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RESEARCH ARTICLE

Node Localization Algorithm for Irregular Regions Based on Particle Swarm Optimization Algorithm and Reliable Anchor Node Pairs

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ABSTRACT In wireless sensor networks (WSN), node localization is a key function, and only by knowing the coordinate positions of the nodes can correct decisions be made. In certain applications, such as smart cities, environmental monitoring, or industrial automation, irregular areas can be complex and affected by environmental complexity and inhomogeneity. Coverage gaps may exist between the nodes to be located and the anchor nodes, and communication paths between the nodes may deviate significantly from the ideal straight line, resulting in a large error between the final positioning result of the algorithm and the actual position. In order to solve this problem, this paper proposes a non-ranging node localization method (RANP-PSO) for irregular regions based on PSO algorithm and anchor node pair selection. The way firstly selects anchor node pairs with higher reliability parameters for the nodes to be located by introducing the hop count constraint mechanism for distance estimation; then uses the regularized least squares method for further constraints on the estimated distances; Finally, the PSO algorithm is utilized to optimize the coordinates of the target node, so as to solve to obtain the position of the node. When the proportion of anchor nodes is 20%, the communication radius of nodes is 30m, and the distribution density of nodes is 0.008, the proposed algorithm reduces the root mean square error by approximately 11.94% compared to AEML and LRAQS algorithms, 7.26% compared to the BDMCL algorithm, and 0.69% compared to the MSVR-DV-Hop algorithm. This demonstrates the advantage of the proposed algorithm in terms of localisation accuracy.

INDEX TERMS Non-ranging, irregular regions, particle optimization algorithm, node localization.

I. INTRODUCTION

Information acquisition has played a crucial role in the development of science and technology since ancient times [1]. With the growing demand for intelligence and digitalization in human society, sensors have been integrated into our lives as an essential means of data collection and acquisition, and they are also developing in the direction of high precision, low power consumption, and intelligence [2], [3]. At present, wireless sensor network technology is widely used in many fields, At present, wireless sensor network technology has been widely used in industrial automation, environmental monitoring, smart cities and many other fields [4]. In the above applications, sensor nodes can only realize the subsequent information processing and related operations under the premise of clarifying their location [5], so the node localization of sensors is significant.

In recent years, research on node positioning technology has mainly focused on algorithm optimisation. Sensor nodes are networked with each other through wireless communication, and based on the known effective position information of a small number of nodes, the nodes can collaborate with each other to complete the positioning, and this approach can effectively reduce the research and development cost

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and improve the portability of the algorithm. In a regular region, the node localisation algorithm may assume that the environment is uniform, while in an irregular region, this assumption no longer holds. Whereas real environments are often irregular, complex and frequently affected by non-line-of-sight propagation, node localisation techniques face multiple challenges in the application of these environments. Firstly, multipath effects and signal occlusion affect positioning accuracy, e.g., wireless signal propagation is impeded in urban buildings and tunnels. Second, environmental variations such as temperature, humidity and dust also affect signal propagation characteristics, e.g., in agricultural fields where humidity variations may cause positioning accuracy problems. Finally, node deployment and maintenance are particularly difficult in restricted spaces and harsh environments.

In order to improve the applicability of node localization algorithms, scholars at home and abroad are now also beginning to optimize node localization algorithms using strategies such as swarm intelligence optimization algorithms, mobile nodes and deep learning. Gopikrishnan [6] et al. proposed a unique localization framework for problems such as obstacles in irregular wireless sensor network environments, i.e., convex optimization method for localization with faster computation and also involves regular nodes in the cooperative localization process to achieve localization, which reduces the localization error to a larger extent. Javed et al. [7] proposed an algorithm that allows a mobile anchor node to fly in a 3D network with a C-shaped path, where the coordinates of the to-be-localized node are calculated by building a distance matrix from the RSSI (Received Signal Strength Indication) values between nodes in the network; Luo et al. [8] proposed an algorithm to localize nodes in the region by moving the anchor nodes, by selecting the appropriate anchor nodes and letting them move irregularly in the area, and finally by particle filtering for distributed localization optimal estimation; Tu et al. [9] proposed an algorithm to classify anchor nodes into two types, optimal and suboptimal, for distance estimation to specific unknown nodes (LRAQS), which reduces the influence of anisotropic factors in irregular regions on the localization results. For optimal anchor nodes, a probability density function is designed to compute the distance between them and the target node; for suboptimal anchor nodes, the distance is computed using the expected number of hops, and then the positional coordinates of the target node are obtained using the Bottle Sea Sheath Optimization Algorithm with quantum behavior. Zhang et al. [10] proposed a high-precision and high-efficiency multi-hop localisation algorithm (AEML), which effectively improves the localisation accuracy of the algorithm by using hyperbolic equations for the error matrix function of the estimated distances between nodes, and by judging and correcting the final localisation anomalies based on geometrical relationships between nodes.

Compared to the localization algorithms based on ranging techniques [11], there are a variety of non-ranging node localization algorithms, the main ones being the center-of-mass localization algorithm [12], [13], APIT algorithm (Approximate Point-In-Triangulation Test) [14], and the most widely used DV-Hop (Distance Vector-Hop) algorithm [15] and so on. Non-ranging node localization algorithms are based on the connectivity between nodes of wireless sensor networks, and node localization is accomplished through collaboration between nodes. Hadir et al. [16] proposed a PSODV-Hop localization algorithm by introducing a Particle Swarm Optimization (PSO) algorithm. It transforms the coordinate solving problem in the final stage into an optimization problem for PSO and analyzes the localization accuracy of the PSODV-Hop localization algorithm under different topologies. localization algorithm in different topologies. Liu et al. [17] proposed a DV-Hop localization algorithm based on corrected average hop count, namely HDCDV-Hop algorithm. The algorithm corrects the estimated distances between the target node and different anchor nodes based on hop count information and anchor node information, and uses an improved differential evolution algorithm to obtain the estimated location of the target node. The results show that compared with the original DV-Hop algorithm, the HDCDV-Hop algorithm has a smaller localization error and more accurate results. Yang [18] proposed the ISAPSO algorithm, an improved adaptive inertia-weighted particle swarm optimisation algorithm. The algorithm prevents the rapid loss of diversity of the particle swarm and the trapping of local optimal solutions during the iteration process, which is a common problem for particle swarm optimisation algorithms. Under different experimental conditions, the ISAPSO localisation estimation algorithm outperforms the other two PSO localisation estimation algorithms. Gou et al. [19] reduced the distance measurement error by using Gaussian-corrected RSSI and introduced an enhanced whale optimisation algorithm to optimise node localisation and improve accuracy. Experiments have demonstrated that this localisation algorithm outperforms the original RSSI algorithm, the whale optimisation algorithm, and the proposed affine transform evolutionary localisation algorithm. Yanfei et al. [20] proposed a wireless sensor network localisation algorithm based on mobile anchor nodes and improved hop count. The algorithm assigns different communication privileges to all nodes to enable different communication ranges. The algorithm calculates the average distance per hop of the three anchor nodes closest to the unknown node and uses it to determine the location of the unknown node by averaging the recorded positions. Simulation results demonstrate that this method has a small positioning error. In their work,

To reduce the impact of interference factors in irregular regions on the positioning results of non-ranging positioning algorithms, this paper proposes a non-ranging positioning method based on PSO algorithm and anchor node pair selection, which reduces the impact of the coverage voids in irregular regions on the positioning results of the algorithms to a greater extent by using the anchor node information in the small area around the to-be-located node to locate. The research in this paper has the following main contributions:

- A hop count constraint mechanism is introduced to set a suitable hop count threshold for the nodes, which reduces the possibility of inter-node communication path detours and improves the accuracy of the distance estimation phase.
- Defines the reliability parameters of the anchor node pairs, selects the appropriate anchor node pairs, and then uses regularized least squares for distance estimation between nodes.
- For the particle swarm algorithm, different weight coefficients are given to prevent the particle swarm algorithm from falling into a local optimum at the later stages of the iteration.

