Cooperative Positioning Method for Multi-unmanned Systems Based on Confidence Evaluation

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(Received 19 May 2025; revised 11 August 2025; accepted 31 August 2025)

Abstract: In order to solve the problem of limited computational resources of multi-unmanned systems airborne navigation platform, a distributed cooperative positioning method based on confidence evaluation is proposed. Firstly, the impact of ranging error, priori information, spatial geometric configuration and adjacent nodes count on cooperative positioning performance are analyzed individually. Secondly, a confidence evaluation method for measurement information of adjacent nodes is designed according to the cooperative positioning principle, which comprehensively considers the coupling relationship between influencing factors. Finally, a distributed cooperative navigation filter based on inter-vehicle ranging is designed. Simulation studies show that confidence evaluation method proposed in this paper can effectively characterize the contribution of measurement information to positioning results, and positioning accuracy under the proposed method is improved by more than 15% compared with the traditional screening methods based on optimal geometric configuration and closest distance.

Key words: confidence evaluation; distributed architecture; cooperative positioning; dilution of precision; multi-source fusion

CLC number: V249.3 **Document code:** A **Article ID:** 1005-1120(2025)S-0038-13

0 Introduction

The unmanned system refers to an information-based physical platform composed of multiple types of motion carriers, which fulfils pre-set procedures with the help of technologies such as mechanical transmission devices, information sensing inputs and intelligent decision planning[1]. According to the different operating environments and mission characteristics of unmanned systems, unmanned systems can be divided into unmanned ground system (UGS), unmanned airspace system (UAS), and unmanned maritime system (UMS)[2]. With the rapid development of sensor technology, communication and sensing network technology, intelligent control algorithms and system theory and other cutting-edge fields, the autonomy, intelligence and universality of unmanned systems have been greatly improved and gradually become an important complementary part of manned systems[3].

With its strong mobility, co-ordination and parallelism, multi-unmanned systems can complete complex, dangerous and repetitive high-intensity tasks in multiple fields in a more efficient, convenient, autonomous and safe way, and it is the inevitable development trend of the future information-based military combat system that is dominated by intelligent multi-unmanned systems[4]. In the complex combat environment, a single type of unmanned system is limited by carrier platform characteristics, mobility, mode of operation, physical structure and other factors, unable to adapt to the combat needs in urban lanes, hills, valleys, underground and other environments. Therefore, multi-unmanned systems consisting of unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs), can complement and increase the efficien-

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How to cite this article: SHI Chenfa, XIONG Zhi, WU Tianxu, et al. Cooperative positioning method for multi-unmanned systems based on confidence evaluation[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2025, 42(S): 38-50.

http://dx.doi.org/10.16356/j.1005-1120.2025.S.004

cy of multi-unmanned systems by means of multidimensional perception, information interaction, cooperative interoperability and other techniques, which can effectively enhance combat survivability and give full play to their overall maximum efficiency[5]. At this stage, the research on multi-unmanned systems mainly focuses on the four parts of environment sensing and information fusion, data communication self-organizing network construction, cooperative navigation and positioning, and formation control, and this paper mainly focuses on the research of cooperative navigation and positioning key technologies[6].

In current multi-unmanned systems navigation and positioning methods, each unmanned carrier itself is configured with inertial sensors, which can complete real-time continuous inertial navigation output position solving in full-time and full-area environment. The inertial navigation has strong anti-jamming ability, and the use of the environment is not subject to regional limitations, so inertial sensors are an important part of the existing combination of navigation methods[7]. However, the disadvantage of inertial navigation is that the navigation error will be accumulated over time, and the high cost, and large volume of high-precision inertial devices. UAV and other small unmanned systems can only carry-lower-precision micro-electro-mechanical system (MEMS) sensors due to the load limitations. And they need to use exogenous information, such as global navigation satellite system (GNSS), and inertial data fusion to complete the navigation and positioning. Exogenous navigation information, such as GNSS, is susceptible to interference and easy to be spoofed, so cooperative positioning based on inter-vehicle ranging is currently an effective method for multi-unmanned systems navigation[8].

Cooperative positioning of multi-unmanned systems is similar to node positioning in wireless sensor networks, where distributed positioning solving can be accomplished between carriers through information sharing and inter-vehicle ranging using geometric constraints[9]. The cooperative positioning accuracy of vehicle depends on the number of reference nodes, the quality of the observation data and other factors, using a filter based on minimum mean-square error which is theoretically able to obtain the optimal estimation after acquiring different qualities of the measurement information in conjunction with its own motion model[10]. However, the communication overhead among vehicles increases, and the growing computational complexity tends to compromise real-time performance[11]. It is necessary to establish performance evaluation systems for cooperative positioning of multi-unmanned systems, and select the measurement information that contributes to its own positioning to participate in the computation. Scholars have carried out the following studies on the performance evaluation of cooperative positioning.

Zhu et al.[12] proposed a novel navigation performance evaluation strategy based on Fisher information and relative entropy. Chen et al.[13] proposed a cooperative navigation method for UAV's swarm based on the cooperative dilution of precision. Yu et al.[14] proposed a method for selecting the optimal detection configuration of heterogeneous unmanned swarms based on geometrically nested cone structures to achieve accurate detection of targets by unmanned swarms. However, the above evaluation methods are only applicable to specific application scenarios and do not consider the coupling of all influencing factors.

In the cooperative positioning process of multi-unmanned systems, the ranging information received from adjacent nodes contains two categories: Anchor nodes and unknown nodes. Traditional dilution of precision (DOP) based evaluation methods can only assess the impact of the geometric configuration of anchor nodes on positioning accuracy, while ignoring priori uncertainty in the state estimates of adjacent nodes[15]. Therefore, in cooperative positioning performance evaluation, it is necessary to represent the uncertainties arising from both priori information and measurements within a unified weighted information fusion framework, which is theoretically more consistent with the modeling approach of the Cramér-Rao Bound.

The remainder of this paper is organized as follows. Section 1 describes the cooperative positioning scenario and the proposed scheme. Section 2 analyzes the influencing factors of cooperative positioning. Section 3 presents the theoretical derivations and algorithm design. Section 4 validates the effectiveness of the proposed algorithm through simulation. Section 5 concludes the paper.

1 Definition of the Problem

1.1 System description

The cooperative positioning scenario of multi-unmanned systems is shown in Fig.1, where the multi-unmanned systems are composed of UAVs and UGVs. Some of UAVs in the swarm are equipped with satellite receivers that can acquire absolute position information. A few UGVs measure the distance and direction of the landmarks, and calculate their own incremental position relative to the landmarks through the position inverse solution, and then finally superimpose the position with the landmarks to obtain their own absolute position information. The above two types of vehicles can obtain absolute position information from external sources which are defined as reference nodes. In the absence of absolute exogenous measurements, UAVs and UGVs that update their navigation states solely through cooperative information are defined as unknown nodes.

