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Mobility Prediction Based Tracking of Moving Objects in Wireless Sensor Networks

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Abstract — This paper investigates the multi-sensor fused localization of moving targets in a wireless sensor network. Each ultra-wide band (UWB) sensor is assigned a stability weight according to its survival time prediction. The measurement accuracy of each sensor into the constraints of the weight distribution based on the interactive multi-model method, a double weight distribution algorithm that considers measurement accuracy and stability is proposed. Based on the double weight algorithm, the measurement information of each UWB sensor, the inertial measurement unit (IMU)-based state vector and the UWB-based state vector by federated Kalman filter are integrated to realize the correction of the IMU. Finally, several numerical simulations are performed to show that the proposed algorithm can effectively suppress the measurement dropout when tracking moving targets in a wireless sensor network, and it can also automatically adjust the weight of each sensor based on the measurement error covariance to improve the tracking accuracy.

Key words — Wireless sensor networks, Interacting multiple model, Information fusion, Object tracking.

I. Introduction

People's demand for precise positioning has been dramatically increasing due to the entrance of more and more smart products into their lives. As the most commonly used positioning method [1], global positioning system (GPS) is favored by its high maturity, high accuracy, and strong robustness, and consequently, it has been widely used in fields such as navigation and intelligent driving. However, it fails to provide effective positioning function in most indoor scenarios, such as household services, factory logistics, cave exploration, and counter-terrorism. In this context, it is of great significance to develop high-precision indoor positioning technology.

Due to its mature technology and high reliability, the inertial measurement unit (IMU) is capable of measuring robot attitude without relying on external information. Therefore, it is a commonly adopted indoor positioning sensor. However, this system is vulnerable to error accumulation over time, and it is not able to self-calibrate the accumulative error. As a solution, internal and external sensors are integrated for the estimation of the robot's attitude and position [2]–[4]. In these systems, the accurate attitude and position information are usually obtained by the sensors mounted inside the object (internal sensors), and external sensors in the environment are used to further calibrate this information.

Positioning technologies based on remote wireless sensors have been widely used in indoor positioning due to the improvement of computing performance, including WiFi [5], ZIGBEE [6], infrared [7], [8], VICON [9], ultra-wide band (UWB) [10], [11], and so on. However, it is generally impossible to cover a large indoor space with a single sensor owing to the limited coverage of current wireless sensors and the inevitable influences of multipath effects and obstacles. Therefore, a large number of sensors, which work as nodes, are required to form a network that can accurately locate objects in a large indoor space. Information, as needed, is first collected by these sensors, then transmitted to the aggregation node that connects the external client, and finally passed to the client after processing. This kind of network, which has been referred to as the wireless sensor network (WSN), can well control the density of deployed sensors according to actual needs, and all

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nodes have equal status. Therefore, the basic positioning function of WSN will not be influenced by failures of individual nodes, thereby presenting strong survivability and robustness. Accordingly, WSN has been widely used in military affairs, agriculture, environmental monitoring, and underground operations [12]. Therefore, the research of dynamic target tracking and state estimation algorithms in WSN has become one of the hotspots.

The current WSN-based positioning can be divided into two categories: static positioning and dynamic positioning, with the former much more mature than the latter. Specifically, it is challenging to position and track dynamic targets due to their complexity and uncertainty. As a countermeasure, WSN relies on the wireless communication and data processing capabilities of sensors to track dynamic targets. Moreover, it is possible to continuously estimate the states of dynamic targets and thus dynamically monitor them by collaboration among sensor nodes, which sense the dynamic targets through processing their dynamic data collections. However, inherent limitations exist in the monitoring, calculation, and handover of sensor nodes, when it comes to dynamic targets with more complex motion modes. Therefore, it is necessary to further research and design the dynamic target tracking method in a WSN based on the static target monitoring algorithm to achieve high-precision tracking and state estimation of dynamic targets [13]–[15].

Based on the above reasons, dynamic target tracking in a WSN has been extensively investigated. For instance, Dehnavi *et al.* [16] used extended Kalman filter (EKF) and unsented Kalman filter (UKF) to filter the noise in underwater communication, and they realized the three-dimensional dynamic target tracking based on the underwater acoustic wireless sensor network (UAWSN). Ran *et al.* [17] improved the performance of multi-target tracking in a WSN and reduced the energy consumption of the system based on the constraint conditions (e.g. energy, measurement distance, and communication limitation) and the latent game method. Similarly, Tikhe *et al.* [18] improved the particle filter (PF) algorithm based on the prior information and the constraints of node coverage, which helped increase the coverage and optimize the energy consumption of the system. All these methods are based on the filtering method to achieve dynamic target tracking, and they rely on the prior information of the system. However, prior information might be inaccurate and even lost during the handovers among sensor nodes due to the differences in the performance and contribution of each sensor node in a WSN. Li *et al.* [19] performs analysis and develops a solution for locating a moving source using time difference of arrival (TDOA) and frequency difference of arrival (FDOA) measurements with the use of a calibration emitter. Accordingly, Harsha *et al.* [20] studied the observed life time in a WSN and managed to prolong the average measurement time in the system based on the clustering method, which reduced the number of sensor handovers and effectively suppressed the impact of prior information dropout. This kind of idea generally originates from the guidance handover method in the field of multi-station relay navigation [21]–[23], and it is favored by its relatively mature research foundation while disfavored by its failure to fully adapt to the sensor handover in the WSN system.

Despite the progress, all the above studies have their limitations. For example, the problem of prior information dropout was not solved, although the performance of dynamic target tracking in a WSN had been improved [16]–[18]. Harsha *et al.* [20] succeeded to alleviate the prior information dropout based on the idea of guidance handover, but they did not consider the influence of the sensor's measurement accuracy.

Given the above phenomena, this study aims to develop a method to suppress the divergence of traditional algorithms caused by the dropout of prior information during sensor handover in a WSN, which is achieved by the following procedures:

- The tracking error caused by the dropout of prior information is reduced by designing a weight distribution algorithm based on the observed life time of the node;
- The accuracy of dynamic target tracking is improved by adopting the interactive multi-model (IMM) method and developing the weight distribution method based on the measurement accuracy of sensor nodes;
- Combine the weights of observed life time and the measurement accuracy to realize the high-precision and stable tracking of dynamic targets in a WSN.

By the above improvements, concept of node survival time in relay navigation is introduced, and it is combined with the method of assigning weight based on accuracy in traditional WSN tracking algorithm, we obtain a high-precision WSN-based dynamic target tracking algorithm that can effectively suppress the sudden disturbance caused by the dropout of prior information, which is the main contribution of this article.

Numerical simulation will be performed at the end of this article to verify the effectiveness of the proposed algorithm, whose overall structure is illustrated in Fig.1. As shown in the figure, in this study, we first assign the stability weights of the UWB sensors based on the idea of relay navigation; then assign the accuracy weights based on the measurement error covariance matrix of the UWB sensors; finally, we normalize the two weights based on the IMM method to achieve a high-precision and high-stability tracking of moving targets in WSNs. And based on our previous work, under the federated Kalman filter (FKF) framework, the WSN measurement information is fused with IMU to correction it mounted on the moving body, which further improves the accuracy and robustness of tracking.