The remainder of the paper is structured as follows: Part II, mainly introduces the related research carried out in designing the RANP-PSO algorithm; Part III, introduces the main architecture and core ideas of the RANP-PSO algorithm; Part IV, describes in detail the experimental testing of the RANP-PSO algorithm with other algorithms under different experimental conditions and analyzes and compares the localization effects with the other algorithms; Part V, summarizes the whole paper, draws the conclusions as well as the direction of the research after that.

II. RELATED STUDIES

Domestic and international research on sensor node positioning technology mainly focuses on hardware design and algorithm optimization [21]. In the hardware design of the sensor node localization module, at this stage, the main purpose is to improve the accuracy and reliability of node localization by integrating more functions in the chip. For example, the base station information, Wi-Fi information, Bluetooth information, and inertial measurement unit (IMU) are utilized for fusion positioning [22]. As for the optimization of the algorithm, there is no need to consider the transformation of the sensor hardware, generally through the nodes to network with each other, and according to the effective position information of some known nodes, it can collaborate to complete the localization [23], this approach has a low cost, the algorithm of high portability characteristics.

At present, scholars at home and abroad have also begun to optimize the node positioning algorithm using strategies such as swarm intelligence optimization algorithm, mobile nodes and deep learning. Aziz [24] designed a localization method based on time difference of arrival (TDOA) and frequency difference of arrival (FDOA), which improves the localization accuracy of the algorithm by introducing the free gradient method and solves the problem of slow convergence of cuckoo algorithm; Roman et al. [25] designed a new distributed localization algorithm (RWNM-DV-Hop) based on the Newton-Raphson method, which effectively reduces the error introduced in the distance estimation phase by weighting the number of hops between neighboring sensor nodes using dynamic scaling parameters; Zhao et al. [26] proposed an improved localization algorithm by combining RSSI and back propagation neural network (BP) model for the problem that the classical localization algorithm produces a large localization error during the localization process, and experiments proved that this algorithm consumes slightly more energy than other algorithms, but the localization effect is significantly improved; Yang et al. [27] proposed a probabilistic KNN (k-Nearest Neighbor) algorithm (P-KNN), which uses the probability of RSSI in the radio map as a weight for calculating the Euclidean distance and filters RSSI values with probability less than 3%. Meanwhile, for passive indoor localization scenarios, the access point (AP) collects RSSI when the mobile terminal (MT) is not connected to the access point. experiments and result analysis for different k values show that the P-KNN algorithm is feasible and effective in passive indoor localization scenarios. Finally, the P-KNN algorithm achieves better average localization accuracy compared to the KNN algorithm.

III. ALGORITHMIC SCHEME FOR ANCHOR NODE PAIR SELECTION AND PARTICLE SWARM OPTIMIZATION

This study mainly focuses on the mesh architecture of wireless sensor networks, which offers high connectivity and fault tolerance. This is beneficial for information exchange and processing during the positioning process. However, the situation of node positioning in irregular areas is more special, such as valleys, lakes, rivers and other regions with more complex geographic environments. The network connectivity of sensor nodes deployed in such locations will be affected by the geographical environment, resulting in coverage holes, leading to communication blind zones [28].

If the nodes are affected by coverage voids between them, the shortest path for communication between them will undergo a detour that does not correspond to the actual situation, thus reducing the localization accuracy to a greater extent, as shown in Figure 1.

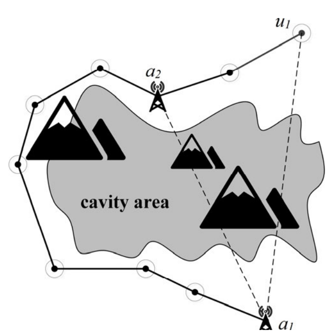


FIGURE 1. The shortest hop paths affected by coverage voids.

In irregular regions where communication blind zones exist, the selection of appropriate node localization algorithms is crucial to ensure localization accuracy and robustness. In irregular regions such as mountainous forests, urban neighborhoods and indoor environments, the environment is complex and varied, and the nodes are unevenly distributed. The signals are prone to non-line-of-sight propagation interference during propagation, which generates multipath effects, and also produces many communication blind zones, which makes it difficult to perform node localization, and the performance of many algorithms is affected.

For example, in irregular networks, the AEML algorithm mainly adapts to the irregular network environment through the adaptive weighting matrix, the weighting matrix may sometimes fail to capture the real changes in the network, and the quality of the links between nodes in irregular areas varies, and some of the links may be broken, weak signals and other problems, which also leads to abnormalities in the distance estimation, which in turn affects the localization results of the AEML algorithm. The BDMCL algorithm relies on the mobile node's own motion model and the information of the blind node, etc., but the node's motion trajectory in irregular environments is more complex, and there are a large number of irregular obstacles in the environment, which leads to a large error in motion prediction. In addition, the communication radius consistency requirement in the BDMCL algorithm may result in the algorithm not being able to adapt quickly even when the network changes. The MSVR-DV-Hop algorithm takes into account the distance estimation and the influence of obstacles, but in indoor environments, where the multipath effect of the signal propagation is more pronounced as well as in dynamic environments, the accuracy of the hop count estimation will be affected, and the accuracy of its localization accuracy will also be greatly influence.

Therefore, for the above situation, this paper proposes a non-ranging localization method (RANP-PSO) for irregular regions based on PSO algorithm and anchor node pair selection; The core idea of this method is to utilize the information of reliable anchor nodes around the target node as much as possible when performing node localization, and then optimize the estimated distances between the nodes using the least squares method, and finally use the PSO algorithm to transform the problem of solving the coordinates of the target node into an optimal finding problem. The localization method is divided into the following steps: constraints on the number of hops between nodes, selection of reliable anchor node pairs for the to-be-localized nodes, minimization of the distance estimation error between the nodes using regularized least squares, and optimization of the position coordinates of the to-be-localized nodes using the PSO algorithm. The overall architecture of the localization method is shown in Figure 2.

In Figure 2: ①CPN: Current node position, ②OLNI: Optimal location of node individuals, ③DAS: Direction and speed, ④GOP: global optimum position.