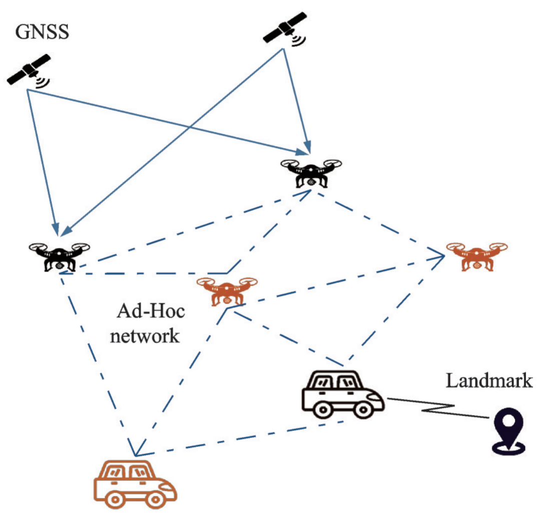


Fig.1 Cooperative positioning scenario for multi-unmanned systems

Each unmanned system carries out cooperative messaging and inter-vehicle ranging through the data link, and makes use of spatial geometric constraints to complete the error correction of inertial navigation sensors. At the same time, inertial navigation, with its high short-term accuracy, can effectively compensate for the non-line of sight (NLOS) and multipath effects in ranging, and the mutual checking of the output data of the two types of sensors can improve the robustness of the positioning system[16].

1.2 Cooperative positioning solution design

MEMS can output the acceleration and angular velocity in the direction of three orthogonal axes under the high-frequency output system, and use the quaternion transforms and integral calculation to complete the updating of the three state quantities of attitude, velocity and position of the vehicle. It aims to maintain the absolute positioning accuracy of the unmanned system in a short period of time, and use the exogenous measurement information to correct and compensate for the cumulative error of the long-time voyage position projection[17]. Usually, the output frequency of MEMS is more than 50 Hz, and the communication frequency of data path is about 1 Hz. Its communication bandwidth is limited by the signal modulation method, power, spectrum resources and other factors, which will only contain the node ID, its own state, absolute position, and the priori information of its position error in the cooperative message transmission. The cooperative positioning scheme for unknown nodes is as follows.

Due to the limited effective ranging distance of the data link, not all platforms in multi-unmanned systems can establish direct data communication with one another. As illustrated in Fig.2, the unknown node can establish data links with m adjacent nodes and n reference nodes. The adjacent nodes exhibit inconsistent priori position errors, and in principle, they can be treated as reference nodes with larger position uncertainties during cooperative positioning computation[18].

When the number of nodes establishing data links with the unknown node is less than or equal to four (i.e., $m+n\leqslant 4$), the filter fuses all available measurements to correct the strapdown inertial navigation system (SINS) errors. When the number of cooperative measurements exceeds this threshold, the varying levels of uncertainty make it suboptimal to fuse all cooperative information directly. Incorporating all measurements increases the observation di-

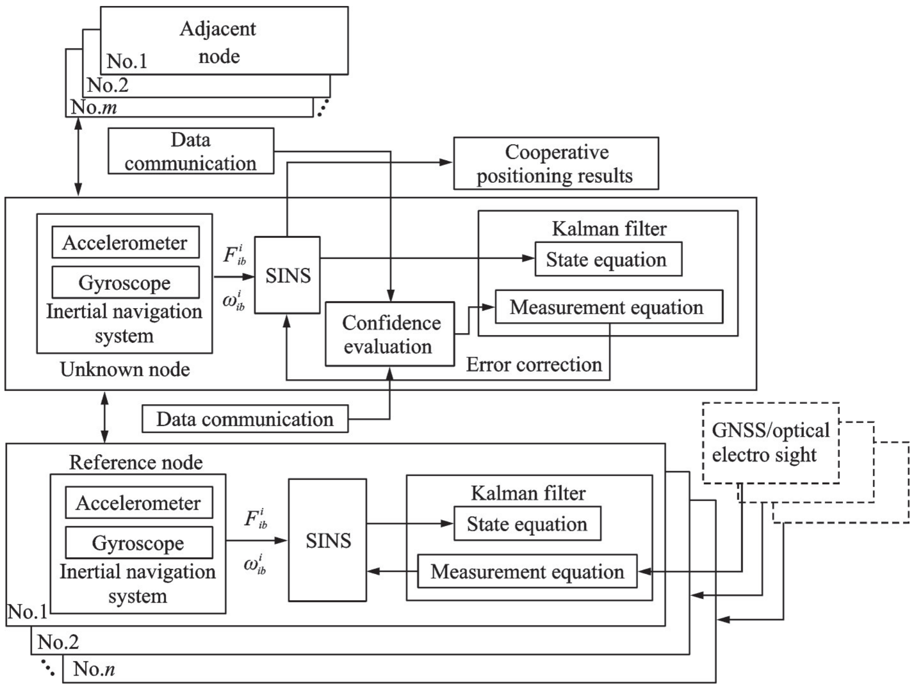


Fig.2 General framework diagram of cooperative positioning

mension of the filter, and the resulting growth in computational complexity degrades real-time performance[19]. Furthermore, if adjacent nodes exhibit strong spatial geometric correlation or noise correlation, the associated cooperative measurements may cause the observation matrix to approach singularity, leading to filter instability. Therefore, confidence evaluation is required to assess the contribution of each node to the cooperative positioning performance. Node selection is then performed based on these contributions, thereby reducing the computational burden while maintaining positioning accuracy.

2 Determinants of Cooperative Positioning Accuracy

In cooperative positioning system, the positioning accuracy of unknown nodes depends on four main factors: Ranging error, priori information of adjacent nodes, spatial configuration, and the number of adjacent nodes. The following theoretical analyses are carried out for the effects of influencing factors on cooperative positioning respectively.

2.1 Analysis of ranging error

The ranging error between vehicles is mainly composed of systematic error and random error. The equipment calibration, systematic bias can usually be reduced by calibrating the equipment on a regular basis. Random error is caused by environmental noise, signal attenuation and other random factors, and is usually assumed to obey a normal distribution. The ranging error model is given as follows

$$\varepsilon = \varepsilon_{\text{sys}} + \varepsilon_{\text{rand}} = \varepsilon_{\text{sys}} + \mathcal{N}\left(0, (\sigma \times d)^2\right) \tag{1}$$

where ε_{sys} is the systematic error; $\varepsilon_{\text{rand}}$ the random error obeying a normal distribution with zero-mean and standard deviation proportional to the measurement distance; σ the proportionality constant related to the equipment and the environment; and d the measurement distance between nodes.