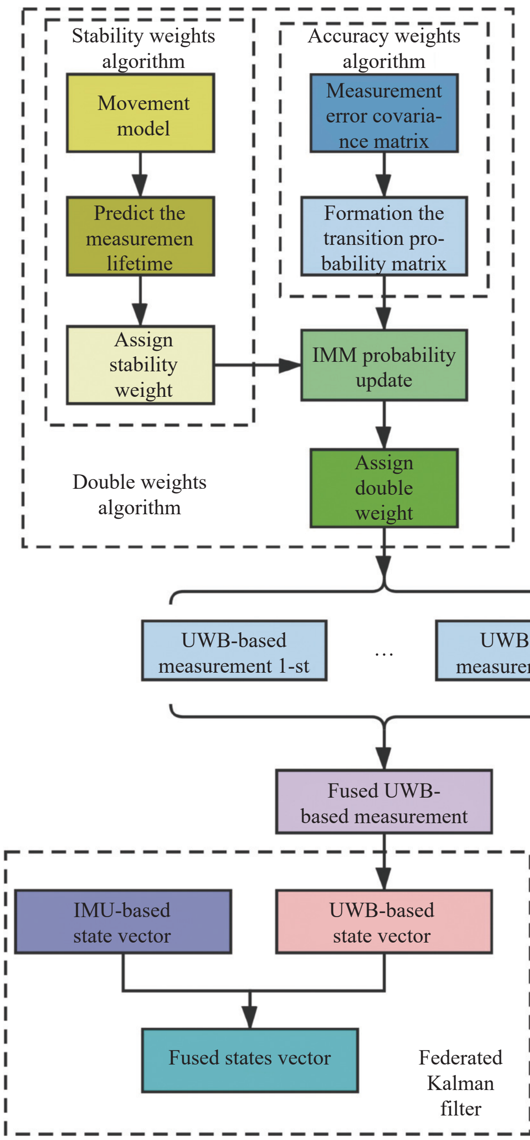


Fig. 1. The flow chart of the algorithm.

The rest of this article is organized as follows. Section II illustrates how dynamic and measurement models of the system are established, analyzes the reasons for the errors during the sensor handover in a WSN, and formulates the main research contents based on the analysis results. In Section III, a stability weight distribution algorithm is developed based on the observed life time of sensor nodes. Section IV takes into consideration the measurement accuracy of the sensor node and develops a weight distribution method that combines measurement stability and measurement accuracy to achieve high-precision, high-stability dynamic target tracking. A numerical simulation is performed in Section V to verify the proposed algorithm. Finally, conclusions are given in Section VI.

II. System Modeling and Problem Description

1. System model

The nonlinear discrete-time system considered in this article can be illustrated as follows:

$$X_{k+1} = A(X_k) + \omega_k \tag{1}$$

$$X_k = [x \;\; y \;\; v \;\; \theta \;\; \varphi]^{\mathrm{T}} \tag{2}$$

where X_k and X_{k+1} are are the state vectors at time k and $k+1$, x and y are the coordinates of the moving body, v is the speed, θ is the yaw angel, φ is the yaw angel changement, ω_k is the process noise of the system, and $A(\cdot)$ is a nonlinear time update, which can be expressed as formula (3) since the movement model studied in this article is a constant turn rate and velocity (CTRV) model:

$$A(X_k) = A\left(\begin{bmatrix} x \\ y \\ v \\ \theta \\ \varphi \end{bmatrix}\right) = \begin{bmatrix} x \\ y \\ v \\ \theta \\ \varphi \end{bmatrix} + \begin{bmatrix} \dfrac{v}{\varphi}(\sin(\theta+\varphi T) - \sin(\theta)) \\ \dfrac{v}{\varphi}(-\cos(\theta+\varphi T) + \cos(\theta)) \\ 0 \\ \varphi T \\ 0 \end{bmatrix} \tag{3}$$

where T is the sampling time. The measurement model of the system is as follows:

$$Z_{ik}^{\mathrm{UWB}} = H_{\mathrm{UWB}} X_k + \nu_{ik}^{\mathrm{UWB}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} X_k + \nu_k^{\mathrm{UWB}} \tag{4}$$

$$Z_k^{\mathrm{IMU}} = H_{\mathrm{IMU}} X_k + \nu_k^{\mathrm{IMU}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} X_k + \nu_k^{\mathrm{IMU}} \tag{5}$$

where Z_{ik}^{UWB} is the measurement vector of each UWB sensor, and Z^{IMU} is the measurement vector of IMU, H^{UWB} and H^{IMU} are respectively their state measurement matrices, ν^{UWB} and ν^{IMU} are independent measurement noises with Gaussian distributions.

The variance of measurement noise and process noise is

$$\begin{aligned} &E\left[w_k w_k^{\mathrm{T}}\right]=Q_k \\ &E\left[\upsilon_k^{\mathrm{IMU}} \upsilon_k^{\mathrm{IMU}^{\mathrm{T}}}\right]=R_k^{\mathrm{IMU}} \\ &E\left[\upsilon_k^{\mathrm{UWB}} \upsilon_k^{\mathrm{UWB}^{\mathrm{T}}}\right]=R_k^{\mathrm{UWB}} \end{aligned} \tag{6}$$

where Q_k is the covariance of process noise; R_k^{IMU} and R_k^{UWB} are the covariances of measurement noise of IMU and UWB sensors.

When the tracking starts, in order to obtain the system state estimation and error covariance at the next moment, the UWB-based state vector X_{k+1}^{UWB} and IMU-based state vector X_{k+1}^{IMU} are estimated by nonlinear Kalman filter. These two state vectors:

$$P_{k+1}=(P_{k+1}^{\mathrm{IMU}-1}+P_{k+1}^{\mathrm{UWB}-1})^{-1} \tag{7}$$

$$X_{k+1}=P_{k+1}(P_{k+1}^{\mathrm{IMU}-1}X_{k+1}^{\mathrm{IMU}}+P_{k+1}^{\mathrm{UWB}-1}X_{k+1}^{\mathrm{UWB}}) \tag{8}$$

2. Problem description

Tracking and positioning of moving targets in a WSN require collaboration among multiple sensors, in the form of either relay or coordination. When the moving target leaves the measurement range of sensor i and enters the measurement range of sensor j, there is a relationship of relay between the two sensors. In contrast, when the moving target is in the measurement range of sensors i and j at the same time, there is a coordinated relationship between the two sensors. Although relay and coordination usually exist at the same time, this study discusses them separately to simplify the scientific problem.

When the two sensors are in a relay relationship, the error in tracking and positioning moving targets in a WSN could be increased, which sometimes even causes the filter to diverge in severe cases. Specifically, when the moving target travels for a long time within the measurement range of sensor i, a large amount of prior information about sensor i would be accumulated in the filter. However, the measurement information of sensor i would disappear when the moving target travels out of the measurement range of sensor i. In this context, the prior information in the filter is mismatched with the actual measurement information, leading to serious errors in filtering. Similarly, mismatching occurs when the moving target enters the measurement range of sensor j, because there is no corresponding prior information in the filter to the measurement information provided by sensor j.