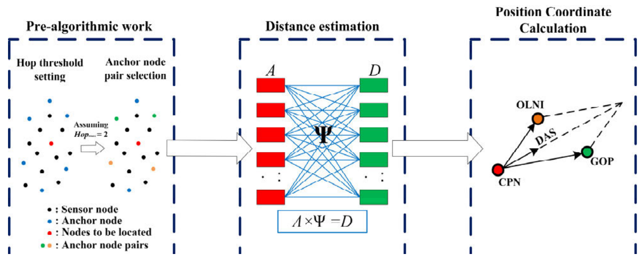


FIGURE 2. The overall architecture of the algorithm.

A. HOP COUNT CONSTRAINTS BETWEEN NODES WITH ANCHOR NODE PAIR SELECTION

In an irregular region, assuming a randomly dispersed arrangement of N sensor nodes, there exist N_a nodes equipped with positional information that can be obtained through a global positioning system (RANP-PSO) device, called anchor nodes, the remaining $N_u(N_u = N - N_a)$ sensor nodes in the region with unknown location information are called regular nodes or nodes to be located. In the experiment, the nodes all have communication radius R, have unique node identification ID and can interact with any node within the communication range for information. In the initial stage of wireless sensor network networking, after flooding the information between nodes, the to-be-localized node obtains information such as location coordinates of the surrounding nodes.

The estimated distance $\tilde{d}_{au}$ between the to-be-localized node u and the anchor node a is obtained by calculation.

$$\tilde{d}_{au} = hop_{au} \times \bar{d} \tag{1}$$

where $\bar{d}$ denotes the average hop_{au} distance between anchor nodes. It can be seen that the two key factors in the localization of node u are the hop count hop_{au} and the average hop distance $\bar{d}$.

According to the study, the non-ranging localization algorithm using communication hops can be roughly divided into two steps: distance estimation and node coordinates calculation. In the former step, the optimization of the hop count error plays a decisive role in the final positioning result of the algorithm [29]. In irregular regions, the shortest hop-count paths may produce detours due to obstacles, uneven distribution of nodes, etc. Therefore, in order to reduce the error generated in the distance estimation phase, this paper proposes a hop count constraint mechanism between nodes, which limits the number of communications between nodes by introducing a hop count threshold parameter in order to select paths with fewer hops in the information flooding phase, so as to achieve localization by using the information of only a small range of anchor nodes, and to control the localization of nodes in a localized range, and to reduce the influence of interference factors in the irregular region on the localization of the algorithm.

The setting of the inter-node hop threshold is mainly related to the number of anchor nodes in the region and the network connectivity [30]. Therefore, the following relationship is obtained by comparing the communication coverage area with $Hop_{\max}$ number in the ideal case with the area S of the area to be monitored:

$$\frac{\pi(Hop_{\max}R)^2}{S} = \frac{e}{N_a} \tag{2}$$

where e denotes the minimum number of anchor nodes required in the region to accomplish node localization; the above is the calculation of the hop threshold in the ideal case, but in irregular regions, affected by factors such as coverage voids and random characteristics of node distribution in the network, and taking into account the area of the region to be monitored by the node, the radius of node communication, the value of $Hop_{\max}$ is generally set to be a few hops slightly more extensive than that in the ideal case, in order to ensure the connectivity of nodes, so as to meet the localization requirements in practical scenarios.

$$Hop_{\max} > \frac{\sqrt{\frac{tS}{N_a\pi}}}{R} \tag{3}$$

In a multi-hop communication environment, each additional node in the path introduces a certain amount of propagation delay and signal attenuation. The hop count limiting mechanism prevents the signal from passing through too many nodes, thus reducing the cumulative error caused by too many hops. By limiting the number of hops, it can ensure that the localization algorithm mainly relies on the closer anchor nodes for localization, effectively reducing the localization error. However, the hop count mechanism may not always be effective. For instance, in cases where anchor nodes are unevenly distributed, it may result in the inability to locate sufficient anchor nodes to restrict the hop count in certain areas. In complex propagation environments, such as those with multipath effects, signal occlusion, or reflections, there is a high probability that signal propagation paths will be bypassed. Additionally, inconsistent node communication radii can cause the hop count limiting mechanism to be unfair to some nodes, rendering it ineffective.

Introducing the hop count constraint mechanism in the algorithm is effective. Still, considering the characteristics of the random distribution of nodes, the selection of anchor nodes will also impact the final localization results of the to-be-localized nodes when they are to be localized [22]. By dividing and filtering the locations of anchor nodes, the information of anchor nodes in the local range around the node to be located is used to select the anchor nodes that can maximally avoid the influence of the irregular region for localization.

Assuming that there exists a to-be-located node u_k and two anchor nodes a_i, a_j, and the number of hops between the to-be-located node u_k and the anchor nodes a_i, a_j obtained after message flooding at the initial stage of the networking is hop_{ik} and hop_{jk}, respectively, the reliability parameter of the anchor nodes a_i, a_j for the to-be-located node u_k is defined as:

$$\lambda_k^{ij} = \frac{d_{ij}}{hop_{ik} + hop_{jk}}, 0 < \lambda_k^{ij} \leq R \tag{4}$$

where λ_k^{ij} can also be expressed as the average hop distance of the anchor nodes a_i, a_j on the shortest hop path through the to-be-localized node u_k. In practice, it is impossible to judge the reliability of an anchor node pair by the number of hops alone, since the nodes are randomly distributed in the region, and the distances between the nodes are not the same. Moreover, the Signal may be detoured during propagation due to obstacles or attenuation of the wireless signal. This will lead to a deviation between the actual signal propagation distance and the ideal straight line distance. And when the value of λ_k^{ij} is close to R, it means that the signal propagation path is more direct, i.e., the fewer the number of nodes of anchor nodes a_i,and a_j in passing through the path u_k of the node to be localized, the lower the possibility of path bypassing, and the smaller the error of node localization is likely to be. Thus in general, for any anchor nodes a_i, a_j, if the hop count between the to-be-localized node and them is smaller, the reliability of the anchor nodes a_i, a_j for the localization of node u_k is considered to be higher [31].

The significance of anchor nodes for reliability can be more intuitively understood by looking at the following two scenarios. As shown in Figure 3, when there is no obstacle between the node u_k and the anchor nodes a_i and a_j, the minimum hop counts hop_{ik} and hop_{jk} from the node u_k to the anchor node a_j and a_j are both 3, and the corresponding maximum estimated distances are both 3R. Therefore, the location where the node u_k most likely resides is in the overlapping portion of two circles centered on the anchor nodes a_j and a_j, with a radius of 3R.

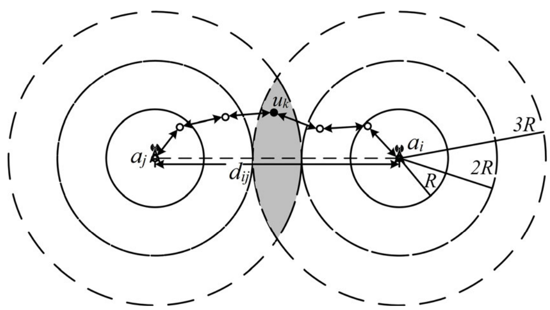


FIGURE 3. The shortest hop path between nodes not affected by voids.