When adjacent nodes are located at different distances around unknown node, the green dots in Fig.3 represent the position error distribution caused by systematic errors, while the blue and purple dots represent the position error distribution caused by signal attenuation. The two ellipses correspond to the constraint regions formed by No.1 and No.2 adjacent nodes based on the ranging error model. The number of particles within each ellipse is identical, indicating that under the same confidence probability, the smaller ellipse area reflects a stronger position constraint on the unknown node. Therefore, when only the ranging error is considered, No.2 adjacent node makes a greater contribution to positioning performance. In time-of-arrival (TOA) based geometric trilateration, it is common practice to select measurements from nearest nodes for cooperative positioning[20].

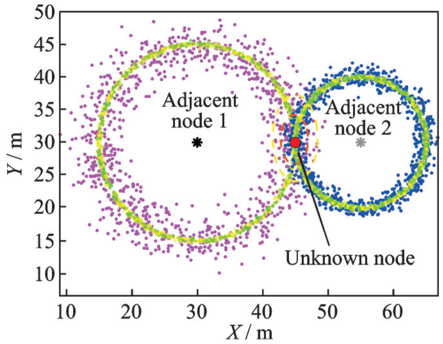


Fig.3 Ranging error influencing factors

2.2 Analysis of priori information

The geometric interpretation based on the covariance ellipse can intuitively describe the influence of priori information of adjacent nodes on the cooperative positioning performance. Taking the 2D plane as an example, when initial positions and position covariances of adjacent nodes are known, the distribution properties of data can be characterized by an ellipse, which is a set of points satisfying the following equation

$$(x-\mu)^{\mathrm{T}}\psi^{-1}(x-\mu)=c \tag{2}$$

where μ is the mean of the positioning result and ψ the covariance and typically treated as a constant; c is associated with the size of the confidence interval.

Fig.4 illustrates the geometric interpretation under heterogeneous priori information for two adjacent nodes, with particles generated according to the Gaussian distribution. In Fig.4, the colored ellipses represent the covariance equiprobability contours (95% confidence) of the corresponding nodes, with their principal axes determined by the eigen-decomposition of the covariance matrix. The narrower shape of the red ellipse along the X-axis indicates a smaller variance in that direction, implying higher position estimation accuracy. In general, the priori uncertainty of the No.1 adjacent node is smaller than that of the No.2 adjacent node.

After ignoring the ranging error between the adjacent node and the unknown node, the contribution of the adjacent node to cooperative positioning can be expressed in terms of the particles in the cross section of the covariance ellipse, and the contribution to the positioning solution with different priori information is shown in the following figure.

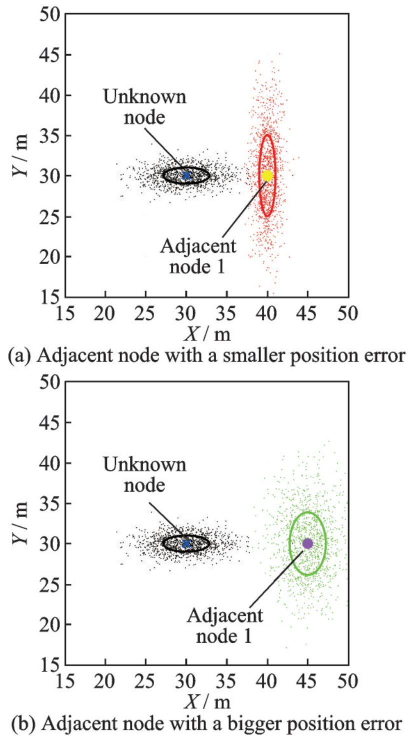


Fig.4 Geometric interpretation of priori information

Cooperative positioning is the combined geometric constraint of measurements from multiple nodes, and selected adjacent nodes with complementary directional constraints can reduce the overall position uncertainty. Fig.5 shows that the smaller width of the circle of particle distribution, the stronger its constraint on the positioning result, and the No.1 adjacent node has a higher contribution compared to the No.2 adjacent node. In three-dimensional space, the covariance matrix can be simplified into an ellipsoid by solving its eigenvalues and eigenvectors. The direction of its main axis is determined by the eigenvectors, and the length of its main axis is determined by the square root of the eigenvalues. The ellipsoid equation characterizes the distribution and directional uncertainty of the priori information of adjacent nodes.

2.3 Analysis of geometric configuration

In satellite navigation systems, geometric dilution of precision (GDOP) is usually used to measure the influence of satellite spatial distribution on

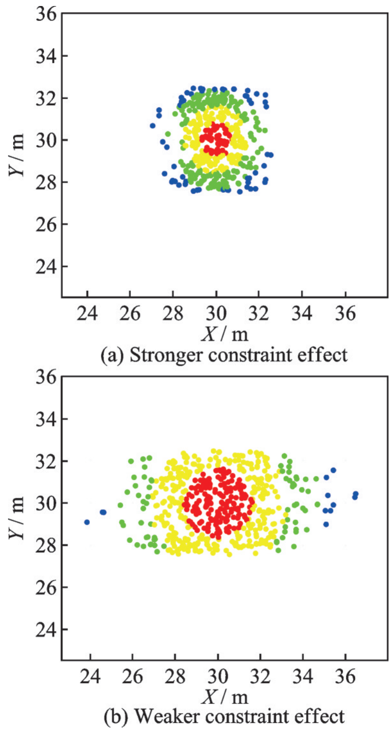


Fig.5 Contribution under different priori information

receiver positioning performance. But GDOP is under the assumption that satellite position error is negligible, and only spatial configuration is considered as an influencing factor[21]. However, in multi-unmanned systems cooperative positioning, adjacent nodes exist with different position confidence, which may have a good spatial configuration distribution but a poor effect on cooperative performance enhancement. And when two adjacent nodes are co-located with the unknown node, geometrical constraints between the nodes are weak, which is easy to produce multiple solutions or no solutions, so a reasonable geometrical configuration needs to be considered in node screening.

