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RESEARCH ARTICLE

Location Optimization Based on Improved 3D DV-HOP Algorithm in Wireless Sensor Networks

YI WU[1], CAN ZHANG[1], LIN TONG[1], AND XIAOSHENG SHI[2]
[1]GAC Research and Development Center, Guangzhou 511434, China
[2]School of Cyber Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
Corresponding author: Xiaosheng Shi (18022322614@163.com)

ABSTRACT The Distance Vector Hop (DV-HOP) localization algorithm, as a non ranging node localization algorithm, its operation is simple, does not require additional measurement equipment support, with low cost. But wireless sensor network is generally used in three-dimensional complex environment. In response to the low positioning accuracy of this algorithm in an environment with randomly distributed nodes, research is conducted to optimize and improve it. Firstly, by combining multiple communication radii, the hops' quantity in nodes is decimalized to diminish errors from the hops' quantity. Then, it calculates the average jump distance of anchor nodes, sets a hop threshold, and eliminates anchor nodes with significant errors. It calculates the range existing anchor nodes and unknown nodes through taking the median. Finally, a particle swarm optimization algorithm was used instead of the maximum likelihood estimation method to obtain the optimized Hop distance correction multi communication radius Particle swarm optimization algorithm DV-HOP (HCMSPSO-DV-HOP) localization algorithm. The improved 3D DV-HOP algorithm was applied to a simulation environment, and through experiments, it was found that the algorithm's average elapsed time was 0.49 seconds; The average positioning accuracy is 96.40%. Compared to other localization algorithms, the localization algorithm designed by the research institute has good localization performance. It provides technical support for WSN applications in various fields.

INDEX TERMS 3D DV-HOP algorithm, wireless sensor network, node positioning, particle swarm optimization.

I. INTRODUCTION

As the boost of the intelligent age of human society, the wireless sensor network's (WSN) value has become increasingly prominent. It is especially widely used in industry and agriculture, environmental protection, military security, social security and other fields [1]. WSN is a network including lots of low-cost, low-consumption, perceptive, computational, and wireless communication capable sensor nodes (SN). If the node location cannot be determined, the various detection information collected will be meaningless. Therefore, optimizing node perception radius, reducing anchor node (AN) energy consumption during node localization, and improving node localization accuracy have always been the focus of scholars' research. In real-world application scenarios, such as deep sea, hills, and other outdoor three-dimensional spatial scenes, it is difficult for numerous SN to be placed in an absolute plane for obtaining a two-dimensional WSN. When most SN are randomly placed into a three-dimensional space (TDS) scene, it is required that the localization algorithm can achieve appropriate accuracy in SN localization in the TDS scene [4]. 3D WSN involves placing SN in a complex TDS, where the nodes obtain physical information about the surrounding environment, thereby obtaining useful information from the actual environment. Humans use this information as a reference to make decisions that are beneficial for human life or industrial production. Currently, the 3D DV-HOP related algorithm without distance measurement is the mainstream algorithm for node position in various application scenarios. However, this algorithm still has significant positioning errors [5]. To this end, the 3D Distance Vector Hop (DV-HOP) positioning algorithm's error analysis is studied,

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and then the count and distance's hop are optimized by combining multiple communication radii (MCR) and setting a hop count (HC) threshold. Finally, a particle swarm optimization (PSO) algorithm was introduced to optimize localization. Finally, the optimized Hop distance correction multi communication radius Particle swarm optimization algorithm DV-HOP (HCMSPSO-DV-HOP) localization algorithm was obtained. The primary content is as follows:

A. This research systematically elaborates on the theory of WSN positioning technology, common positioning algorithms, research hotspots, and algorithm applications. And it analyzes the algorithm principle and performance of DV-HOP algorithm (DHA), extending DHA for three-dimensional network environment.

B. This study aims to optimize the 3D DHA for its low accuracy. Firstly, by combining MCR, the hops' quantity in nodes is reduced to a decimal point, reducing the error from the hops' quantity. Then, the average hop distance (AHD) of AN is counted, and by setting a hop threshold, the AN with larger errors are abandoned to overcome the hop distance (HD) error from the polygonal topology structure in nodes. After calculating the appropriate jump distance, it uses the PSO algorithm based on linear decreasing weights instead of the MLE estimation method. Finally, simulation experiments were conducted to analyze the constructed localization algorithm.