When the two sensors are in a coordinated relationship, there might be differences between them in observing the same moving target due to the presence of measurement noises that may arise from multipath effects, distance, electromagnetic interference, component errors, and so on. Information conflicts may occur if the observed information with certain differences from two sensors cannot be efficiently fused. This can bring about computing resource waste to the system, and in severe cases may cause the filter to diverge.

To conclude, the main issues this study wants to address are:

- How to effectively suppress the influence caused by measurement information dropout when the sensors are in a relay relationship?
- How to efficiently fuse the information of each sensor when the sensors are in a coordinated relationship?

Accordingly, the solutions this study adopts are:

- Treat measurement information dropout as a sudden disturbance of the system, predict the occurring moment of this sudden disturbance based on the motion model of the moving target, and assign weights according to the predicted moment, thereby suppressing the impact of measurement information dropout;
- Regard each sensor as a separate measurement model to efficiently fuse different measurement information based on the idea of the interactive multiple model (IMM), which has been positively demonstrated as an effective multi-information fusion method;
- Design an information fusion algorithm that takes into account both sensor relay and coordination, so as to improve the overall tracking precision of the system and reduce the positioning error.

In this article, we adopted the DUKF algorithm proposed in previous work to estimate the state of the moving body. Compared with traditional nonlinear filtering algorithms (such as EKF, UKF, etc.), the DCKF has advantages like low computational complexity and strong robustness. More specific theoretical analysis and simulation verification can be found in literature [24], which will not be repeated here.

III. Measurement Stability Improvement via Survival Time Prediction

1. Prediction of the observed life time

Based on the motion model of the moving object and Markov chain, Duan [25] predicted the motion path of the moving object and calculated the routing life time between each node according to this predicted motion path. Eventually, they determined the communication topology based on the length of the routing life time to realize high-stability communication between moving bodies. This method is capable of effectively ensuring the stability of the communication between the moving object and the base station in the multi-station relay navigation. Similarly, it can also be applied to the dynamic tracking of the moving object in a WSN so as to predict the measurement time of the sensor. Specific procedures are as follows:

The coordinates of the i-th sensor in a WSN are defined as

$$X_{\text{sensors}}^{i} = \begin{bmatrix} x_s^i & y_s^i \end{bmatrix} \tag{9}$$

Given the CTRV model as shown in (3), it is feasible to regard (7) as the nonlinear recursive formula of an array and rewrite it in the form of a general term formula. In this context, formula (8) can describe the state of the moving body at any time:

$$\begin{aligned} X_k &= \begin{bmatrix} x_k & y_k & v_k & \theta_k & \varphi_k \end{bmatrix}^{\mathrm{T}} \\ &= \begin{bmatrix} x_1 & y_1 & v_1 & \theta_1 & \varphi_1 \end{bmatrix}^{\mathrm{T}} \\ &\quad + \sum_{i=1}^{k-1} \begin{bmatrix} \frac{v_1}{\varphi_1}(\sin(\theta_1 + i\varphi_1 T) - \sin(\theta_1 + i\varphi_1 T)) \\ \frac{v_1}{\varphi_1}(-\cos(\theta_1 + i\varphi_1 T) + \cos(\theta_1 + i\varphi_1 T)) \\ 0 \\ i\varphi_1 T \\ 0 \end{bmatrix} \end{aligned} \tag{10}$$

Extracting the position information in (8) yields

$$\begin{aligned} &X_k^{\text{position}} \\ &= \begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \\ &\quad + \sum_{i=1}^{k-1} \begin{bmatrix} \frac{v_1}{\varphi_1}(\sin(\theta_1 + i\varphi_1 T) - \sin(\theta_1 + i\varphi_1 T)) \\ \frac{v_1}{\varphi_1}(-\cos(\theta_1 + i\varphi_1 T) + \cos(\theta_1 + i\varphi_1 T)) \end{bmatrix} \end{aligned} \tag{11}$$

Based on (8) and (9), the following equation is established:

$$r_i = \sqrt{(x_s^i - x_k) + (y_s^i - y_k)} \tag{12}$$

where r^i is the i-th measurement range of the i-th sensor.

Suppose the system predicts that the moving body will go out of the measurement range of the i-th sensor at time k_2 and the observed life time predicted by the i-th sensor at time $k\,(k < k_2)$ is lt_k^i, formula (12) can be rewritten as

$$r_i = \sqrt{(x_s^i - x_{k_2}) + (y_s^i - y_{k_2})}, \quad k_2 > k \tag{13}$$

Solution of (11) yields the value of k_2. Then, based on k and k_2, we can get the value of lt_k^i:

$$\mathrm{lt}_k^i = k_2 - k \tag{14}$$

Therefore, the observed life time between the moving body and the i-th sensor at time k can be predicted based on the motion model of the moving body.

2. Distribution of measurement stability weights

As has been mentioned in the above section, we predict the measurement time of each sensor to the moving body at time k based on the method by Duan [25]. The communication life time predicted based on this method has been demonstrated to be capable of efficiently judging the communication stability between nodes and moving objects in a network with fixed communication nodes [25], [26]. In this study, we evaluate the measurement stability of fixed sensor nodes in a network to moving objects based on the same method. Therefore, it is believed that the observed life time lt_k^i predicted in this study can also be effective in evaluating the measurement stability.

Assuming that the moving body at time k can be observed by a total of i-th sensors, the prediction matrix of the observed life time of each sensor to the moving body at time k can be obtained according to the method described in Section III.1:

$$\mathrm{lt}_k = \begin{bmatrix} \mathrm{lt}_k^1 & \mathrm{lt}_k^2 & \dots & \mathrm{lt}_k^i \end{bmatrix} \tag{15}$$

Based on (13), we can assign the measurement stability weight of the sensor at the time k:

$$\omega_{\text{stability}}^{ik} = \frac{\mathrm{lt}_k^i}{\sum_{n=1}^{i} \mathrm{lt}_k^n} \tag{16}$$

where $\omega_{\text{stability}}^{ik}$ is the measurement stability weight of the i-th sensor to the moving body at time k.

Considering the system described in Section II.1 and taking the UWB sensor as an example, we assume that the measurement of the moving body by the i-th UWB sensor at time k is Z_{ik}^{UWB}. Therefore, the measurement of the moving body by the UWB sensor at time k can be obtained based on the stability weight calculated by (16):

$$Z_k^{\text{UWB}} = \sum_{n=1}^{i} \omega_{\text{stability}}^{nk} Z_{nk}^{\text{UWB}} \tag{17}$$

where Z_k^{UWB} is the measurement of the moving body by the UWB sensor after fusion at time k.