However, when the communication path is bypassed due to obstacles between the node u_k and the anchor node a_i and a_j, the minimum number of hops between the node u_k and the anchor node a_i is changed from 3 to 4, as shown in Figure 4.

Although the position of the node u_k is not changed, the uncertainty of the localization result in this case is greatly increased, which also means that a more significant localization error may occur. After the initial networking message flooding, to obtain the estimated distance $\tilde{d}_{ik}(k \in [1, N_u], i \in [1, N_a])$ between the to-be-localized node u_k and the anchor node a_i. First, the anchor node a_i constructs $N_a - 1$ anchor node pairs with the remaining $N_a - 1$ anchor nodes, then calculates the reliability parameter λ_k^{i,N_a-1} between the to-be-localized node u_k and each anchor node pair, and

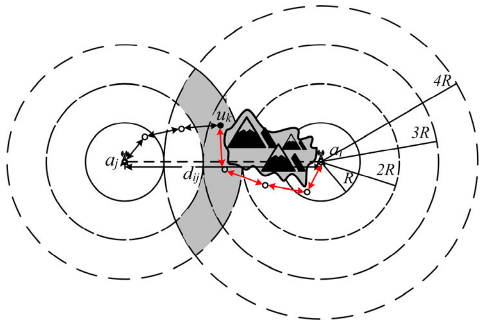


FIGURE 4. Hop count paths between nodes affected by voids.

determines whether the number of hops of the shortest path hop_{i,N_a-1} between them satisfies the maximum threshold of hop $Hop_{\max}$. With the guarantee of $hop_{i,N_a-1} \leq Hop_{\max}$, the distance $\tilde{d}_{i,N_a-1}$ between anchor node pairs a_i and a_{N_a-1} is estimated using Eq. (1). Finally, the anchor nodes are sorted by reliability parameters and the two anchor node pairs with the largest reliability parameters are selected for the next step.

It is assumed that there exist two anchor node pairs a_i, a_j and a_o, a_p with maximum reliability parameters and $\lambda_k^{ij} \geq \lambda_k^{op}$, $i \neq j$, $o \neq p$, but it is important to note that there exists a situation where there is one and only one common anchor node in the two sets of anchor node pairs.

The selection of two groups of anchor node pairs is based on the consideration that if only one group of anchor node pairs is used for localization, the situation that the localization coordinates of the to-be-localized node u_k in Figure 5 are symmetric for the anchor node pairs a_i and a_j may occur, resulting in the formation of the false localization point u'_k. The selection of two groups of anchor node pairs can effectively avoid the occurrence of such a situation, thus reducing the localization error of the algorithm [32].

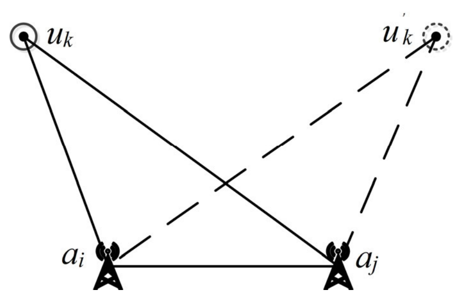


FIGURE 5. False positioning points.

B. INTER-NODE DISTANCE ESTIMATION BASED ON REGULARIZED LEAST SQUARES METHOD

Through the inter-node hop count constraint mechanism and anchor node pair reliability parameter in Section III-A, the to-be-localized nodes can be given more accurate anchor nodes selected for localization. Meanwhile, to further improve the accuracy of inter-node distance estimation, regularized least squares [33], [34] is used to compute the distance between the node pairs to be localized and the anchor nodes based on equal constraints and generalization performance.

It is assumed that for the to-be-localized node u_k, there are two groups of anchor node pairs a_i, a_j and a_o, a_p with high-reliability parameters for which the position coordinates can be calculated. Taking the anchor node pair a_i and a_j as an example (a_o and a_p have the same calculation steps as them), firstly, after flooding the messages between nodes at the initial stage of networking, the to-be-located node will record the location information of the anchor node pairs a_i and a_j, the minimum number of hops as well as the minimum number of hops between itself and the anchor node pairs a_i and a_j.

Then, the minimum number of hops hop_{ij} between a_i and a_j is denoted as a 2×2 matrix $\boldsymbol{A}$, the minimum number of hops between the to-be-localized node u_k and the anchor nodes a_i and a_j is denoted as a 2×1 matrix $\boldsymbol{U}$, and the distance d_{ij} between the anchor nodes a_i and a_j is denoted as a 2×2 matrix $\boldsymbol{D}$.

$$\boldsymbol{A} = \begin{bmatrix} hop_{ij} & 0 \\ 0 & hop_{ij} \end{bmatrix} \tag{5}$$

$$\boldsymbol{U} = \begin{bmatrix} hop_{ik} \\ hop_{jk} \end{bmatrix} \tag{6}$$

$$\boldsymbol{D} = \begin{bmatrix} d_{ij} & 0 \\ 0 & d_{ij} \end{bmatrix} \tag{7}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{8}$$

$$\boldsymbol{A} \cdot \Psi = \boldsymbol{D} \tag{9}$$

where (x_i, y_i) denotes the coordinates of anchor node a_i and (x_j, y_j) denotes the coordinates of anchor node a_j.

The relationship that exists between the hop count matrix $\boldsymbol{A}$ and the distance matrix $\boldsymbol{D}$ is shown in Figure 6. Using the idea of the least squares method of solution, the objective function can be expressed as [35]:

$$\Psi = \arg_{\Psi} \min \|\boldsymbol{A} \cdot \Psi - \boldsymbol{D}\|^2 + \alpha \|\Psi\|^2 \tag{10}$$

where $\|L\|$ denotes the $L2$ paradigm and α is a parameter that tends to 0 added to the algorithm to avoid overfitting the

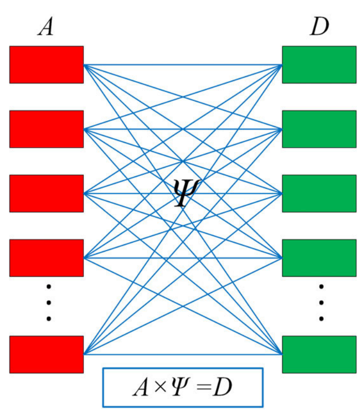


FIGURE 6. Mapping between the hop count matrix and the distance matrix.

objective function. So the solution to the above least squares problem can be obtained as:

$$\Psi = \boldsymbol{A}^{+} \cdot \boldsymbol{D} \tag{11}$$

$$\boldsymbol{A}^{+} = (\boldsymbol{A}^T\boldsymbol{A})^{-1}\boldsymbol{A} \tag{12}$$

where $\boldsymbol{A}^{+}$ is the generalized inverse matrix of $\boldsymbol{A}$, and where $\alpha \|\Psi\|^2$ is denoted by the constant G:

$$\Psi = (\boldsymbol{A}^T\boldsymbol{A} + G\boldsymbol{I})^{-1}\boldsymbol{A} \cdot \boldsymbol{D} \tag{13}$$

where $\boldsymbol{I}$ denotes the unit matrix of the same order as $\boldsymbol{A}$.