II. RELATED WORKS

WSN communicates wirelessly, perceiving and monitoring surrounding environmental information by distributing SN as network terminals. It is a collaborative sensing network. WSN is a major component of the Internet of Things architecture, which has arouse experts and scholars' concerns over the world. Luo et al. proposed routing protocol design to solve the problems of underwater wireless sensor network (UWSN), such as high ocean interference and noise, and limited battery energy. Then the researchers summarized the underwater routing protocols (URP)recently and analyzed the different URP's functions in detail, providing more ideas for the research of UWSN [2]. Kim et al. found that machine learning technology (ML) can reduce computational complexity, increase the feasibility of finding the optimal solution for WSN deployment, and improve energy efficiency by deploying WSN in real environments. Through investigation, various application developments of ML technology in WSN were discussed [6]. Chowdhury et al. discussed different energy-saving schemes for WSN in different research communities, such as duty cycle methods, cross layer design, and data aggregation, for diminishing nodeconsumption, thereby saving the energy of the entire WSN [7]. Jia et al. comprehensively discussed the resource efficient distributed state estimation and security technologies currently used on WSN. Finally, relevant scholars discussed several challenging issues under distributed state estimation for potential future research [8]. Dawood et al. developed a rectangular antenna to improve the efficiency of converting microwaves into electrical energy in WSN, using a rectifier bridge circuit directly connected to a regular antenna to convert radio waves into electrical signals [9]. Karthikeyan et al. found that currently WSN mainly forwards data to database servers through intermediate SN, and this distributed routing technology reduces the energy of SN, thereby reducing network lifespan. To this end, it reviewed and analyzed collaborative routing algorithms for security and load balancing [10]. Kumar et al. used an improved convolutional neural network to identify malicious nodes and then isolated them into malicious list boxes to avoid security risks in WSN. This research extends the related algorithm to cluster trusted nodes [11].

It is very essential for determining the related information of the target node in WSN, and only by combining the position information can the data obtained by the sensor have practical significance. The optimization and application of node localization technology has always been a key research direction for scholars. Deng et al. proposed a hybrid and parallel chaotic particle algorithm based on DE/current to optimal operator. Then, the study dynamically optimized the hybrid distance vector hopping algorithm using an improved particle algorithm to accurately locate unknown nodes (UN) in WSN [12]. For diminishing the error, Yu et al. used the related method to initialize the memory of the gray wolf (GW) population, and then introduced the beetle antenna search for optimizing the GW population in time. The positioning of the improved GW algorithm has been enhanced through simulation comparison [13]. Song et al. proposed a special localization algorithm to address the issues of high demand for AN, low sampling frequency in the Monte Carlo mobile node algorithm [14]. Tian proposed a algorithm DV-MDS-SA to address the issue of significant positioning errors in the application of DV-HOP and MDS-MAP positioning algorithms in depressed areas. Finally, it uses a special algorithm for optimizing the position estimation of the localization algorithm [15]. Zhang et al. used genetic algorithms to analyze the communication constraints between location nodes and a small number of anchor points to construct a positioning model for the needs of smart city WSN construction [16]. Xia proposes a remote real-time position positioning method through the relevant node positioning algorithm to address the issues of low accuracy, low efficiency, and poor performance of current positioning methods [17]. For enhancing the accuracy of relevant network nodes, Yuan R improved the initial value calculation method. Then he proposed a WSN node localization algorithm that reduces the initial value of the Kalman filter [18]. Yan et al. studied the privacy preserving localization problem of USN in non-uniform underwater media and introduced a ray compensation strategy to optimize the deep reinforcement learning (DRL) localization algorithm. It accurately locates nodes while hiding private location information of underwater sensor networks [19].

Based on the above literature, it can be concluded that there are many studies on node localization technology in WSN, and scholars continue to improve and optimize localization methods through research. Although there are numerous research achievements on WSN localization mechanisms, most of them are oriented towards planar localization. It lacks a positioning system suitable for complex three-dimensional environments. Compared with the relatively simple two-dimensional planar positioning in the network environment, the complex three-dimensional spatial environment has stricter requirements for positioning algorithms, stronger spatial complexity, and stricter requirements for implementation conditions such as network connectivity and node number. To this end, research will extend the DHA to TDS and enhance and optimize it. It has positive significance for WSN applications.