In Fig.6, when three adjacent nodes possess a favorable spatial geometric distribution and have small priori position errors, the cooperative positioning error is theoretically equal to ranging error multiplied by the geometric dilution factor. But when two adjacent nodes are co-located, the GDOP tends to infinity, and the positioning solution of unknown nodes cannot be completed. Previous studies based on the optimal geometric configuration mainly use empirical inference, which can only optimally configure the position distribution of reference nodes under a limited number, so as to derive coupling relationship between the ratio of reference nodes at different heights and the pitch angle. But in the case of inconsistent position confidence of reference nodes, the traditional node screening strategy based on empirical inference is no longer applicable.

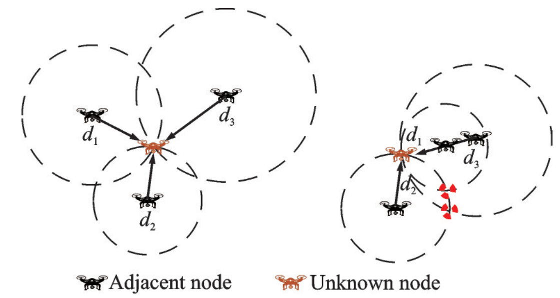


Fig.6 Contributions under different geometric distributions

2.4 Analysis of node count

When many adjacent nodes surround an unknown node, and effects of ranging error and prior information are ignored, increasing the amount of measurement information enlarges the system's geometric matrix, effectively reducing the sensitivity of the positioning solution to input perturbations and thereby enhancing the system's geometric strength. However, when the geometric distribution of reference nodes therein reaches the optimal configuration, the positioning accuracy can be close to the theoretical optimum, and the additional increase in the number of reference nodes enhances the positioning results less, and the existence of the performance saturation phenomenon can be characterized by the logarithmic curve.

$$\mathrm{Err}(N)=A\cdot\log N+B \tag{3}$$

where $\mathrm{Err}(N)$ is the positioning error in the presence of N adjacent nodes; A the slope of the curve, reflecting the sensitivity of the system positioning error to changes in the number of adjacent nodes; and B the initial positioning accuracy of the system.

Meanwhile, in complex environments such as cities, canyons and forests, data link signals may generate interference, multipath effects and NLOS errors, which may cause jumps in the positioning results if the wrong measurement information cannot be isolated. Therefore, when the number of adjacent nodes meets the minimum number of requirements for positioning solving, it is necessary to establish a confidence evaluation system and screen the adjacent nodes with high contribution for the measurement updating calculation.

3 Cooperative Positioning Method Based on Confidence Evaluation

In this subsection, the weighted cooperative dilution of precision (WCDOP) is constructed to characterize the adjacent nodes' confidence level by considering the influencing factors of the positioning performance, and the positioning information is obtained by fusing the selected measurement with an inertial navigation system.

3.1 Confidence evaluation methodology

The position of the unknown node in the earth-centered, earth-fixed (ECEF) coordinate system is $\boldsymbol{x}=(x, y, z)$. Assuming that m adjacent nodes with data communication can be established, the positions of the adjacent nodes are $\boldsymbol{x}_{ri}=(x_{ri}, y_{ri}, z_{ri})$, respectively, and the true distance between adjacent nodes and the unknown node is $d_i=\|\boldsymbol{x}-\boldsymbol{x}_{ri}\|$. Considering the priori information about the position error of adjacent nodes $\delta\boldsymbol{x}_{ri}$ and their own position error $\delta\boldsymbol{x}$, the measured distance d_i' is denoted as

$$d_i'=\|\boldsymbol{x}+\delta\boldsymbol{x}-(\boldsymbol{x}_{ri}+\delta\boldsymbol{x}_{ri})\|+\varepsilon_i \tag{4}$$

where $\delta\boldsymbol{x}$ is the position correction vector $[\delta x, \delta y, \delta z]^{\mathrm{T}}$, $\delta\boldsymbol{x}_{ri}$ the priori position error of the No.i adjacent node, and ε_i the ranging error.

In solving for the positioning of unknown node using a closed-form analytic algorithm, the non-linear quantitative equations first need to be converted into pseudo-linear equations, and then the optimal solution of the objective function is solved using optimization theory.

After linearizing Eq.(4) and neglecting higher order terms, we obtain

$$d_i'\approx\|\boldsymbol{x}-\boldsymbol{x}_{ri}\|+\frac{\partial d_i}{\partial x}\delta x+\frac{\partial d_i}{\partial y}\delta y+\frac{\partial d_i}{\partial z}\delta z+\frac{\partial d_i}{\partial x_{ri}}\delta x_{ri}+\frac{\partial d_i}{\partial y_{ri}}\delta y_{ri}+\frac{\partial d_i}{\partial z_{ri}}\delta z_{ri}+\varepsilon_i \tag{5}$$

The element of No.i row of the ranging residual vector $\boldsymbol{\nu}$ is $\nu_i=d_i'-d_i$, which can be obtained by bringing the results of linear approximation

$$\nu_i\approx\frac{\partial d_i}{\partial x}\delta x+\frac{\partial d_i}{\partial y}\delta y+\frac{\partial d_i}{\partial z}\delta z+\frac{\partial d_i}{\partial x_{ri}}\delta x_{ri}+\frac{\partial d_i}{\partial y_{ri}}\delta y_{ri}+\frac{\partial d_i}{\partial z_{ri}}\delta z_{ri}+\varepsilon_i \tag{6}$$

Represent the ranging residuals of all adjacent nodes in vector form

$$\boldsymbol{\nu}=\boldsymbol{G}\delta\boldsymbol{x}+\boldsymbol{J}\delta\boldsymbol{x}_{ri}+\boldsymbol{\varepsilon} \tag{7}$$

where $\boldsymbol{G}$ is the geometric matrix with $n\times 3$ dimension, $\boldsymbol{J}$ the adjacent node position error impact matrix with $n\times 3n$ dimension, and $\boldsymbol{\varepsilon}$ the ranging error vector.

The regression estimates under observations with different variances are obtained by introducing weighted matrix, and $\boldsymbol{W}$ is as follows

$$\boldsymbol{W}=\mathrm{diag}\left(\frac{1}{\sigma_{x_{r1}}^2},\frac{1}{\sigma_{x_{r2}}^2},\cdots,\frac{1}{\sigma_{x_{rm}}^2}\right) \tag{8}$$

where $\sigma_{x_{ri}}^2$ is the variance of the total position error of adjacent nodes.