Finally, the estimated distance matrix $\tilde{D}$ between the to-be-localized node u_k and the anchor node pair a_i and a_j can be expressed as follows, based on the hop count matrix $\boldsymbol{U}$ between them:

$$\tilde{D} = \begin{bmatrix} \tilde{d}_{ik} \\ \tilde{d}_{jk} \end{bmatrix} = U \cdot \psi = U(A^TA + GI)^{-1}A \cdot D \tag{14}$$

C. PARTICLE SWARM ALGORITHM BASED NODE POSITION COORDINATE CALCULATION

The PSO algorithm is a search algorithm used to solve the optimization in computational mathematics and one of the most classical intelligent algorithms, which solves the problem by constructing the fitness function of the corresponding problem [36], [37]. The localization of nodes in wireless sensor networks fits well with the PSO algorithm, so the localization problem of nodes can be transformed into the optimization problem of particle swarm algorithm.

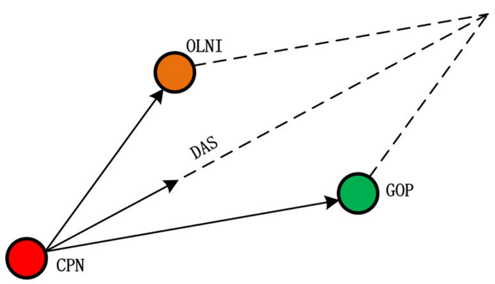


FIGURE 7. Schematic diagram of node location optimization.

Suppose there are N_u nodes to locate and they have two attributes: position $\boldsymbol{P}_k^t = (p_{k,1}^t, p_{k,2}^t, \cdots, p_{k,D}^t)$ and velocity $\boldsymbol{V}_k^t = (v_{k,1}^t, v_{k,2}^t, \cdots, v_{k,D}^t), k \in [1, N_u]$. In each iteration, the to-be-localized node records the positions it has visited and searches for its optimal position $P(best)_k^t$ and the global optimal position $Q(best)_k^t$ of all to-be-localized nodes by continuously updating the position and the velocity [38], and the Kth node's position and velocity update formula is expressed as follows:

$$\begin{aligned} v_{k,d}^{t+1} &= wv_{k,d}^t + r_1c_1(P(best)_{k,d}^t - p_{k,d}^t) \\ &\quad + r_2c_2(Q(best)_{k,d}^t - p_{k,d}^t) \end{aligned} \tag{15}$$

$$p_{k,d}^{t+1} = p_{k,d}^t + v_{k,d}^{t+1} \tag{16}$$

where t denotes the number of iterations; w denotes the inertia parameter; c_1 denotes the weight of the optimal position of the to-be-localized node itself, and c_2 denotes the weight of all the to- be-localized node that have been to the optimal position; r_1 and r_2 denote the random numbers that are uniformly distributed in the interval [0, 1];and d denotes the dimension of the region in which the to-be-localized node is located. In this paper, only the node's optimization in the 2D plane is considered without considering the height of the deployment area and the height of the node itself.

When using the particle swarm algorithm to solve for the coordinates of the node to be located, the particle swarm is first initially initialised by randomly generating a certain number of particles in the solution space of the problem to represent potential node locations, and setting an initial individual optimal solution and a globally optimal solution for each particle.

Then the fitness function is constructed according to the problem. Assuming that the two anchor node pairs a_i, a_j and a_o, a_p with the highest reliability parameter have been selected for the to-be-localized node and the estimated distances between the to-be-localized node, u_k, and the anchor nodes a_i, a_j, a_o, and a_p have been obtained by using regularized least Squares computation as $\tilde{d}_{ik}$, $\tilde{d}_{jk}$, $\tilde{d}_{ok}$, and $\tilde{d}_{pk}$, respectively, the constructed fitness function, $f(\tilde{x}_k, \tilde{y}_k)$, is as follows:

$$\begin{aligned} f(\tilde{x}_k, \tilde{y}_k) = w_k^{ij} &\begin{pmatrix} \left|\sqrt{(x_i - \tilde{x}_k)^2 + (y_i - \tilde{y}_k)^2} - \tilde{d}_{ik}\right| \\ + \left|\sqrt{(xj - \tilde{x}_k)^2 + (y_j - \tilde{y}_k)^2} - \tilde{d}_{jk}\right| \end{pmatrix} \\ + w_k^{op} &\begin{pmatrix} \left|\sqrt{(x_o - \tilde{x}_k)^2 + (y_o - \tilde{y}_k)^2} - \tilde{d}_{ok}\right| \\ + \left|\sqrt{(x_p - \tilde{x}_k)^2 + (y_p - \tilde{y}_k)^2} - \tilde{d}_{pk}\right| \end{pmatrix} \end{aligned} \tag{17}$$

where (x_i, y_i), (x_j, y_j), (x_o, y_o), (x_p, y_p) are the positions of the anchor nodes in coordinates a_i, a_j, a_o, a_p, respectively; $(\tilde{x}_k, \tilde{y}_k)$ is the estimated position coordinates of the to-be-localized node u_k;w_k^{ij}, w_k^{op} represent the weight coefficients of the anchor nodes for the node u_k by the anchor node pairs a_i, a_j, and a_o, a_p, respectively. Because for the to-be-localized node, the reliability parameters of different anchor node pairs are different, giving different weight coefficients can effectively improve the node's localization accuracy, and also can avoid the particle swarm algorithm easily falling into the problem of local optimization in the late iteration.

$$w_k^{ij} = \frac{\lambda_k^{ij}}{\lambda_k^{ij} + \lambda_k^{op}} \tag{18}$$

$$w_k^{op} = \frac{\lambda_k^{op}}{\lambda_k^{ij} + \lambda_k^{op}} \tag{19}$$

Once the fitness function is constructed, the individual and global optimal solutions can be updated, and then Eq. (15) and Eq. (16) are used to update the positions of the particles, and then the next cycle of iterative optimization is performed until the maximum number of iterations is reached to output the global optimal solution, i.e. the optimal coordinates of the node to be located are found.

IV. EXPERIMENTAL SIMULATION AND RESULT ANALYSIS

The design of experimental conditions was carried out by reviewing recent research papers in the field of node localisation in irregular regions. The localization effectiveness of the algorithm designed in this paper is also compared with four algorithms, LRAQS [9], AEML [10], BDMCL [39] and MSVR-DV-Hop [40], to form a comparative experiment. And the key experimental conditions are extracted from the papers of several algorithms mentioned above, including sensor node deployment, communication range, signal processing method, signal attenuation and so on. Combined with the existence of common conditions in the experiments of different papers, a series of experiments in this article are designed to compare the node localisation performance of several algorithms by trying to take into account the needs of various algorithms.

This section describes a 2D simulation scenario for the irregular region node localization algorithm. The scenario consists of a C-shaped region with a gap range of 40*70 and several randomly deployed wireless sensor nodes. The experiment involved setting a range of anchor node ratios and node communication radius values, as well as certain parameters of the particle swarm optimization algorithm, such as maximum particle velocity and learning factor. For all experiments after the first one, the hop count threshold was set to $Hop_{\max} = 4$, and the specific parameter settings are shown in Table 1.