3. Specific steps of the stability weight distribution algorithm based on survival time prediction

Combining the methods described in Sections III.1 and III.2, we can obtain an algorithm for the weight distribution of sensors based on the observed life time of sensor nodes. This algorithm can effectively evaluate the measurement stability of sensors in a WSN and assign the weight of each sensor based on such stability.

In order to obtain the fused measurement information of the sensor at time k, the following steps of the algorithm are implemented:

Step 1. At time k, each sensor in the network observes the moving body to generate a measurement matrix $[\ Z_{1k}^{\mathrm{UWB}}\ \ Z_{2k}^{\mathrm{UWB}}\ \ \dots\ \ Z_{ik}^{\mathrm{UWB}}\ ]$;

Step 2. Position information is extracted from the state information of the moving body at time k;

Step 3. The observed life time lt_k^i of each sensor on the moving body at time k is sequentially predicted based on the position information of the moving body at time k and formulas (13) and (14);

Step 4. The observed life time of each sensor on the moving body is introduced into (16) to calculate the measurement stability weight $\omega_{\mathrm{stability}}^{ik}$ of the i-th sensor at time k;

Step 5. The obtained measurement stability weight is introduced into (17) to obtain the fused measurement information Z_k^{UWB} of each UWB sensor on the moving body at time k.

After obtaining the UWB-based measurement information Z_k^{UWB}, the state vector of the remote sensors in a WSN, X_k^{UWB} and its covariance matrix P_k^{UWB} can be calculated based on DCKF. They are then substituted into (7) and (8) to improve the accuracy of the IMU.

Similar methods can be also applied for other remote sensors with similar structures, such as WiFi, sonar, infrared sensors, and laser sensors.

Consequently, the weight of the sensor will decrease as the possibility of measurement dropout increases when the proposed algorithm is employed to track and locate the moving target in a WSN. Therefore, the algorithm is able to effectively suppress the disturbance caused by frequent changes in the sensor topology and improve the correcting accuracy. Specific simulation verification will be presented later in this article.

IV. IMM Based Double Weight Algorithmz

1. Analysis of the fusion method based on measurement accuracy

As have been previously introduced, some methods can effectively improve the stability of measurement by suppressing the extra disturbance caused by sensor handover in the field of multi-station relay navigation. However, multi-station relay navigation is generally used in the aviation field where the experimental scene is wide, the moving body is rarely shielded, and the communication and detection range is only limited by distance. In this environment, all nodes in the multi-station relay navigation are generally assumed to have the same communication and navigation quality [25], [26].

In contrast, many factors can affect the WSN multi-sensor coordinated tracking and positioning of moving objects in an indoor environment, including multipath effects, electromagnetic interference, component errors, and other reasons. Consequently, each sensor may have different accuracy in measuring moving objects. Therefore, it is crucial to consider the measurement accuracy of the sensor when performing multi-sensor information fusion in a WSN.

There have been several fusion methods of multi-sensor tracking and positioning, such as simple fusion (SF), weight covariance fusion (WCF), and covariance intersection (CI). SF is not suitable for this research because it is vulnerable to system divergence when there are many fusion projects and much process noise. In comparison, WCF and CI have good stability but their accuracy is greatly affected by the prior information. In other words, the fusion accuracy of WCF and CI will be affected and the calculation load will be very large when the prior information of the system is not sufficient.

The main problem in the multi-sensor coordinated tracking is the insufficiency of prior information for state estimation due to frequent handover of sensors. Meanwhile, the measurement error and variance of each sensor have been determined in advance. Accordingly, this study introduces the IMM to address this problem. The basic idea is to combine the prior information (e.g., the distribution and variance of measurement errors of each sensor) into a model set. The model set includes all currently activated sensors that perform independent filtering. Eventually, the filtered output of each sub-models are fused based on the optimization theory. Since the measurement model with a smaller measurement error can more accurate reflect the real state of the moving body, the IMM method has the potential of globally optimal estimation [27]–[29].

The following section will present a detailed introduction of the measurement accuracy weight distribution algorithm based on IMM.

2. Measurement accuracy weight based on IMM

In general, the weight of the measurement accuracy at time $k+1$ can be calculated based on that at time k of the system described in Section II.1. First, the state transition matrix of all sensors is supposed as

$$p=\begin{bmatrix} p_{11} & p_{12} & \dots & p_{1i} \\ p_{21} & \ddots & & \\ \vdots & & \ddots & \\ p_{i1} & & & p_{ii} \end{bmatrix} \tag{18}$$

where p_{ij} is the state transition probability, that is, the probability of switching from one sensor to another.

Suppose that the measurement accuracy weight of the sensor at time k is $\mu=[\ \mu_k^1 \quad \mu_k^2 \quad \dots \quad \mu_k^i\ ]$. The normalized function can be calculated based on the weight and the state transition matrix in (19):

$$\bar{c}_i=\sum_{n=1}^{i} p_{ni}\mu_k^n \tag{19}$$

Then, the mixing probability that corresponds to switching from sensor n-th to sensor i-th based on the normalized function can be obtained:

$$\mu_{k|k}^{ni}=\frac{p_{ni}mu_k^n}{\bar{c}_i} \tag{20}$$

Subsequently, the mixed state estimation and mixed covariance estimation based on the mixed probability can be acquired:

$$\hat{X}_{k|k}^{i}=\sum_{n=1}^{i}\hat{X}_{k|k}^{n}\mu_{k|k}^{ni} \tag{21}$$

$$P_{k/k}^{i}=\sum_{n=1}^{i}\mu_{k|k}^{ni}[P_{k|k}^{n}+(\hat{X}_{k|k}^{n}-\hat{X}_{k|k}^{i})(\hat{X}_{k|k}^{n}-\hat{X}_{k|k}^{i})^{\mathrm{T}}] \tag{22}$$

The mixed state estimation $\hat{X}_{k+1}^i$ and the mixed covariance estimation $\hat{P}_{k+1}^i$ at time $k+1$ can be obtained by introducing $\hat{X}_{k|k}^i$ and $\hat{P}_{k|k}^i$ as the initial state and covariance into the Kalman filter. In this study, the derivative cubature Kalman filter (DCKF) algorithm proposed by He *et al.* [24] is adopted.

Then, the updated likelihood function is calculated based on the mixed state estimation and mixed covariance estimation at time $k+1$ as well as the new measurement information:

$$\varLambda_{k+1}^{i}=\frac{\exp\left\{-\dfrac{\nu_i^{\mathrm{T}}S_{k+1}^{i}\nu_i^{\mathrm{T}}}{2}\right\}}{\sqrt{(2\pi)^n\left|S_{k+1}^{i}\right|}} \tag{23}$$

where ν_i is the residual of the i-th sensor, and S_{k+1}^i is the innovation covariance of the i-th sensor at time $k+1$.

The probability at time $k+1$ can be obtained by substituting equations (19) and (23) into (24):

$$\omega_{\text{accuracy}}^{i|k+1}=\frac{\varLambda_{k+1}^{i}\bar{c}_i}{c} \tag{24}$$

where c is the normalization constant, and c can be expressed as $c=\sum\limits_{n=1}^{i}\varLambda_{k+1}^{n}\bar{c}_n$.