The objective function is constructed as follows

$$\min_{\delta\boldsymbol{x}}(\boldsymbol{\nu}-\boldsymbol{G}\delta\boldsymbol{x})^{\mathrm{T}}\boldsymbol{W}(\boldsymbol{\nu}-\boldsymbol{G}\delta\boldsymbol{x}) \tag{9}$$

Normally $\boldsymbol{G}$ is full rank, which ensures the uniqueness and stability of the solution, obtained by taking derivative of objective function with respect to $\delta\boldsymbol{x}$ and setting the derivative to zero

$$\delta\boldsymbol{x}=(\boldsymbol{G}^{\mathrm{T}}\mathbf{WG})^{-1}\boldsymbol{G}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{\nu} \tag{10}$$

The covariance matrix of $\delta\boldsymbol{x}$ directly reflects the distribution of estimation error and is defined as

$$\mathrm{Cov}(\delta\boldsymbol{x})=E[(\delta\boldsymbol{x}-E[\delta\boldsymbol{x}])(\delta\boldsymbol{x}-E[\delta\boldsymbol{x}])^{\mathrm{T}}] \tag{11}$$

where $E[\cdot]$ is the mean and $\mathrm{Cov}(\cdot)$ the covariance.

It is assumed that ranging error ε_i satisfies a normal distribution with zero-mean, the variance is positively correlated with the distance, and individual ranging errors are independent of each other. The priori position errors $\delta\boldsymbol{x}_{ri}$ of each adjacent node is independent of each other.

From the systematic error propagation model, the covariance matrix of ranging residual vector $\boldsymbol{\nu}$ is defined as

$$\mathrm{Cov}(\boldsymbol{\nu})=\boldsymbol{J}\mathrm{Cov}(\delta\boldsymbol{x}_{\mathrm{r}})\boldsymbol{J}^{\mathrm{T}}+\mathrm{Cov}(\boldsymbol{\varepsilon}) \tag{12}$$

where $\mathrm{Cov}(\delta\boldsymbol{x}_{\mathrm{r}})$ is composed of $\mathrm{Cov}(\delta\boldsymbol{x}_{ri})$ which reflects the distribution of position error of each adjacent node. $\mathrm{Cov}(\delta\boldsymbol{x}_{ri})$ is the $\mathrm{diag}(\sigma_{x_{ri}}^2, \sigma_{y_{ri}}^2, \sigma_{z_{ri}}^2)$. $\mathrm{Cov}(\boldsymbol{\varepsilon})$ is ranging error covariance, which is positively correlated with the size of distance by the ranging error model and $\boldsymbol{R}=k\cdot\mathrm{diag}(d_1^2, d_2^2, \cdots, d_n^2)$

is obtained according to the ranging error model $\sigma_i^2 = kd_i^2$.

Substituting Eq.(12) into Eq.(11), then expanding and defusing $\mathrm{Cov}(\delta \boldsymbol{x})$ which can be defined as

$$\mathrm{Cov}(\delta \boldsymbol{x}) = (\boldsymbol{G}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{G})^{-1}[\boldsymbol{G}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{J}\mathrm{Cov}(\delta \boldsymbol{x}_r)\boldsymbol{J}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{G} + \sigma^2\boldsymbol{G}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{R}\boldsymbol{W}\boldsymbol{G}](\boldsymbol{G}^{\mathrm{T}}\boldsymbol{W}\boldsymbol{G})^{-1} \tag{13}$$

The position covariance $\mathrm{Cov}(\delta \boldsymbol{x})$ contains the contributions of all influencing factors, where the diagonal element directly quantifies positioning accuracy of unknown node in three-axis direction, describes the uncertainty of positioning solution, and can provide a basis for optimizing cooperative positioning performance by defining the WCDOP as

$$\mathrm{WCDOP} = \mathrm{trace}(\mathrm{Cov}(\delta \boldsymbol{x}))^{1/2} \tag{14}$$

3.2 Cooperative positioning filter design

In cooperative positioning of multi-unmanned systems based on confidence evaluation, the east-north-up (ENU) geographic system is used as navigation coordinate system, and the state quantities in cooperative positioning filter are defined as

$$\boldsymbol{X} = [\boldsymbol{\varphi} \quad \delta\boldsymbol{v} \quad \delta\boldsymbol{p} \quad \boldsymbol{\varepsilon}_{\mathrm{b}} \quad \boldsymbol{\varepsilon}_{\mathrm{r}} \quad \boldsymbol{\nabla}]^{\mathrm{T}} \tag{15}$$

where $\boldsymbol{\varphi} = [\varphi_{\mathrm{E}} \quad \varphi_{\mathrm{N}} \quad \varphi_{\mathrm{U}}]$ is the platform error angle of inertial navigation system in east, north, and up directions; $\delta\boldsymbol{v} = [\delta v_{\mathrm{E}} \quad \delta v_{\mathrm{N}} \quad \delta v_{\mathrm{U}}]$ the velocity error of vehicle in east, north, and up directions; $\delta\boldsymbol{p} = [\delta L \quad \delta\lambda \quad \delta h]$ the latitude, longitude, and altitude errors of vehicle; $\boldsymbol{\varepsilon}_{\mathrm{b}} = [\varepsilon_{\mathrm{b}x} \quad \varepsilon_{\mathrm{b}y} \quad \varepsilon_{\mathrm{b}z}]$ the gyroscopic constant drift error; $\boldsymbol{\varepsilon}_{\mathrm{r}} = [\varepsilon_{\mathrm{r}x} \quad \varepsilon_{\mathrm{r}y} \quad \varepsilon_{\mathrm{r}z}]$ the gyroscopic first-order Markovian drift error; $\boldsymbol{\nabla} = [\nabla_x \quad \nabla_y \quad \nabla_z]$ the accelerometer first-order Markovian state quantity.

The state transfer equation in discrete form is constructed from the inertial error differential equation

$$\boldsymbol{X}^{(k)} = \boldsymbol{\Phi}^{(k|(k-1))}\boldsymbol{X}^{(k-1)} + \boldsymbol{G}^{(k-1)}\boldsymbol{W}^{(k-1)} \tag{16}$$

where $\boldsymbol{\Phi}^{(k|(k-1))}$ is the error state transfer matrix, $\boldsymbol{G}^{(k-1)}$ the system noise matrix, and $\boldsymbol{W}^{(k-1)}$ the system noise.

When unknown node receives cooperative measurement information, it completes confidence evaluation according to Eq.(13). When the system is set to select measurement information of four adjacent nodes to participate in cooperative positioning solution, then after traversing various permutations and combinations, four nodes are designated as optimal cooperative nodes when the value of WCDOP is smallest.

In summary, the cooperative positioning algorithm for multi-unmanned systems based on confidence evaluation is outlined in flowchart shown in Fig.7.