TABLE 1. Simulation parameters of the algorithm.

Simulation parameters	Setting value
Area Scope	$100m\times100m$
Void range	$40m\times70m$
Total number of nodes	$40-140$
Anchor node ratio, incremental step	$4\%-28\%, 4\%$
communication radius, incremental step	$15m-40m, 5m$
Number of simulations	100
Degree of radio irregularity	0.05
Number of iterations	50
Population size	30
Learning factor c_1 c_2	1.4945
Maximum particle velocity	$10m/s$
Evaluation indicators	$MDE, RMSE$

Considering the environmental interference factors that exist in real application scenarios, which make the radio range of a node, not a fixed value, i.e., the radio range of a node is not ideally circular [41], the degree of radio irregularity DOI was also added to the simulation and the relevant settings for the sensor nodes were made using Eq. (20).

$$P(d) = \begin{cases} 0, & 1 + DOI < \dfrac{d}{R} \\ \dfrac{1}{2} + \dfrac{d-R}{2 \cdot DOI \cdot R}, & 1 - DOI \leq \dfrac{d}{R} \leq 1 + DOI \\ 1, & 1 - DOI > \dfrac{d}{R} \end{cases} \tag{20}$$

All the experimental data are obtained by simulation and analysis using MatlabR2018b software under Windows 10, 64-bit operating system with Intel Core i7-1270P CPU @ 3.20GHz, 16GB RAM.

Table 1 illustrates some of the parameters set during the simulation experiments using MATLAB software such as area scope and void range.

The reason for using the C-type irregular region in the simulation is that the C-type region is very representative among irregular regions, and common regions, such as O-type and S-type can be combined from the C-type region. Figures 8 and 9

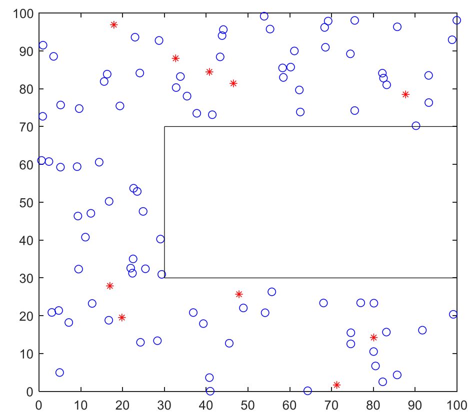


FIGURE 8. Example of node deployment in an irregular area of type C.

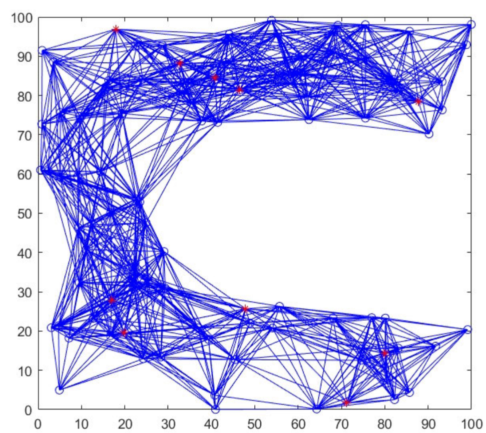


FIGURE 9. Example of network topology between nodes in an irregular region of type C.

show examples of network topology relationships between node deployment and nodes in irregular C-type areas, respectively.

To validate the localization prediction performance of the model, we introduce the mean distance error (MDE) between the to-be-localized node and the anchor node and the root mean square error (RMSE) of the position coordinates, and define their formulas as follows:

$$MDE = \sum_{k=1}^{N_u} \frac{\sum_{s=i}^{su} \left| \tilde{d}_{sk} - d_{sk} \right|}{4 \cdot N_u}, (su = i, j, o, p) \tag{21}$$

$$RMSE = \frac{\sum_{k=1}^{N_u} \sqrt{(\tilde{x}_k - x_k)^2 + (\tilde{y}_k - y_k)^2}}{100 \cdot N_u \cdot R} \tag{22}$$

where $\tilde{d}_{ik}, \tilde{d}_{jk}, \tilde{d}_{ok}, \tilde{d}_{pk}$ and $d_{ik}, d_{jk}, d_{ok}, d_{pk}$ are the estimated and true distances between the node to be localised, u_k, and the anchor nodes, a_i, a_j, a_o, and a_p, respectively; N_u is the number of nodes to be localised; (x_k, y_k) and $(\tilde{x}_k, \tilde{y}_k)$ are the true coordinates of u_k and the estimated coordinates finally obtained by the algorithm, respectively; and R is the communication radius of the node.

A. EFFECT OF HOP COUNT THRESHOLD ON THE ESTIMATION ERROR OF INTER-NODE DISTANCE

In large-scale sensor networks, if all nodes interact and transmit information, it will bring extremely high communication overhead and energy consumption. By setting a suitable hop threshold, not only can we effectively reduce the interference of disturbing factors in the irregular area on the localization results, but also improve the efficiency of the network, achieve more efficient data transmission, reduce the energy consumption of the nodes, and prolong the service life of the nodes.

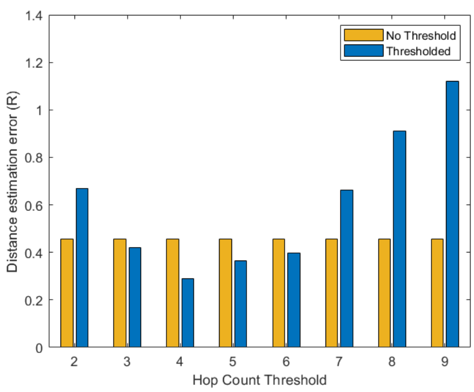


FIGURE 10. Effect of hop threshold on distance estimation error.

The comparison experiment in Figure 10 shows that the distance estimation error of the node tends to decrease and then increase when a hop threshold restriction is applied, while the error is almost unaffected when there is no hop threshold restriction. Therefore, when node localization, choosing a suitable hop threshold can effectively reduce the node localization error and improve the accuracy of node localization. Through multiple simulation experiments and comparisons, it is found that the distance error is minimized when the hop threshold of $Hop_{\max} = 4$ is taken in this simulation.

B. EFFECT OF ANCHOR NODE RATIO ON ALGORITHM LOCALIZATION ERROR

This section focuses on the effect of the proportion of anchor nodes on the estimated distance in a C-type irregular region using MDE and RMSE. In the simulation experiments, the node communication radius R is set to $30m$, and the trend of the anchor node ratio is $4\% - 28\%$ with a step size of 4%.

As shown in the bar chart of Figure 11(a), as the proportion of anchor nodes increases, the probability of deploying an anchor node around the node to be localised rises with it, and the average distance error of the RANP-PSO algorithm in the distance estimation phase gradually decreases.