The estimated system state and covariance at time $k+1$ can be calculated by substituting equation (24) into (25) and (26):

$$\hat{X}_{k+1}=\sum_{n=1}^{i}\omega_{\text{accuracy}}^{n|k+1}\hat{X}_{k+1}^{n} \tag{25}$$

$$\hat{P}_{k+1}=\sum_{n=1}^{i}\omega_{\text{accuracy}}^{n|k+1}[\hat{P}_{k+1}^{n}+(\hat{X}_{k+1}^{n}-\hat{X}_{k+1})(\hat{X}_{k+1}^{n}-\hat{X}_{k+1})^{\mathrm{T}}] \tag{26}$$

3. Double weight algorithm

Efforts have been made in Sections III.2 and IV.2 to develop the method for the calculation of predicted stability weights based on the observed life time and that of predicted accuracy weights based on IMM. These two weights are combined in this section to propose a double weight distribution algorithm that takes into account both measurement accuracy and stability for tracking and IMU correcting of moving targets in a WSN.

Algorithm 1 Procedure of the double weight algorithm

Input: $X_k^{\text{UWB}}, P_k^{\text{UWB}}, X_{\text{sensors}}^i, Z_{ik}^{\text{UWB}}, Z_k^{IMU}, p$

Output: $X_{k+1}^{\text{UWB}}, P_{k+1}^{\text{UWB}}$

1: Extract the general term formula X_k^{position} of the position information in the state vector based on (10) and (11);

2: Introduce X_k^{position} into (13) to calculate lt_k^i;

3: Introduce lt_k^i into (16) to calculate the stability weight $\omega_{\text{stability}}^{ik}$;

4: Set the stability weight $\omega_{\text{stability}}^{ik}$ of each sensor as the initial model probability;

5: Introduce μ_k^i and p into (16) to calculate the normalization function $\bar{c}_i$;

6: Introduce $X_k^{\text{UWB}}, P_k^{\text{UWB}}, Z_{ik}^{\text{UWB}}$ into the DCKF to obtain the estimated state and covariance based on the measurement of each sensor at time $k+1$;

7: Obtain the residual error v_k^i and innovation covariance S_{k+1}^i at the same time from the DCKF;

8: Introduce v_k^i and S_{k+1}^i into (23) to get the updated likelihood function $\varLambda_{k+1}^n$;

9: Calculate the normalization constant $c=\sum_{n=1}^{i}\varLambda_{k+1}^{n}\bar{c}_n$ based on the likelihood function $\varLambda_{k+1}^i$ and the normalization function $\bar{c}^i$;

10: Introduce Λ^i_{k+1}, $\bar{c}^i$ and c into (24), since the measurement stability weight has been added in step 1 to 4, we can obtain the weight after fusion of measurement accuracy $\omega^{i|k+1}_{\text{double}}$;

11: Introduce $\omega^{i|k+1}_{\text{double}}$ and the state estimation of each sensor into (25) to calculate the state estimation X_{k+1} after the final fusion;

12: Introduce $\omega^{i|k+1}_{\text{double}}$ into (26) to obtain the covariance P^{UWB}_{k+1} after fusion;

13: Use X^{UWB}_{k+1} and P^{UWB}_{k+1} as the input for the next time and repeat steps 1 to 13 until the tracking ends.

14: **End**.

Taking the system described in Section II.1 as the object, procedure of the algorithm has been shown in Algorithm 1. After obtaining the UWB-based state vector X^{UWB}_k and its covariance matrix P^{UWB}_k based on the algorithm 1, the corrected system state vector X_{k+1} and its covariance matrix P_{k+1} can be obtained based on (7) and (8).

The accuracy weight of each remote sensor can be integrated based on stable measurement during the application of this method to tracking and correcting the moving target in a WSN. As a results, the state estimation of the moving target will be more accurate. Specific simulation examples for verification will be given in Section V.

V. Simulations

In order to comprehensively evaluate the performance of the proposed algorithm, two sets of numerical simulations are performed on an x86 PC with Intel Core i9 10900k CPU and 32 GB memory using MATLAB 2019a.

The first set aims to verify the effectiveness of the tracking and positioning algorithm that incorporates measurement stability weights proposed in Section III, with the strong trace unscented Kalman filter (STUKF) algorithm as the reference. The positioning accuracy of the simulation is viewed as the main performance evaluation index. The second set aims to verify the effectiveness of the tracking and positioning algorithm that introduces measurement stability and accuracy weights at the same time as proposed in Section IV, using the algorithm without state vector decomposition as the reference. More specifically, the second set is to verify the measurement that the state decomposition method will not cause a dropout of accuracy for the system studied in this article and it can effectively improve the real-time performance of the calculation. The estimation error of the pose information and the calculation time of the simulation are regarded as the main performance evaluation indexes.

In these simulations, the weight algorithms proposed in Sections III and IV are adopted to fuse the measurement information of UWB sensors, for correcting the IMU-based state vectors under the FKF framework.

The models for numerical simulations are described in Section II.1. Uncorrelated Gaussian white noise is added as the process noise of the system, and the noise of the position information conforms to a normal distribution. Specific parameters of simulations as shown in Table 1. In order to make it easier to transplant the algorithm to a physical platform for testing in the future, the measurement noise and process noise are set based on the actual components shown in Fig.2, and the specific parameters are shown in Table 1. In this context, the results of the numerical simulations can be as cdropout as possible to the actual situation.

As shown in Fig.3, the simulation environment is a two-dimensional square with a size of 1000 m by 1000 m. Blue asterisks indicate the sensors placed in the two-dimensional space, and they jointly form a WSN; the green solid line is the true trajectory of the moving body; the blue dotted line is the trajectory of the moving body tracked by the stability weight algorithm proposed in Section III; and the red solid line is the trajectory of the moving body tracked by the Double weight algorithm proposed in Section IV.

1. Simulation of the stability weight algorithm

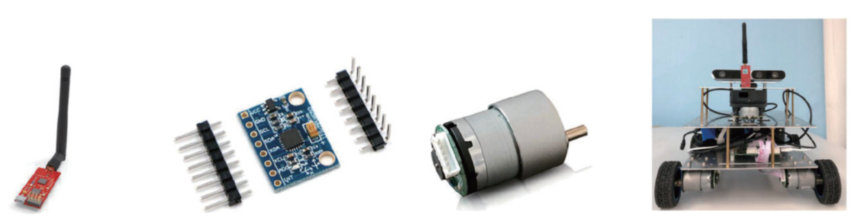
This simulation is to verify the effectiveness of the measurement stability weight algorithm in tracking moving targets in a WSN. Specifically, the measurement stability weight method and the strong trace unscented Kalman filter (STUKF) proposed in Section III.3 are used to perform numerical simulations to record and evaluate the positioning accuracy of moving objects. The results are shown in Figs.4 and 5.

