and is evenly distributed at different locations. The GDOP is usually calculated by PDOP and TDOP, and the calculation formula is as shown in (4).

$$GDOP^2 = PDOP^2 + TDOP^2 \tag{4}$$

When UWB is locating, a tag can sometimes search for many base station information at the same time. However, for precise positioning, as long as three base station signals are sufficient, and tags can be calculated by algorithms to retrieve reliable base station signals. Assume that the spatial distribution of the base station is as shown in Figure 2.

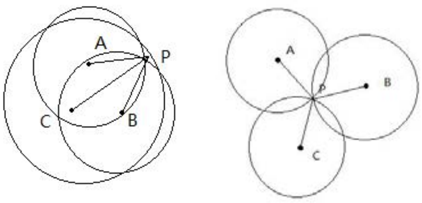

Fig.2 Base station spatial distribution comparison chart

As shown in Fig2, if the distance of two base stations selected by the tag is too close, these two base stations will have an overlapping area at a smaller angle. With the distance increasing, the area becomes larger as well as the accuracy error. If the selected base stations are separated by a suitable distance, the intersection of the base station signals can be more clearly resolved, and the error can be reduced.

Assuming that the three-dimensional coordinates of the base station and the tag are respectively (x_n, y_n, z_n) and (x_T, y_T, z_T), when n=3, the GDOP calculation formula is as follows.

$$ex = [x_n - x_T, y_n - y_T, z_n - z_T] \tag{5}$$

$$h = (x_n - x_T)^2 + (y_n - y_T)^2 + (z_n - z_T)^2 \tag{6}$$

$$t_n = \frac{ex}{h} \tag{7}$$

$$GDOP_1 = \| t1.x \times t2.x + t1.y \times t2.y + t1.z \times t2.z | \tag{8}$$

$$GDOP_2 = \| t2.x \times t3.x + t2.y \times t3.y + t2.z \times t3.z | \tag{9}$$

$$GDOP_3 = \| t1.x \times t3.x + t1.y \times t3.y + t1.z \times t3.z | \tag{10}$$

We selected the largest GDOP value as the geometric precision factor of the base station group, and the geometric accuracy factors of each base station group are compared with each other, then select the group with the smallest geometric precision factor value for positioning calculation.

2.4. Experimental verification and analysis of results

In the previous section, this paper proposes a positioning accuracy improvement algorithm that utilizes redundancy information of multiple base station and combines geometric accuracy factors. In order to verify the practicability of the algorithm, this section applies UWB's measured data for analysis. Five UWB base stations are set in the scene.

We divide the base station into five groups A1 (0, 1, 2, 3), A2 (0, 1, 2, 4), A3 (0, 1, 3, 4), A4 (0, 2, 3, 4) and A5 (1, 2, 3, 4), when no base station is occluded, we can measure and calculate the positioning estimate of each base stations group, and the standard deviation is counted as a threshold.

The verification experiment is divided into two scenarios, and the location of the base station group in the first scenario is well distributed. We set the NLOS-free base station as the first experimental scenario and the base station 2 as NLOS base station for the latter scenario. The experimental results are shown in Figure 3. The blue points are the base stations, the red points are the positioning coordinates where there is no NLOS base station, the green points are the positioning coordinates when base station 2 is the NLOS base station.

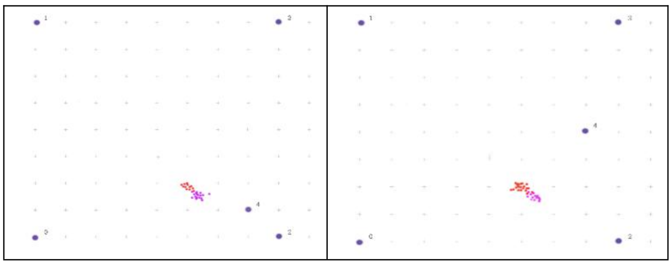

Fig.3 Scene 1 and Scene 2 tag positioning coordinate points

Based on the experiments of the above two scenarios, the standard deviations of the eight base station combinations are respectively counted, as shown in Table 1 and Table 2.