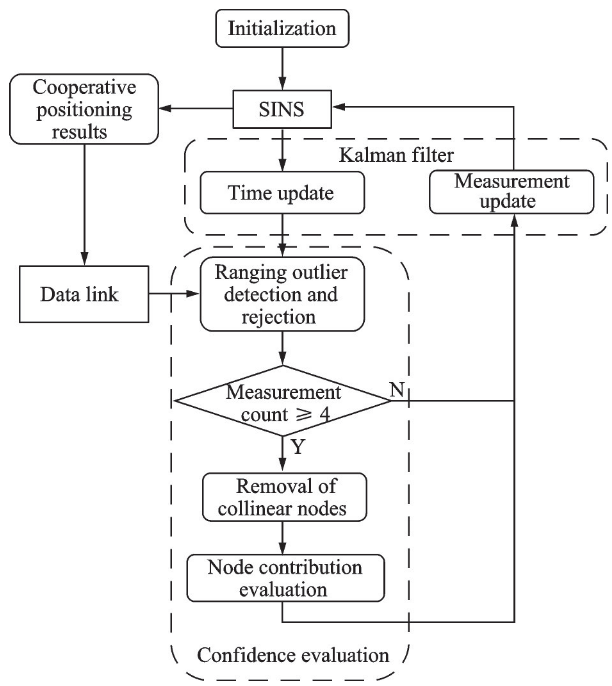


Fig.7 Flowchart of cooperative positioning algorithm

The construction of system measurement model is completed in Section 3.1, but the geographic system is used in inertial navigation system, and transformation matrix $\boldsymbol{H}_{\mathrm{e}}^{\mathrm{g}}$ needs to be used to establish a uniform magnitude of position error in both coordinate systems.

$$\boldsymbol{H}_{\mathrm{e}}^{\mathrm{g}} = \begin{bmatrix} -(R_{\mathrm{N}}+h)\sin L\cos\lambda & -(R_{\mathrm{N}}+h)\cos L\sin\lambda & \cos L\cos\lambda \\ -(R_{\mathrm{N}}+h)\sin L\sin\lambda & (R_{\mathrm{N}}+h)\cos L\cos\lambda & \cos L\sin\lambda \\ [R_{\mathrm{N}}(1-f)^2+h]\cos L & 0 & \sin L \end{bmatrix} \tag{17}$$

where R_{N} is the radius of curvature of prime vertical and f the earth oblateness.

The cooperative positioning system measurement equation is as follows

$$\boldsymbol{Z}^{(k)} = [0_{n\times 6} \quad \boldsymbol{H}_i\boldsymbol{H}_{\mathrm{e}}^{\mathrm{g}} \quad 0_{n\times 9}]\boldsymbol{X}^{(k)} + \boldsymbol{V}^{(k)} \tag{18}$$

where $\boldsymbol{V}^{(k)}$ is the total error of the cooperative node after the preferred selection.

4 Experimental Simulation and Results

In this subsection, the validation of the confidence evaluation will be accomplished through simulation, using cooperative positioning filters to fuse the measurement information, and the positioning results are analyzed finally.

4.1 Simulation condition setting

Multi-unmanned systems consist of six platforms, including UAVs and UGVs. Considering the existence of five adjacent nodes around No.6 unknown node, it can obtain information of ID, timestamp, position, and position error of adjacent nodes through the data link, in which two nodes can obtain absolute position information through GNSS/optical electro sight (OES) as a high-precision reference node. The other three nodes can only correct state quantity of their own projected position through a cooperative algorithm, so they have larger position error. The configured barometric altimeter measures the change of atmospheric pressure and combines with standard barometric pressure model to obtain real-time altitude information and perform damping calculation. The initial distribution of all nodes is shown as Fig.8.

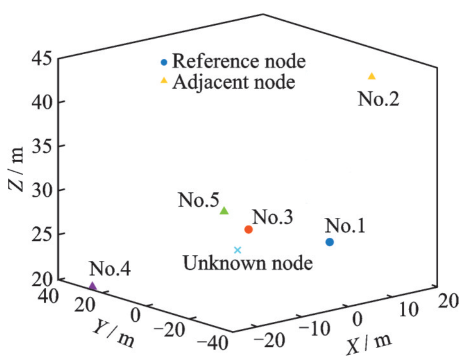


Fig.8 Initial position distribution

The trajectory generator is used in simulation to generate different motion modes of unmanned systems. And at the same time, angular velocity meter, gyroscope, GNSS, barometric altimeter, ranging and other sensors' information is simulated according to characteristics of the motion. The configuration of simulation sensor parameters is shown in Table 1.

Table 1 Sensor configuration and simulation parameters

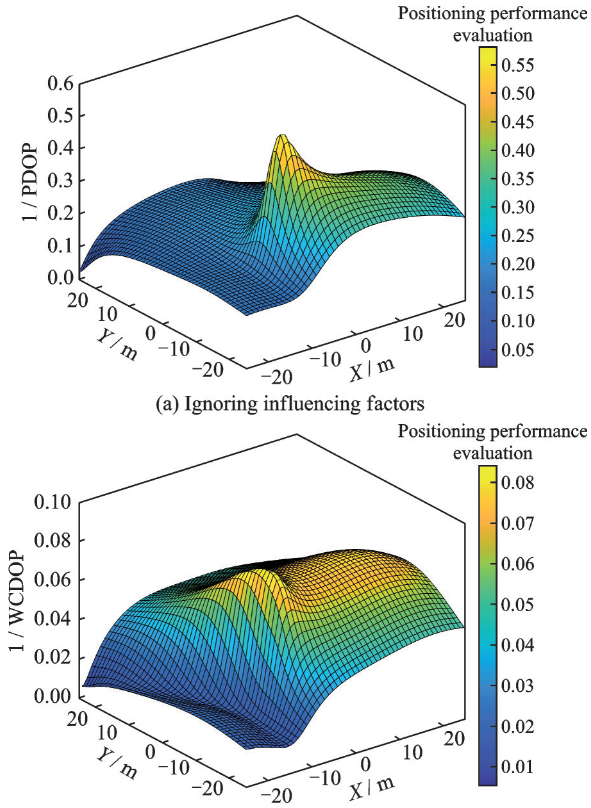
Sensor	Parameter	Value
GNSS	Position noise standard deviation/m	0.5
	Update frequency/Hz	1
Gyroscope	Random constant drift/((°)•h^{-1})	10
	White noise/((°)•h^{-1})	10
	First-order Markov drift/((°)•h^{-1})	10
	First-order Markov correlation time/s	3 600
	Update frequency/Hz	50
Accelerometer	First-order Markov drift/g	10^{-4}
	First-order Markov correlation time/s	1 800
	Update frequency/Hz	50
Barometric altitude	Height measurement error/m	5
Wireless ranging	Ranging noise/m	1
	Update frequency/Hz	1

4.2 Analysis of simulation results

Firstly, the confidence evaluation proposed in this paper is validated by setting No.1 and No.3 as high-precision reference nodes, and No.2, No.4 and No.5 with large position errors. Simulation results of the variation surface of positioning performance of unknown nodes on a plane with a height of 25 m are given, respectively. When only geometric configuration is considered, the position dilution of precision (PDOP) is typically employed to evaluate positioning performance, defined as $\mathrm{PDOP}=\mathrm{trace}(\mathrm{Cov}(\delta \boldsymbol{x}))^{1/2}$, with an equal weighted matrix set to $\boldsymbol{W}=\boldsymbol{I}$.