III. OPTIMIZATION DESIGN OF WSN NODE LOCATION BASED ON 3D DV-HOP ALGORITHM

A. WSN NODE LOCALIZATION BASED ON 3D DV-HOP ALGORITHM

WSN communicates wirelessly, perceiving as well as monitoring surrounding environmental information by distributing SN as network terminals. It is a kind of collaborative sensing network [20], [21]. Figure 1 indicates the WSN network.

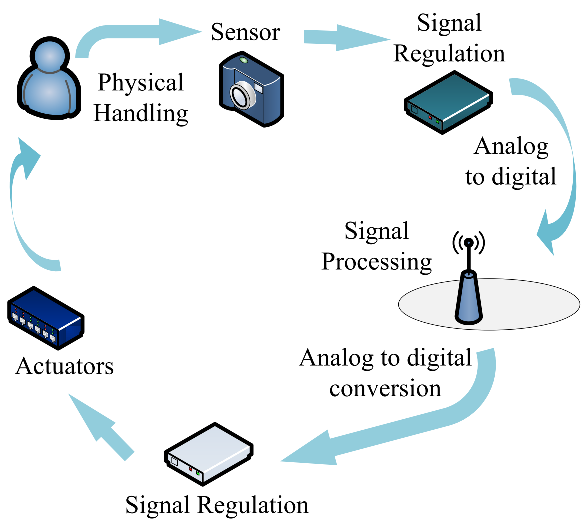


FIGURE 1. Wireless sensor network structure.

It has low wiring cost, high monitoring accuracy, good system fault tolerance, and remote control. The energy carried by WSN nodes is limited, which requires consideration of how to fully utilize the energy of grounding when designing the entire WSN. In traditional networks, nodes usually have sufficient energy supply, and more attention is paid to improving the networks' service and throughput. Meanwhile, the WSN nodes' quantity is large, and the entire network's topology is often complex. The computing and storage hardware resources of nodes are limited, and due to WSN being typically deployed in some harsh environments. This makes nodes very prone to failure. Therefore, the positioning of nodes is very important. The hardware structure of wireless SN consists of four parts, namely perception unit, information processing unit, wireless communication unit, and power supply module. Figure 2 illustrates the common wireless SN.

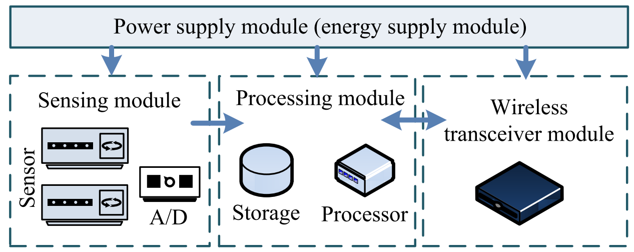


FIGURE 2. Schematic diagram of wireless sensor node structure.

WSN localization algorithm is essentially a multi constrained optimization problem, which is generally separated into two categories: distance based and distance free. The localization algorithm utilizes a specific ranging module as a tool to estimate the coordinate position of UN by directly determining the angle values in nodes. The UN' coordinates are closely related to the range or angle in nodes. Therefore, in ranging algorithms, it cannot be ignored to accurately obtain the information in nodes. If there are errors in the measurement information, it will affect the subsequent calculation steps, leading to the accumulation of errors and increasing the positioning error. The Range Free localization algorithm generally does not require the hardware devices, and estimates the distance based on the AN's coordinates and the specific relationship in the location node and the AN. The coordinate calculation of UN is generally achieved through the use of trilateral positioning or MIE estimation methods.

The DV-HOP localization algorithm has the characteristics of simple implementation, no need for additional measurement equipment support, and low cost.

The algorithm first obtains the hops' minimum number in nodes through flooding. All AN broadcast their own data information to the network through flooding. The initial value of the number of hops for the AN is 0. The UN communicates with each AN, receives data information from the anchor point, increases the hops by 1, and then continues forwarding. UN only store the minimum of hops for multiple packets sent by the same AN. Through this, the hops from the AN are obtained. Then, it calculates the AHD of each node through equation (1).

$$Hopsize_i = \frac{\sum_{j=1, j\neq i}^{N} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{j=1, j\neq i}^{N} h_{ij}} \tag{1}$$