Fig.4 is the average positioning error of each iteration in 500 Monte Carlo experiments. As is shown in this figure, the derived UKF algorithm based on stability weights has better positioning accuracy and lower tracking errors than the existing STUKF algorithm.

Since the residuals in the STUKF algorithm are forced to be orthogonal, the estimated value of the state can be quickly adjusted to the normal range when a sudden disturbance occurs. However, the STUKF algorithm is not able to effectively smoothen the sudden disturbance. In contrast, the stability weight distribution method proposed in this study can predict the moment of sudden disturbance in advance based on the motion model of the moving body, and timely reduce the weight of the sensor that may be subjected to measurement dropout. In this context, the proposed method can effectively suppress and smoothen the impact of

Table 1. Parameters of simulation

Item	Parameters
Initial state	X coordinate: 100 (cm)
	Y coordinate: 100 (cm)
	Velocity: 10 (cm/s)
	Yaw angel: $\pi/50$ (°)
	Yaw angel changement: $\pi/160$ (°)
Measurement range of UWB sensors	100+$N(0,30)$ (m)
Simulation time	100 (s)
Sampling time	$T = 1$ (s)
Initial covariance	$P_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 0.05 & 0 \\ 0 & 0 & 0 & 0 & 0.001 \end{bmatrix}$
Initial estimate	$gX_1 = \begin{bmatrix} 100 \\ 100 \\ 10 \\ \pi/50 \\ \pi/160 \end{bmatrix} + \begin{bmatrix} N(0,1) \\ N(0,1) \\ N(0,0.5) \\ N(0,0.05) \\ N(0,0.001) \end{bmatrix}$
The driving matrix of process noise	$G_k = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & T & 0 & 0 \\ 0 & 0 & 0 & 0 & \pi T/3 \\ 0 & 0 & 0 & 0 & \pi/3 \end{bmatrix}$
Distribution of process noise w_k	$w_k = \begin{bmatrix} 0 \\ 0 \\ N(0,0.5) \\ 0 \\ N(0,0.1) \\ N(0,0.01) \end{bmatrix}$
Initial covariance of process noise Q_1	6-order diagonal identity matrix
Measurement noise of UWB sensors	Random value from $N(0,16)$ to $N(0,36)$
White noise of gyro	$N(0,0.05)$
Constant drift of gyro	0.1°/h
White noise of accelerometer	$N(0,0.001)$
Constant bias of accelerometer	$10^{-3}g$
White noise of magnetometer	$N(0,0.1)$



(a) UWB sensor (b) IMU sensor (c) DC geared motor (d) Wheeled mobile robot

Fig. 2. The sensors and the mobile robot involved in this article. (**a**) The UWB sensors (YCHIOT, Wenzhou, China), which are commercial products provided by the company of YCHIOT, with the module of Mini3s; (**b**) The spatial motion sensor chip MPU6050 as the IMU sensor (Digi-Key Electronics, Thief River Falls, Minnesota, USA); (**c**) The odometer84 constructed by the DC gear motors MG513 with an encoder (Fenghua Transmission, Kunshan, China); (**d**) The wheeled mobile robot platform (Ruiqu Technology, Foshan, China) that realizes the precise localization by carrying the above sensors.

sudden disturbance caused by the dropout of measurement, thereby maintaining the accuracy of tracking and positioning of moving objects in a WSN.

Fig.5 is one sample trajectory of 500 Monte-Carlo trials, which can also support the above conclusion.

2. Simulation of the double weight algorithm

This simulation is to verify the effectiveness of the double weight algorithm that combines measurement

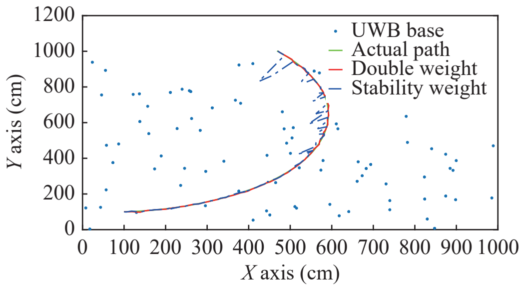


Fig. 3. Simulation environment.

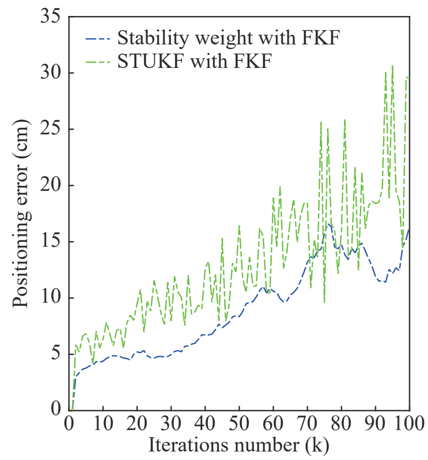


Fig. 4. Average positioning error in 500 Monte Carlo experiments (stability weights and STUKF).

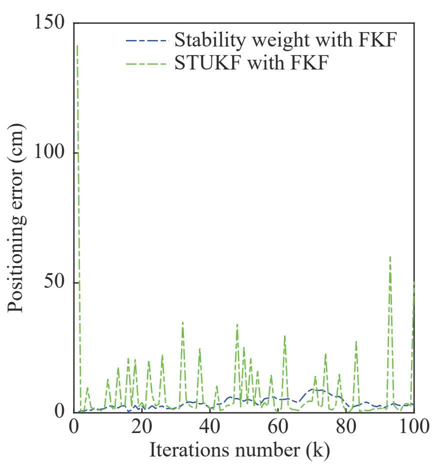


Fig. 5. Positioning error of the stability weight algorithm and the STUKF algorithm in selected simulations.

accuracy and measurement stability in tracking moving targets in a WSN. Based on the method in Section IV.3, three methods are applied in the numerical simulation to record and evaluate the positioning accuracy and estimating error corvariance of the moving object, namely the double weight algorithm, the measurement stability weight algorithm, and STUKF. The simulation results are shown in Figs.6–8.

Fig.6 is the average positioning errors in 500 times Monte-Carlo trials can be seen from this figure that the

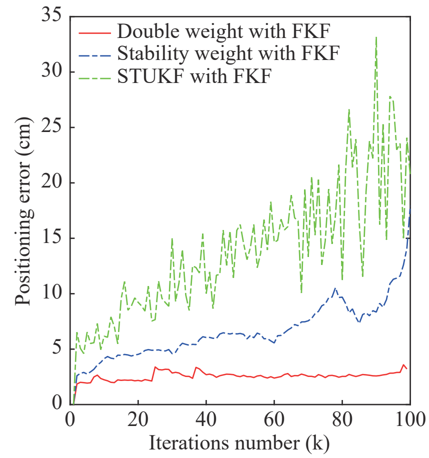


Fig. 6. Average positioning error in 500 Monte Carlo experiments (three algorithms).