Table .1 Base station group positioning evaluation standard deviation

Std of Scene	A1(0, 1,2,3)	A2(0, 1,2,4)	A3(0, 1,3,4)	A4(0, 2,3,4)	A5(1, 2,3,4)	NLOS
Scene1	0.034	0.044	0.041	0.035	0.037	-
	0.395	0.457	0.041	0.476	0.472	2
Scene2	0.041	0.045	0.057	0.044	0.049	-
	0.467	0.473	0.057	0.501	0.503	2

Table .2 Base station group accuracy factor value without NLOS base station

	A(0,1,3)	A(0,1,4)	A(0,3,4)	A(1,3,4)
GDOP1	0.797	0.726	0.814	0.873
GDOP2	0.815	0.726	0.809	0.892
Error 1	0.0472	0.0359	0.0491	0.0537
Error 2	0.0496	0.0361	0.0483	0.0559

It can be seen from the analysis in Table 1 that when there is no NLOS base station, the standard deviation of the combined values of the five base stations is relatively low. When the base station 2 is occluded to cause NLOS error, the standard deviation of the base station group including the base station 2 is greater than when the base station is not blocked. Only the standard deviation of the A3 (0, 1, 3, 4) base station group is similar to the standard deviation when no base station is occluded. Therefore, when there is an NLOS base station, the base station group without the NLOS influence can be selected by calculating the standard deviation of the base station group.

It can be seen from the analysis in Table 2 that when the base station Geometric Dilution of Precision (GDOP) is degraded, the positioning error also increases. Therefore, after determining whether there is an NLOS base station, the base station group with the best GDOP can be continuously filtered according to the GDOP value to improve positioning accuracy.

Joint Tables 1 and 2 can be found that when the accuracy factor of the base station group deteriorates, the standard deviation of the base station group also increases due to the increase of the error, which may cause some small non-line-of-sight occlusion. Certainly, at this time, it is possible to try to set a dynamic standard deviation threshold according to the GDOP value to assist in judging the non-line-of-sight base station.

3. FUSION POSITIONING ALGORITHM BASED ON UWB/IMU

3.1. Electronic Image Files (Optional)

For competitive skiing scenarios, UWB positioning requires high precision and high refresh rate. The method of bidirectional ranging can effectively reduce the error caused by the clock frequency between devices to obtain high-precision distance information, which also needs to transmit three messages to complete a ranging. By streamlining the transmission of data packets, in high-rate transmission mode, every data transmission takes about 0.5ms, and a distance measurement takes 1.5ms. When the pure ALOHA protocol sends a message occupancy rate of 18% per unit time, there is a 97% chance that the sent message does not conflict with other messages, which can also complete 180ms/1.5ms=120 times of ranging within 1000ms, and requires four base station data for one positioning to calculate, the system can perform up to 30 times of positioning in 1s.

In the case of single-label positioning, since the small probability of information collision, 60 times of positioning can be performed within 1s of testing, which can meet the high refresh rate requirement of motion positioning. However, as the number of tags increases, the probability of information collision increases, and the refresh rate decreases. In this condition can we 1) streamline data packets and reduce data frame transmission time to reduce information collision probability; 2) use the slotted ALOHA protocol to allocate time slots for signal transmission and reception to improve the refresh rate of the positioning. However, the above method can only improve the refresh rate of the positioning to some extent. While we can consider adding an IMU sensor to the label board, and using the short-time and high-precision characteristics of the IMU sensor to assist in positioning without the UWB signal.

3.2. Fusion positioning algorithm modeling

We merged UWB positioning information with the IMU measurement information, and the current position is predicted in real time using the IMU sensor based on the previous position estimation. Before the new UWB data is obtained, the current position can only be predicted by the data of the IMU sensor.

However, the positioning error of the IMU sensor increases with the running time, so when the new UWB data is received, the current position is updated using the UWB data. By continuously performing these two steps, it is possible to take advantage of both and to accurately position the athletes in real time. Assuming that the frequency of the IMU sensor is 100 Hz and the frequency of the UWB is 20 Hz, then five IMU sensor data points can be used for position prediction between each UWB update.