From Fig.9, it can be seen that when ignoring position error influences, the optimal position gain can be obtained with the plane coordinates around (−7, −13), where only the amplification effect of spatial geometric distribution on position error is considered. When priori information, ranging error, and geometric distribution are considered in performance evaluation, the overall WCDOP value becomes larger, which reasonably characterizes the coupling relationship between position error and three influencing factors.

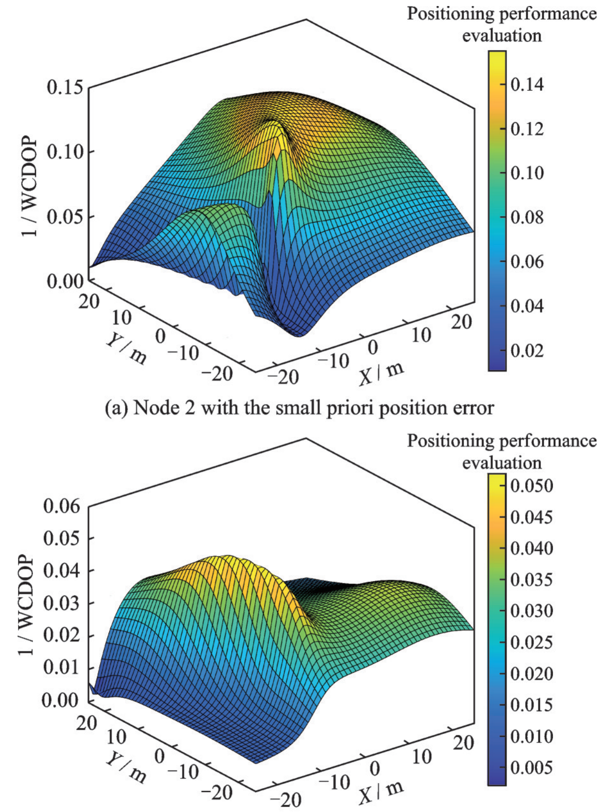
Due to the better elevation angle of the No.2 node compared to others, this node has a greater degree of contribution to the positioning performance improvement when considered only in terms of its spatial geometrical configuration. When the size of priori position error of the No.2 node is not consistent, its performance variation curve is shown in following figures.



(a) Ignoring influencing factors

(b) Consideration of influencing factors

Fig.9 Positioning performance change curves



(a) Node 2 with the small priori position error

(b) Node 2 with the large priori position error

Fig.10 Positioning performance under different priori position error

Fig.10 shows that when priori position error of No.2 node is smaller, its contribution to the positioning solution is larger. When priori position error becomes larger, even though it is more advantageous in spatial geometric configuration, the region that can obtain a larger gain in positioning performance is concentrated in the plane formed by perpendicular projections of No.1, No.3, No.4, and No.5 nodes. In cooperative positioning systems, only the number of adjacent nodes is increased, and other influencing factors are ignored. It does not significantly improve positioning accuracy. The system first screens nodes with high contribution when performing measurement update.

After completing the simulation verification of confidence evaluation for adjacent nodes, different maneuvering trajectories are assigned to all nodes according to the motion characteristics of quadrotor UAVs and UGVs, while keeping the parameter configurations of various navigation sensors consistent with those in Table 1. Motion trajectories of multi-unmanned systems are shown in Fig.11. It is assumed that each platform can broadcast and receive cooperative information via the data link, and that all navigation information is time-synchronized,

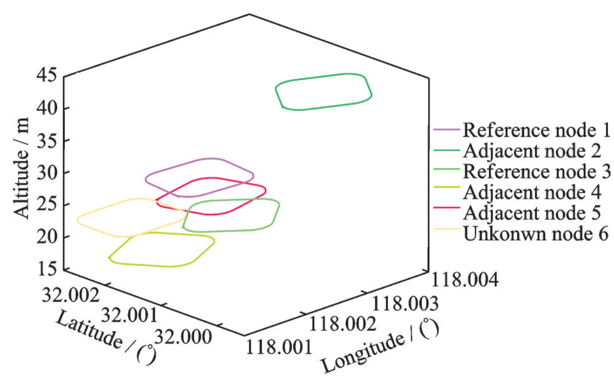


Fig.11 Trajectories of multi-unmanned systems

with no out-of-sequence or delayed measurements present[22].

In order to comprehensively verify the effectiveness of the cooperative positioning algorithm proposed in this paper, the node information after confidence evaluation and screening (Method 1) is used for filter updating, and the results are compared with those obtained using the nearest nodes (Method 2), and nodes selected via the optimal geometric configuration (Method 3), representing two alternative selection mechanisms. Cooperative positioning error curves along three axes of platform are shown as Fig.12.