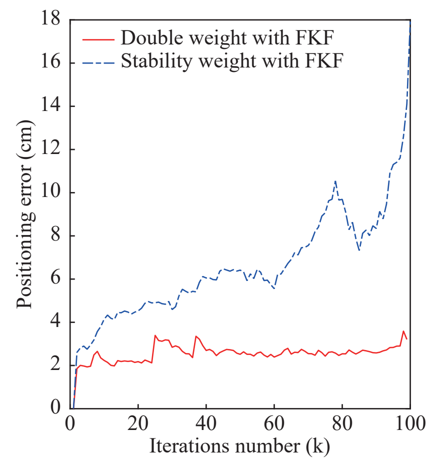


Fig. 7. Average positioning error in 500 Monte Carlo experiments (stability weights and double weights).

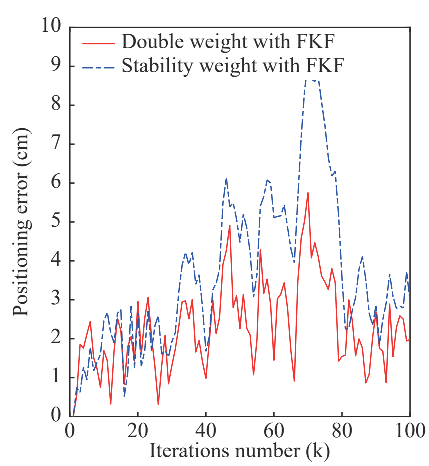


Fig. 8. Positioning error of double weight and stability weight algorithms in selected simulations.

two weight algorithms proposed in this article have much higher positioning accuracy than the STUKF.

Fig.7 is the comparison of the positioning error between the stability weights algorithm and the double weights algorithm. It can be seen from the figure that although they have similar positioning errors in the initial phase, the stability weight algorithm proposed in Section III does not consider the accuracy of the measurement when fusing the measurement information, so with the iteration number Increase, gradually unable to suppress the drifts and bias of IMU, and eventually lead to the syetem divergence. However, the double weights algorithm does not have this problem.

Table 2 shows the average error of 500 Monte Carlo experiments. We can see that after introduced the stability weight, the average error is significantly lower than the STUKF (reduced about 31.7%). After further introduced the measurement accuracy weight, the average error is reduced about 66.2% relative to the stability weight algorithm (and reduced about 76.8% relative to the STUKF).

Table 2. The average error of 500 times Monte Carlo experiments

Item	Average error (cm)
STUKF	13.0622
Stability weight	8.9320
Double weight	3.0247

Fig.8 is the positioning error curves of a set of experiments randomly selected from the 500 times Monte-Carlo trials. As is shown in Fig.8, the tracking accuracy of the double weight algorithm is higher than that of the measurement stability weight method proposed in the above section. Although the measurement stability weight method can effectively suppress the impact of sudden disturbances, it is a method that is directly borrowed from other fields and does not fully consider the measurement accuracy difference among sensors in a WSN. In contrast, the double weight method assigns weights based on the measurement accuracy and stability of each sensor, thereby contributing to optimized tracking and positioning accuracy.

Fig.9 is the UWB-based average estimation error covariance (X-axis and Y-axis) for each iteration in 500 Monte Carlo experiments. As shown in the Fig.9, the convergence time of the three algorithms are comparable, and in the term of converged value, we can get similar conclusions as before. The double weights algorithm has the best performance. Although the stability weights algorithm is improved compared to the STUKF, its performance is not as good as the double weights algorithm because it does not consider the accuracy of the measurement during fusion.

It can be seen from the results of the two sets of simulations that the measurement stability weight algorithm proposed in this article can effectively suppress the sudden disturbance caused by the sensor handover and thus improve the tracking and correcting accuracy of the moving target. Furthermore, the double weight algorithm is proposed to optimize the tracking and correcting accuracy by fusing the accuracy weight of the sensor based on the IMM method, which presents a significant performance improvement compared with the traditional STUKF algorithm.

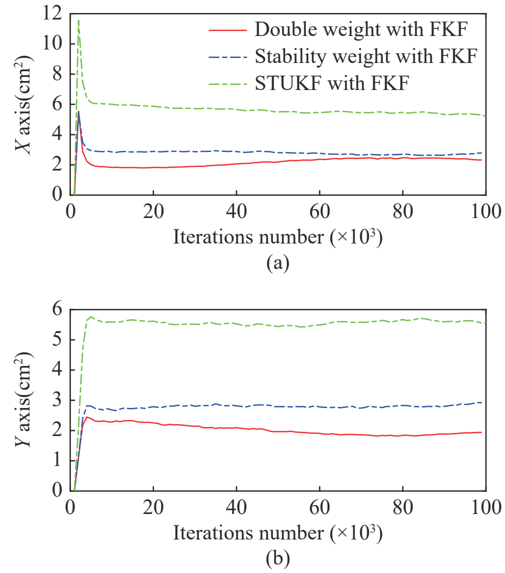


Fig. 9. Average estimated error covariance in 500 Monte Carlo experiments (three algorithms). (a) X axis; (b) Y axis.

Our numerical simulations verify that the algorithm has good performance under ideal conditions in 2D environment. In theory, if the information of Z axis is added in the system state vector, the algorithm proposed in the article can be applied in the 3D environment. However, considering the effect of nonlinearity on the convergence of the algorithm, whether it can be directly applied to the 3D object is still needs further research and simulation verification. In the same way, considering the complexity of the real environment, the performance of the algorithm on the physical platform requires further research and simulation verification.

VI. Conclusions

This paper has developed a weight distribution algorithm for tracking moving targets in a WSN. This algorithm has employed the DCKF to predict the measurement stability based on the motion model of the moving body, determined the weight of the measurement accuracy based on the measurement error covariance of each sensor, and eventually integrated the measurement stability and accuracy weights to assign the final weights. As verified by the simulation results, the proposed algorithm has effectively suppress the measurement dropout when tracking moving targets in a WSN, and has optimized the weights of each sensor based on the measurement error covariance to improve the tracking accuracy. Therefore, it is safe to conclude that the proposed algorithm has achieved good performances in effectively suppressing measurement dropout caused by sensor handover in a WSN.

However, the current algorithm can only deal with localization problems in Gaussian noise environments, and all measurement anchor points in the environment are required to be stationary. Given the above shortcomings, our next work will mainly focus on the following two aspects:

- Investigate the state estimation and filtering problem in the experimental environment with non-Gaussian noise, in response to this problem, the algorithm proposed in [30] may have reference value;
- Explore the cooperative positioning of multiple moving bodies, with the ultimate goal of realizing the relative positioning of moving bodies in a dynamic wireless sensor network;
- Further research and verify the performance of the algorithm in the 3D environment and physical platform.

References

[1] X. W. Dong, Y. Zhou, Z. Ren, *et al.*, "Time-varying formation control for unmanned aerial vehicles with switching interaction topologies," *Control Engineering Practice*, vol.46, pp.26–36, 2016.

[2] X. Feng, T. S. Zhang, T. Lin, *et al.*, "Implementation and performance of a deeply-coupled GNSS receiver with low-cost MEMS inertial sensors for vehicle urban navigation," *Sensors*, vol.20, no.12, article no.articleno.3397, 2020.