When not using IMU-assisted positioning, the UWB sensor can only provide position information $z = P_x, P_y$, and the curve motion is insufficiently fitted. The IMU can provide acceleration, angle, angular velocity information, and has extremely high precision in a short time. According to the information of IMU, the CTRUM (constant turn rate and Uniform motion) model is built. The acceleration, speed, angle, and angular velocity information are also added to the model. We input $x = [p_x, p_y, v, \alpha, \psi, \dot{\psi}]$ as position parameters, the variable acceleration and angular acceleration during the motion were treated as the noise of the speed，then $v = \begin{bmatrix} v_{a,k} \\ v_{\dot{\psi},k} \end{bmatrix}$. If the current position parameter is x_k, the speed is v_k, then we consider the update of the positional parameter (x_{k+1}) of the noise, as shown in (11).

$$x_{k+1} = f(x_k, v_k) = x_k + x_p + \varepsilon \tag{11}$$

The first term of the formula is the position of the previous moment, the second term is the position update formula, and the third term is the error term. Update formula as (12).

$$x_p = \begin{bmatrix} \frac{v_k}{\dot{\psi}_k}(-\sin(\psi_k + \dot{\psi}_k \Delta t) - \sin(\psi_k)) + \frac{1}{2}(\Delta t)^2 \cos(\psi_k) \cdot v_{a,k} \\ \frac{v_k}{\dot{\psi}_k}(-\cos(\psi_k + \dot{\psi}_k \Delta t) + \cos(\psi_k)) + \frac{1}{2}(\Delta t)^2 \sin(\psi_k) \cdot v_{a,k} \\ \Delta t \cdot v_{a,k} \\ 0 \\ \dot{\psi}_k \Delta t \\ 0 \end{bmatrix} \tag{12}$$

3.3. UKF Design

The problem solved by UKF is the state of the known system and its variance x_k, p_k, and the new state and variance after solving the nonlinear function$x_{k+1} = f(x_k)$. The UKF believes that each state (x_k , p_k)can be represented by several Sigma points(X_{sig}). When it acts on the nonlinear function $f(x)$, it only needs to apply Sigma point (X_{sig}) to a nonlinear function $f(x)$ to obtain $f(X_{sig})$ .The new state X_{k+1} , P_{k+1} can be calculated by $f(X_{sig})$. Considering that the nonlinear relationship of noise $f(x_k,v_k)$ is included in the calculation model, the data x_k needs to be augmented during prediction. After the augmentation, $X_a = [P_x, P_y, v, \alpha, \psi, \dot{\psi}, v_{\dot{\alpha}}, v_{\ddot{\psi}}]$.

The key point X_{sig} selection formula is as shown in (13):

$$X_{k|k} = \left[x_{k|k} \quad x_{k|k} + \sqrt{(\lambda + n_x)P_{k|k}} \quad x_{k|k} - \sqrt{(\lambda + n_x)P_{k|k}}\right] \tag{13}$$

n_x represents the number of parameters in $x_{k|k}$, λ is the spread condition of point Sigma, the empirical value $\lambda = 3 - n_x$ is applied.

$$x_{k+1|k} = \sum_{i=1}^{n_\sigma} \omega_i x_{k+1|k,i} \tag{14}$$

$$P_{k+1|k} = \sum_{i=0}^{2n_0} \omega_i (x_{k+1|k,i} - x_{k+1|k})(x_{k+1|k,i} - x_{k+1|k})^T \tag{15}$$

The mathematical description of the UKF fusion positioning algorithm is shown in Algorithm 1, and the flow chart is shown in Figure 4.

Algorithm 1 UKF-based fusion localization algorithm

i. *Initialize system state x_k, P_k.*
ii. *According to the state x_k, P_k generates sigma point X_k.*
iii. *Prediction of future sigma point $X_{k+1|k}$ based on computational model (ctrum).*
iv. *According to the predicted sigma point $X_{k+1|k}$, a state prediction $x_{k+1|k}$ and $P_{k+1|k}$ are generated.*
v. *Receive the measured value, and convert the predicted sigma point $X_{k+1|k}$ to the predicted measured value $Z_{k+1|k}$.*
vi. *According to the difference between the predicted measurement value $Z_{k+1|k}$ and the actual measurement value z_{k+1} , the system status $x_{k+1|k+1}, P_{k+1|k+1}$ is updated.*

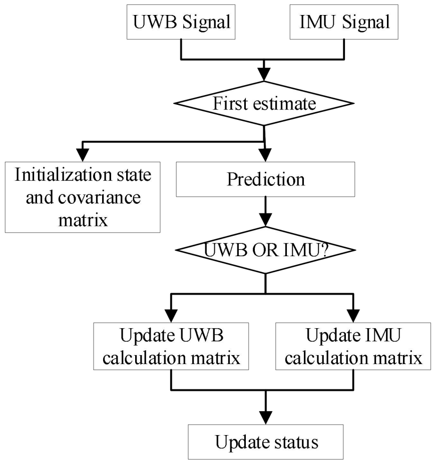

Fig.4 UKF fusion algorithm flow chart

4. EXPERIMENT AND ANALYSIS

In the previous section, a fusion algorithm using UKF with UWB information and IMU information was proposed. In order to verify the reliability of the algorithm, the single-sensor algorithm of KF, the single-sensor algorithm of UKF, and the UKF fusion algorithm based on CTRUM model are used to perform dynamic positioning experiments.