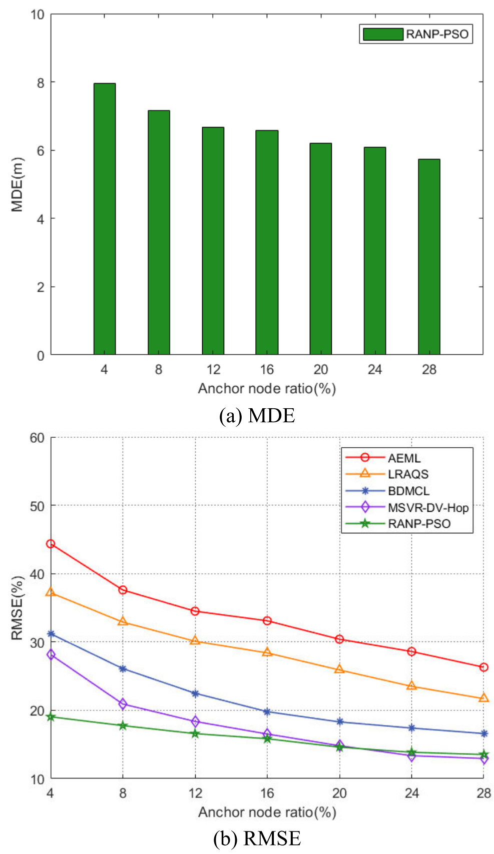


FIGURE 11. Effect of anchor node ratio on algorithm localization error.

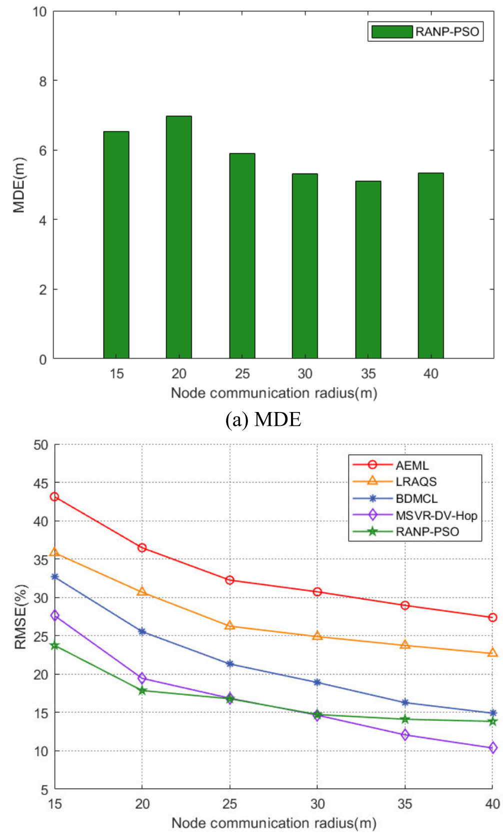
From the line graph in Figure 11(b), it can be seen that the root mean square error of the five algorithms shows a decreasing trend as the proportion of anchor nodes increases. The overall decreasing trend of the remaining four compared algorithms is larger, but on the whole the RANP-PSO algorithm has a better localisation effect, which is relatively less affected by the proportion of anchor nodes. Although the AEML algorithm uses adaptive weighted estimation and can adapt to the irregular network environment, it does not have the powerful global search capability and optimization ability of the RANP-PSO algorithm in dealing with the localization problem. The LRAQS algorithm deals with the reliable anchor pairs by designing different distance estimation equations, but due to the simplification of the equations or the limitation of the assumptions, its localization accuracy is not as good as that of the RANP-PSO algorithm that employs The BDMCL algorithm is optimized for the Monte Carlo positioning algorithm, although it solves some of the problems in the Monte Carlo algorithm, it does not incorporate advanced optimization techniques such as hopping constraints and regularized least squares as the RANP-PSO algorithm does, so the RANP-PSO algorithm is relatively better in terms of the overall positioning effect. However, as the number of anchor nodes increases to a certain percentage, the multi-dimensional support vector regression algorithm used by the MSVR-DV-Hop algorithm is able to estimate the distance more accurately when the number of anchor nodes is higher, and therefore the localization error will appear slightly smaller than that of the RANP-PSO algorithm.

However, in practical applications, uncertain factors such as the natural environment and building occlusion can significantly interfere with RSSI-based node localization algorithms, resulting in higher localization uncertainty. The RANP-PSO algorithm can effectively reduce the influence of interference factors and reduce network communication overhead by selecting appropriate hop thresholds and anchor node pairs with higher reliability for localization. Simulation experiments show that the RANP-PSO algorithm achieves significantly better localization results in irregular regions compared to similar algorithms.

C. EFFECT OF NODE COMMUNICATION RADIUS ON ALGORITHM LOCALIZATION ERROR

In a network consisting of sensor nodes, the size of the communication radius affects the connectivity of the network, which in turn has a significant impact on the localization results of the nodes. In the simulation experiments in this section, referring to the results of the simulation experiments in the previous subsection, the proportion of anchor nodes is set to 20% , the radius of node communication R is 15m − 40m (step 5m). As shown in Figure 12, it demonstrates the effect on the algorithm's localization accuracy when the node communication radius is varied from small to large.

As can be seen in Figure 12(a), it can be seen that when the communication radius R of the RANP-PSO algorithm is varied in the range of 15m − 30m, the MDE in the distance estimation phase shows an overall decreasing trend. But when the communication radius R when it grows to 35m − 40m, the error remains essentially unchanged. This is because the RANP-PSO algorithm obtains anchor nodes with higher reliability for localization by limiting the communication range of the nodes in the pre-localization phase by setting a suitable hop threshold. As the communication radius



(a) MDE
(b) RMSE

FIGURE 12. Effect of communication radius on algorithm localization error.

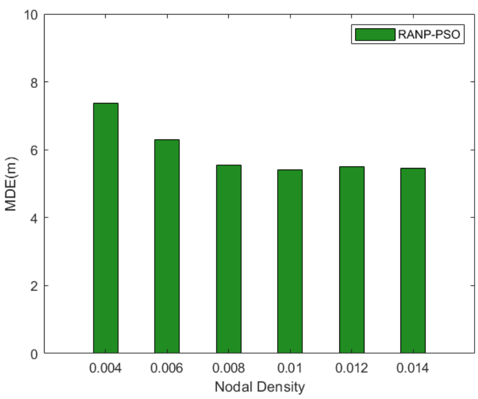
increases in an irregular region, the number of anchor nodes within the communication range of the node to be localized may be larger, the possibility of shortest communication path bypass between nodes becomes larger, and the corresponding estimated distance error may increase. In Figure. 12(b), it can be seen that the average localization error of all five algorithms decreases gradually as the communication radius increases. However, for the BDMCL and MSVR-DV-Hop algorithms, as the communication radius increases, the nodes to be localized are able to select more anchor nodes within their communication range to use RSSI to estimate and correct the distance between the nodes, so that their localization algorithms error reduction is significantly larger than that of the AEML and LRAQS algorithms.