In equation (1), (x_1, y_1) and (x_2, y_2) serve as the coordinates of ANi and j; h_{ij} serves as the number of hops in two AN; N serves as the number of AN; $Hopsize_i$ is the AHD across the entire network for each AN. After obtaining the AHD, select the HD of the nearest AN for each UN as the HD of the UN. It obtains the range from the UN to the

AN through equation (2).

$$d_{ij} = Hopsize_i \times h_{ij} \tag{2}$$

In equation (2), d_{ij} represents the range from UNi to node j. Finally, the coordinates of UN are estimated using the mathematical geometric method MLE estimation. Most traditional DV-HOP positioning algorithms are oriented towards planar positioning and lack a positioning system suitable for three-dimensional load three-dimensional environments. Compared with the relatively simple two-dimensional flat surface in the network environment, the complex three-dimensional spatial environment has stricter requirements for positioning algorithms and stronger spatial complexity. Its requirements for implementation conditions such as network connectivity and number of nodes are more stringent. The models of the 2D and 3D DHA are shown in the figure.

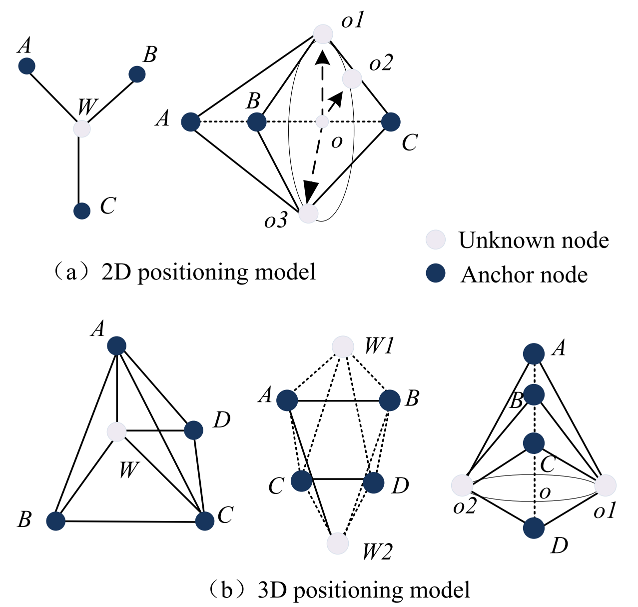


FIGURE 3. 3D and 2D DV-HOP algorithm positioning model.

3D DV_HOP is calculated on a two-dimensional basis, converting coordinates into three-dimensional, and obtaining the average jump distance as shown in equation (3).

$$Hopsize_i' = \frac{\sum_{j=1,j\neq i}^{N} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2}}{\sum_{j=1,j\neq i}^{N} h_{ij}} \tag{3}$$

In equation (3), (x_i, y_i, z_i) and $\left(x_j, y_j, z_j\right)$ serve as the coordinates of known nodes (KN)i and j. From this, the distance between nodes is obtained. According to the distance formula between two points, obtain equation (4).

$$\begin{cases} \sqrt{(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2} = d_1 \\ \sqrt{(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2} = d_2 \\ \sqrt{(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2} = d_3 \end{cases} \tag{4}$$

By derivation it obtains the coordinates of UN, which is demonstrated in equation (5).

$$X = \left(A^T A\right)^{-1} A^T b \tag{5}$$

In equation (5), A and b are different matrices, as shown in equation (6).

$$\begin{cases} A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) & 2(z_1 - z_n) \\ 2(x_2 - x_n) & 2(y_2 - y_n) & 2(z_2 - z_n) \\ \cdots & \cdots & \cdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) & 2(z_{n-1} - z_n) \end{bmatrix} \\ b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + z_1^2 - z_n^2 + d_n^2 - d_1^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 + z_2^2 - z_n^2 + d_n^2 - d_2^2 \\ \cdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + z_{n-1}^2 - z_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix} \end{cases} \tag{6}$$

The 3D DHA is showcased in Figure 4.