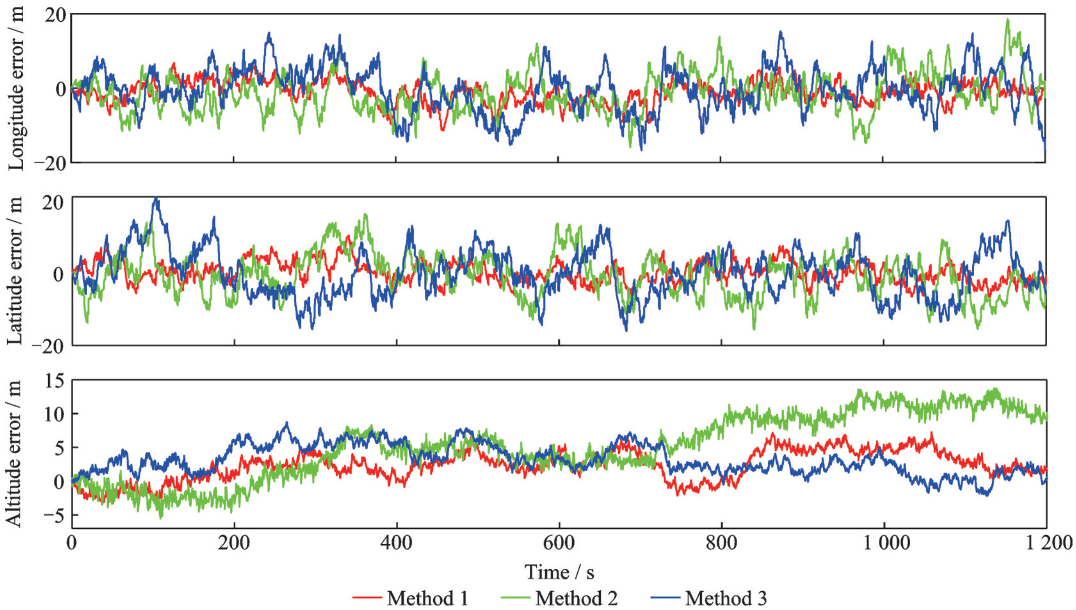


Fig.12 Cooperative positioning error curves

To visually compare the positioning performance under different node selection mechanisms, the root mean square error (RMSE) in different directions is defined as

$$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{\boldsymbol{x}}_i-\boldsymbol{x}_i^{\mathrm{true}})^2} \tag{19}$$

where N is the number of data samples, $\hat{\boldsymbol{x}}$ the cooperative positioning result of platform, and $\boldsymbol{x}^{\mathrm{true}}$ the true position of the platform.

The RMSE of positioning for different selection mechanisms is given in Table 2.

Table 2 RMSE of unknown node

Method	Longitude error/m	Latitude error/m	Altitude error/m
Highest confidence	3.21	2.96	3.01
Nearest distance	3.81	3.12	4.18
Optimal configuration	3.70	3.43	3.48

Using the information from nearest nodes can reduce the impact of ranging noise. However, it may result in an overly concentrated spatial distribution of selected nodes, thereby degrading geometric constraints and significantly reducing positioning accuracy in vertical direction. Using information from nodes with optimal geometric configuration can slightly improve the overall positioning accuracy, but it does not take into account priori position errors of adjacent nodes. As a result, nodes with favorable geometric distribution but large position uncertainty may be introduced into the solution, causing noise to propagate throughout multi-unmanned systems.

Simulation results indicate that, compared with traditional selection methods based on optimal geometric configuration and nearest distance, the use of the highest-confidence nodes prioritizes retaining node information that is both geometrically constraining and positionally reliable. This approach avoids geometric degradation and reduces the influence of ranging noise, thereby improving the positioning accuracy of platforms by more than 15%.

To reflect the overall cooperative positioning accuracy of multi-unmanned systems, No.2, No.4, and No.5 nodes are solved using the above algorithm, and cumulative distribution function (CDF) of the total positioning error for all nodes is presented. The overall cooperative positioning error of platforms is defined as

$$E=\sqrt{\mathrm{Err}_{\mathrm{E}}^2+\mathrm{Err}_{\mathrm{N}}^2+\mathrm{Err}_{\mathrm{U}}^2} \tag{20}$$

where $\mathrm{Err}_{\mathrm{E}}$, $\mathrm{Err}_{\mathrm{N}}$, $\mathrm{Err}_{\mathrm{U}}$ are the estimation errors of cooperative positioning results in the east, north, and up directions, respectively.

In Fig.13, a steeper CDF curve indicates that cooperative positioning errors are more concentrated within a smaller range, implying better stability and consistency of positioning results. A curve positioned further to the left indicates higher positioning accuracy at the same cumulative probability. With Method 2, achieving 80% CDF requires 13.5 m,

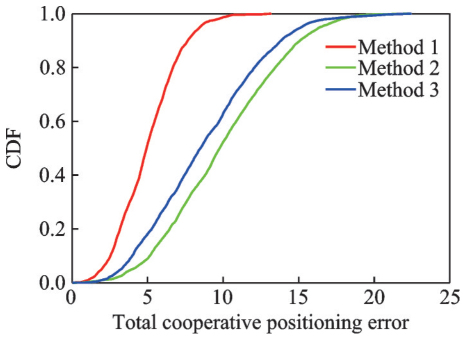


Fig.13 Cumulative distribution of the total cooperative positioning error

indicating the poorest positioning accuracy and stability. Method 3 performs between the proposed method and Method 2, reaching 80% cumulative distribution within 11 m. For the proposed method, the total cooperative positioning error is less than 8.5 m at 95% CDF. These simulation results verify the effectiveness of the proposed algorithm in suppressing the propagation of ranging errors and priori position uncertainties in cooperative positioning system, thereby improving the overall positioning accuracy of multi-unmanned systems.

5 Conclusions

Under the satellite denial or restricted environment, multi-unmanned systems can complete time update of navigation state volume by constructing the inertial recursive model. The confidence evaluation method is used to complete screening of measurement information, followed by the distributed cooperative filter to correct its own positioning error, which reduces the dependence on large bandwidth and high frequency of group communication in multi-unmanned systems cooperative navigation. The size of the swarm number supports dynamic expansion, which reduces the computational complexity while ensuring the positioning accuracy.

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Acknowledgements This work was supported in part by National Natural Science Foundation of China (Nos.62073163, 62103285, 62203228), National Defense Basic Research Program (No.JCKY2020605C009), Aeronautic Science Foundation of China (Nos.ASFC-2020Z071052001, 202055052003), Foundation Strengthening Program Technology 173 Field Fund (No.2021-JCJQ-JJ-0308).

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Competing interests The authors declare no competing interests.

(Production Editor: WANG Jie)

基于置信度评估的多无人系统协同定位方法

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摘要：针对多无人系统机载导航平台计算资源受限的问题，提出了一种基于置信度评估的分布式协同定位方法。首先，从测距误差、先验信息、空间几何构型、相邻节点数量4个方面单独分析其对协同定位性能的影响；其次，根据协同定位原理设计了相邻节点量测信息的置信度评估方法，综合考虑各影响因素之间的耦合关系；最后，设计了一种基于机间测距的分布式协同导航滤波器。仿真研究表明，本文所提的置信度评估方法能有效地表征量测信息对定位结果的贡献度，相较于传统基于几何构型最优和基于距离最近这两种筛选方法，所提方法的定位精度提高超过15%。

关键词：置信度评估；分布式架构；协同定位；精度因子；多源融合