[3] H. Ahmed, I. Ullah, U. Khan, *et al.*, "Adaptive filtering on GPS-aided MEMS-IMU for optimal estimation of ground vehicle trajectory," *Sensors*, vol.19, no.24, article no.articleno.5357, 2019.

[4] Y. Zhuang, M. W. Gu, W. Wang, *et al.*, "Multi-robot cooperative localization based on autonomous motion state estimation and laser data interaction," *Science China Information Sciences*, vol.53, no.11, pp.2240–2250, 2010.

[5] S. A. Golden and S. S. Bateman, "Sensor measurements for Wi-Fi location with emphasis on time-of-arrival ranging," *IEEE Transactions on Mobile Computing*, vol.6, no.10, pp.1185–1198, 2007.

[6] M. Sugano, T. Kawazoe, Y. Ohta, *et al.*, "Indoor localization system using RSSI measurement of wireless sensor network based on ZigBee standard," in *Proceedings of the 6th IASTED International Multi-Conference on Wireless and Optical Communications*, *Wireless Sensor Networks*, Banff, Canada, pp.503–508, 2006.

[7] S. Lee and J. B. Song, "Mobile robot localization using infrared light reflecting landmarks," in *Proceedings of 2007 International Conference on Control, Automation and Systems*, Seoul, Korea, pp.674–677, 2007.

[8] T. Nägeli, C. Conte, A. Domahidi, *et al.*, "Environment-independent formation flight for micro aerial vehicles," in *Proceddings of 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Chicago, IL, USA, pp.1141–1146, 2014.

[9] A. Kushleyev, D. Mellinger, C. Powers, *et al.*, "Towards a swarm of agile micro quadrotors," *Autonomous Robots*, vol.35, no.4, pp.287–300, 2013.

[10] Z. Li, W. Dehaene, and G. Gielen, "System design for ultra-low-power UWB-based indoor localization," in *Proceedings of 2007 IEEE International Conference on Ultra-Wideband*, Singapore, pp.159–164, 2007.

[11] H. B. Li, J. Wang, and C. Y. Wang, "Discussion on affection factors of UWB indoor kinematic positioning," *Journal of Navigation and Positioning*, vol.6, no.1, pp.45–48, 2018. (in Chinese)

[12] N. Sharma and K. Sharma, "Routing and clustering optimization techniques in WSN: a review," in *Proceedings of the 8th International Conference on Computing, Communication and Networking Technologies*, Delhi, India, pp.1–7, 2017.

[13] V. Jindal, A. K. Verma, and S. Bawa, "Quantitative reduction in communication load for energy efficiency in WSN," *Wireless Personal Communications*, vol.85, no.4, pp.2795–2810, 2015.

[14] B. Li, W. J. Wang, and Q. Y. Yin, "A distributed localization in wireless sensor networks utilizing AOD estimation and synthetical uniform circular array," *Science China Information Sciences*, vol.58, no.6, pp.1–11, 2015.

[15] K. X. Guo, X. X. Li, and L. H. Xie, "Simultaneous cooperative relative localization and distributed formation control for multiple UAVs," *Science China Information Sciences*, vol.63, no.1, article no.119201, 2020.

[16] S. M. Dehnavi, M. Ayati, and M. R. Zakerzadeh, "Three dimensional target tracking via underwater acoustic wireless sensor network," in *Proceedings of 2017 Artificial Intelligence and Robotics*, Qazvin, Iran, pp.153–157, 2017.

[17] X. M. Ran and D. L. Fang, "Distributed sensor allocation algorithm for target tracking based on potential game," *Journal of Electronics & Information Technology*, vol.39, no.11, pp.2748–2754, 2017. (in Chinese)

[18] K. Tikhe and N. Sohni, "PF-RBF based energy efficient target tracking routing algorithm for WSN," in *Proceedings of 2016 International Conference on Automatic Control and Dynamic Optimization Techniques*, Pune, India, pp.532–537, 2016.

[19] J. Z. Li, F. C. Guo, and W. L. Jiang, "Source localization and calibration using TDOA and FDOA measurements in the presence of sensor location uncertainty," *Science China Information Sciences*, vol.57, no.4, pp.1–12, 2014.

[20] P. M. Harsha and R Kanakaraju, "Network lifetime enhancement of clustering approach using handoff mechanism in WSN," in *Proceedings of 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology*, Bangalore, India, pp.809–812, 2016.

[21] M. F. Qi, L. H. Dou, B. Xin, *et al.*, "Optimal path planning for vehicles under navigation relayed by multiple stations," in *Proceedings of the 2017 IEEE International Conference on Systems, Man, and Cybernetics*, Banff, Canada,

pp.1465–1470, 2017.

[22] M. F. Qi, L. H. Dou, B. Xin, *et al.*, "Optimal path planning for an unmanned aerial vehicle under navigation relayed by multiple stations to intercept a moving target," in *Proceedings of the 56th Annual Conference on Decision and Control*, Melbourne, Australia, pp.2744–2749, 2017.

[23] M. F. Qi, L. H. Dou, B. Xin, *et al.*, "A branch-and-bound approach for path planning of vehicles under navigation relayed by multiple stations," in *Proceedings of the 11th Asian Control Conference*, Gold Coast, pp.168–173, 2017.

[24] C. Y. He, C. Tang, and C. P. Yu, "A federated derivative cubature Kalman filter for IMU-UWB indoor positioning," *Sensors*, vol.20, no.12, article no.articleno.3514, 2020.

[25] C. H. Duan, "An improved routing protocol based on Gauss-Markov model in Ad Hoc networks utilizing prediction of link quality," in *Proceedings of 34th Chinese Control Conference*, Hangzhou, China, pp.6507–6511, 2015.

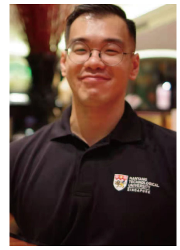
[26] T. Chao, "LAR routing stability protocol based on mobility prediction," in *Proceedings of the 35th Chinese Control Conference*, Chengdu, China, pp.6878–6882, 2016.

[27] Y. H. Xue, G. H. Tian, and F. Y. Zhou, "Multi-pattern information representation and acquisition in intelligent space," in *Proceedings of 2011 Chinese Control and Decision Conference*, Mianyang, China, pp.2477–2482, 2011.

[28] M. Zhang, S. Knedlik, and O. Loffeld, "An adaptive road-constrained IMM estimator for ground target tracking in GSM networks," in *Proceedings of the 11th International Conference on Information Fusion*, Cologne, Germany, pp.1–8, 2008.

[29] X. Bi, W. Wang, J. Gao, *et al.*, "The improved IMM tracking algorithm for high-speed maneuvering target," in *Proceedings of the IET International Radar Conference 2015*, Hangzhou, China, pp.1–4, 2015.

[30] L. Wang, J. Wan, Y. Liu, *et al.*, "Cooperative localization method for multi-robot based on PF-EKF," *Science in China Series F: Information Sciences*, vol.51, pp.1125–1137, 2008.



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