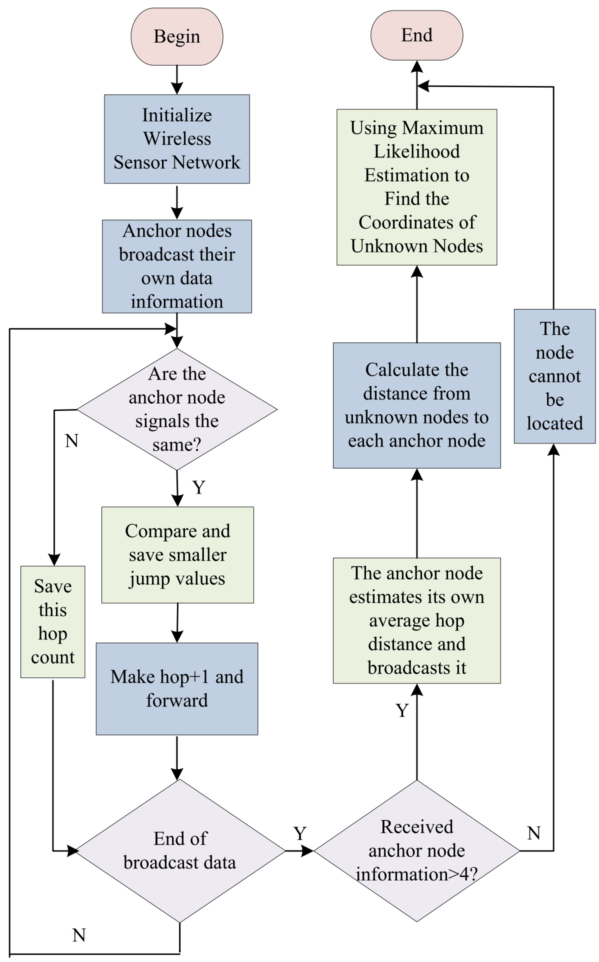


FIGURE 4. Schematic diagram of 3D DV-HOP algorithm flow.

The DHA is a widely used localization algorithm that does not require ranging, but it still has low localization accuracy when nodes are randomly deployed. To this end, research is conducted to analyze the error influencing factors of the algorithm.

Firstly, there are blind spots in the algorithm. In WSN, due to the needs of the actual environment, it is relatively rare for nodes to be uniformly distributed. In most cases, the distribution of nodes is irregular, and nodes are scattered in the experimental area. This leads to the numerous nodes' presence in certain areas of the monitoring area, and several nodes in a few other areas. And this part of the area is at a certain distance from the area with many nodes, making it difficult for a few nodes to communicate. This type of node is called an isolated node.

Secondly, in WSN, the larger the AN's ration in total nodes, the smaller the localization error of nodes in the network. However, when the AN's rationachieves a certain value, the positioning of nodes could be infinitely close to a specific value; In time, the nodes' ratio continuously grow, and the positioning only changes within a small range. Moreover, if the nodes within the communication radius (CR) of AN is too large, the calculated AHDcould be smaller than the true value, increasing positioning error and communication consumption.

Thirdly, the algorithm utilizes HC information when estimating node distance, so accurate HC information is of great value. However, in the actual process, there is a significant error in the jump value.

Fourthly,The algorithm utilizes jump distance information when estimating node distance. However, due to the fact that nodes are arranged in a broken line topology in actual network topology streets, the algorithm defaults to arranging nodes in a straight line when calculating the range in nodes. When calculating the range from UN to KN, the nearest AN's jump distance is utilized, ignoring the corresponding jump range of KN, resulting in errors.

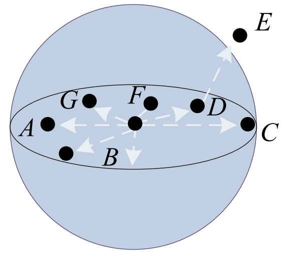
Fifthly, after obtaining the HC and HD, the algorithm multiplies the two to calculate the range in nodes. Then, the coordinates' position can be evaluated using the quadrilateral measurement method. But both algorithms equips certain errors.

Based on the above operations, the study analyzed the error influencing factors of the 3D DHA, providing a theoretical basis for subsequent optimization algorithms.

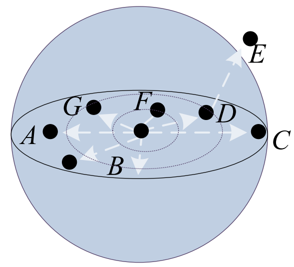
B. OPTIMIZATION STRATEGY OF 3D DV-HOP ALGORITHM

When AN communicate with neighboring nodes, the hops of neighboring nodes within the CR is recorded as one hop, but the range in each neighboring node and the AN varies, resulting in significant errors. For solving the error problem caused by a single CR, an optimization method using MCR is studied. The three-dimensional models are shown in Figure 5.