As the communication radius of the anchor node increases to a certain value, the MSVR-DV-Hop algorithm can estimate the distance more accurately by using RSSI hierarchy and multi-dimensional support vector regression. Therefore, the localization error will be slightly smaller than that of the RANP-PSO algorithm. However, a large communication radius is not common in practical scenarios because it can cause problems such as multipath effects and increased energy consumption. Therefore, compared to other algorithms, the RANP-PSO algorithm is more advantageous in dealing with the problem of node localization in wireless sensor networks in irregular areas.

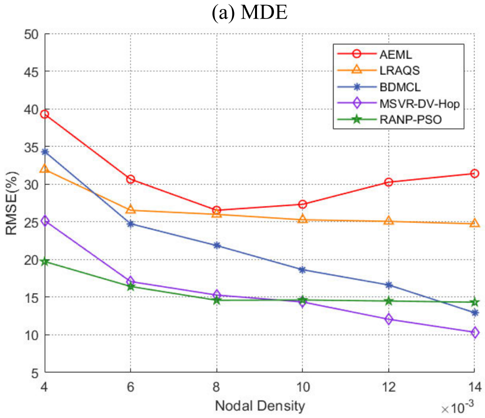
D. EFFECT OF NODE DISTRIBUTION DENSITY ON ALGORITHM LOCALIZATION ERROR

In the simulation experiments in this subsection, the proportion of anchor nodes is set at 20% and the radius of node communication $R = 30m$ to analyse the effect of changes in the density of node distribution (the ratio of the total number of nodes to the area of the region) on the algorithm's localisation in a C-shaped irregular region.

From Figure 13(a), it can be seen that the RANP-PSO algorithm can effectively reduce the error of distance estimation in the early stage when the node density gradually increases. According to the curve analysis in Figure 13(b), when the node density of the AEML algorithm is small, it is unable to obtain enough anchor node measurements, and the average localization error is large; with the increase of the node density, the connectivity of its network is improved, and the error is gradually reduced; but when the node density is too large, the algorithm is easy to overfitting, and the negative effects of the computational complexity and the communication overhead are dominant, which results in the increase of error. The localization errors of the HAS -PSO algorithm and LRAQS algorithm also show a decreasing trend of localization error with the increase of node density, but when the node density increases to a certain degree, the increase of the number of anchor nodes is limited to improve the localization accuracy, so when the node density increases to a certain degree, it will tend to stabilize.



(a) MDE



(b) RMSE

FIGURE 13. Effect of node distribution density on algorithm localization error.

As the node density increases, the target node can get more useful information from the surrounding nodes, so the localization errors of the two RSSI-based ranging algorithms, BDMCL and MSVR-DV-Hop, show a decreasing trend with the increase of node density. The RMSE of RANP-PSO algorithm and LRAQS algorithm decreases with the increase of node density, and the RMSE tends to be stabilized after a certain degree of decrease because the nodes to be localized can obtain enough reliable information from the surrounding nodes to be used for localization, and thus the tendency of the RMSE decrease decreases gradually. In practical applications, it is generally required to deploy as few sensor nodes as possible to complete the monitoring in the area, so the RANP-PSO algorithm is relatively better in terms of comprehensive consideration of various factors.

E. TIME COMPLEXITY ANALYSIS OF ALGORITHMS

In non-ranging node localization algorithms, the time complexity of the nodes is mainly in the information flooding phase, the distance estimation phase and the coordinate finding phase. The calculation of the time complexity of the RANP-PSO algorithm is divided into three main aspects: first, in the initial message flooding of the network, the reliability parameter between the to-be-localized node and all pairs of anchor nodes are obtained by using Eq. (4), the complexity of this operation is $O(N_a \cdot (N_a - 1)/2)$; second, in the distance estimation phase, the two sets of anchor nodes of higher reliability are selected for the to-be-localized node and the distance between them is calculated, the complexity of this operation is $O(4)$; and third, the estimated coordinates of the to-be-localized node is computed using the Particle Swarm algorithm, the complexity of this operation is $O(N_u \cdot t)$.

Therefore, the time complexity of the RANP-PSO algorithm is $O(N_a \cdot (N_a - 1)/2 + N_u \cdot t)$, which is slightly higher compared to the time complexity $O(N_a^2/2 + N_a \cdot N_u)$ of the AEML algorithm, and about the same compared to the time complexity $O(N_a^2/2 + N_a/2 + Pops \cdot I)$ of the LRAQS algorithm. The BDMCL and MSVR-DV-Hop algorithms, on the other hand, the use of RSSI correction in estimating the distance between nodes is very computationally intensive, so the time complexity of these two algorithms is not considered. Therefore, in terms of comprehensive performance, the RANP-PSO algorithm is more advantageous in terms of time complexity than other algorithms in the same category.

In the simulation experiments in irregular regions, there are still some limitations relative to the real world, and the subsequent optimisation of the design still needs to be continued. For example: although the C-type region is representative, and the common O-type, S-type and other regions can be combined from the C-type region, the C-type region cannot fully represent all the irregular terrain in the real world, resulting in some deviations between the simulation model and the actual scene. Wireless signal propagation models are often based on simplifying assumptions that may not hold in irregular and complex regions. For example, in indoor positioning, signal propagation models may not accurately predict the effects of multipath effects and signal occlusion on signal strength. The structure and materials of a building can affect the signal propagation path, resulting in a large discrepancy between the actual received signal and the model prediction. Moreover, in real-world positioning systems, sensors and devices may have performance limitations. For example, in sensor network positioning, if the sensors used have low sensitivity, they may not be able to accurately detect signals at long distances, which can also lead to positioning errors.

V. SUMMARIZE

Compared to ranging algorithms, non-ranging algorithms have many advantages of easy implementation, such as: low cost, and high portability. Aiming at the problem of shortest path deviation between nodes due to irregular regional coverage gaps, this paper proposes a non-ranging node localization method RANP-PSO based on PSO algorithm and reliable anchor node pairs. The method effectively eliminates the influence of some interfering factors in the irregular region on the positioning effect of the algorithm by optimizing the calculation of the two phases of distance estimation and position coordinates. In the distance estimation phase, the two anchor node pairs with the highest reliability are selected within a small range by introducing a hop count constraint mechanism, and the error in estimating the distance is reduced using regularized least squares. In the position coordinate computation phase, the PSO algorithm is used to optimize the node coordinates in order to solve the position coordinates of the node to be localized. By conducting simulation experiments, the results show that compared with mainstream similar node localization algorithms for irregular regions, the RANP-PSO algorithm has certain advantages over similar localization algorithms in irregular regions.

In future research, we will pay more attention to how to optimize the node localization scheme in practical application scenarios, the transition from theoretical research to practical exploration, and solve various problems encountered in sensor node localization in practical applications.

VI. CONCLUSION

Aiming at the problem of shortest path deviation between nodes due to irregular regional coverage gaps, this paper proposes a non-ranging node localization method RANP-PSO based on PSO algorithm and reliable anchor node pairs. The method effectively eliminates the influence of some interfering factors in the irregular region on the positioning effect of the algorithm by optimizing the calculation of the two phases of distance estimation and position coordinates. By conducting simulation experiments, the results show that compared with mainstream similar node localization algorithms for irregular regions, the RANP-PSO algorithm has certain advantages over similar localization algorithms in irregular regions.

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