In the dynamic positioning scenario, in order to determine the performance of the filtering algorithm, the redundancy information of base station was not used in the experiment. The three base stations were fixed at a fixed position, the coordinates were determined by a laser range finder, the wire was bent into a fixed track, and the label is fixed on the roller on the slide rail to simulate the motion state of the skier. Figure 5 shows the label motion trajectories of the three filtering algorithms, in which the red line is the reference trajectory made of the wire. Among them, yellow, green and blue are the errors of KF algorithm, UKF algorithm and UKF fusion algorithm, respectively. Table 3 gives the error statistics for the three filtering algorithms.

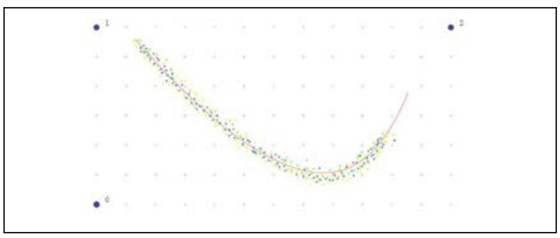

Fig.5 Plane trajectory of three kinds of filtering algorithms in dynamic experiments

Table .3 Error statistics of three filtering algorithms in the experiment

Direction		KF	UKF	CT-UKF
Z Axis	Mean	0.0673	0.0432	0.0343
	Max	0.347	0.175	0.097
Y Axis	Mean	0.0453	0.0397	0.0317
	Max	0.239	0.153	0.086

Analysis of the experimental results can be concluded:

- In the UWB positioning process, the experimental label movement is irregular and affected by some factors such as environment, also due to the Kalman filter was constrained by the Gaussian linear model, it was difficult to accurately estimate the system noise and measurement noise at the same time. The result of the positioning could not fit the reference trajectory, and the filtering result had a large error, which is less practical in skiing.
- When using UKF for filtering, since it can analyze the system noise, the smoother output could be obtained after filtering, and the delay would be less. However, due to the limitation of the sensor parameters, the observation function and the motion function set in the filtering were relatively simple, and the positioning result can only fit the reference trajectory to some extent.
- When using the unscented Kalman-based fusion algorithm for filtering, we constructed a more elaborate CTRUM motion function model based on IMU information. And the UKF can solve the characteristics of very complex observation functions and motion functions to further improve the accuracy and reliability of filtering., then the positioning result that is better fitted to the reference trajectory is obtained.

5. CONCLUSION

- In this paper, the multi-base station redundancy information was used to calculate the group standard deviation and geometric precision factor of each base station, and the non-line-of-sight base station was selected according to the standard deviation. When there was no non-line-of-sight base station, we selected a group of base station with the best geometric position for position calculating according to the geometric precision factor, which improved the positioning accuracy. The test results show that when there is only one non-line-of-sight base station, the method can accurately screen out it, which reduces the positioning error caused by the non-line-of-sight base station; when there is no non-line-of-sight base station, the best geometric position can be selected, which can reduce the error by more than 10% comparing where is no screening.
- This paper studied the influence of accuracy factor of the base station group on the threshold of the non-line-of-sight base station. The method for judging non-line-of-sight base stations based on dynamic thresholds weighted by precision factors was proposed. The experimental results showed that this method could reduce the misjudgment of non-line-of-sight base stations due to the geometric position difference of the base station group.
- In this paper, a fusion algorithm based on CTRUM model combined with Unscented Kalman Filter (UKF) fusing UWB information and IMU information is proposed. The experimental results showed that the algorithm could improve the fitting effect of the predicted value on the real value when performing curve motion, and the positioning accuracy can be improved when the UWB information refresh rate is insufficient.
- When two or more base stations were occluded during the positioning process, since the non-line-of-sight base station screening method based on redundant information could not select all non-line-of-sight base stations, at this point we can consider using adaptive unscented Kalman filter (AUKF). We can use the prior threshold information in the LOS environment, when the test information is larger than the prior threshold, the built-in noise covariance matrix of the measured noise can achieve the filtering robustness and improve the accuracy of the filtering solution. This part will be carried out in future work.

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