Through error analysis of the 3D DHA, the conclusion that the main factors influencing the accuracy of the algorithm attribute to HC, HD, and estimation method can be obtained. Therefore, research mainly improves the algorithm in two: HC and HD. A three-dimensional DHAin view ofHD correction with MCR (HCMCDV-HOP) has been proposed. This study improves the method of knowing the HD of nodes. Firstly, it calculates the critical quantity of hops for each



(a) Single communication radius



(b) Three communication radius

FIGURE 5. Three-dimensional model of single communication radius and multiple communication radius algorithms.

AN and sets a threshold. Then, based on the comparison between the threshold and the jump values of other nodes, it removes AN that introduce significant errors. Finally, each KN involved in the calculation is given a weight value, and the AHD of the AN is obtained. The calculation method for the HC threshold is shown in equation (7).

$$t_i = \max\left(\frac{d_{i1}}{R}, \frac{d_{i2}}{R}, \dots \frac{d_{iM}}{R}\right) \tag{7}$$

In equation (7), M is the endpoints' quantity in a TDS; d serves as the distance from each endpoint to AN i. When the number of hops from other AN to the target AN exceeds the threshold t_i, when calculating the target AN'sHD, it indicates that the topology structure of the nodes in the network is arranged in multiple lines, which can cause significant errors. Therefore, AN with hops greater than the threshold are no longer used for calculation. It obtains the average jump distance through equation (8).

$$c_{ij} = \frac{1}{{d_{ij}}/{R} - hops_{ij}} \tag{8}$$

In equation (8), c_{ij} is the weight coefficient of ANj when calculating the AHD of KNi; d_{ij} is the actual range in two AN; $hops_{ij}$ is the hops' quantity between two AN; R is the CR. The weight calculation method is shown in equation (9).

$$w_{ij} = \frac{c_{ij}}{\sum_{l\neq i}^{s} c_{ij}} \tag{9}$$

In equation (9), s serves as the KN' quantity; The AHD of ANi is shown in equation (10).

$$Hopsize_i = \sum\nolimits_{j\neq i}^{s} w_{ij} \times \frac{d_{ij}}{hops_{ij}} \tag{10}$$

Taking into account the connectivity of the network, this study optimizes the distance calculation formula from UN to corresponding AN as equation (11).

$$d_{ij} = 1/2\left(\text{Hopsize}_i + \text{Hopsize}_j\right) \times h_{ij} \tag{11}$$

The specific process of the 3D DHA with MCRin view of skip distance correction is as follows: In the first stage, the AN is introduced with three communication radii to broadcast data. During network initialization, AN first broadcast packet information to the network at a CR of $R/3$, while recording the hops' quantityin adjacent AN as 1/3 hops. After time F, the AN then propagates the packet information to the network at the CR2$R/3$. If the node receiving the AN does not have the AN'sHC, the HC will be recorded as 2/3. If there is a hop value, the original hop (OH) will be forwarded. After passing through time T again, the AN propagates the packet information to the network at the CRR. After receiving AN information from neighboring nodes, if it is found that there are no data packets stored for the AN, the HC is marked as 1. If there is HC, the OH value will be forwarded through the above process, and each node can obtain the minimum HC between the AN. In the second stage, after obtaining the minimum number of hops, the AHD of the AN is optimized by setting the hop threshold through the hop value. In the third stage, when calculating the range from UN to AN, the corresponding AN jump distance is taken into account. It takes the median of the two jump distances as the average jump distance. Finally, the maximum likelihood estimation (MLE) method is utilized to count the final coordinates, which is a parameter estimation method used when the distribution type of the population is known. The idea is to multiply the probability of small events occurring in all sets and then take the maximum value. However, when using the MLE method for counting the final coordinates, it is easy to encounter the situation of matrix irreversibility. In response to this, the study adopts Particle Swarm Optimization (PSO) to calculate the estimated coordinates of UN. The process of PSO algorithm is shown in Figure 6.

PSO is an intelligent evolutionary algorithm. It regards every individual as a particle without weight or volume in the D-dimensional search space. Firstly, it initializes the environment for particle optimization and sets the objective conditions required for particle optimization. Then it adjusts its speed and direction based on the disparity in the historical best value and the current value, continuously approaching the optimal solution. The calculation method for the optimal position of a certain particle is indicated in equation (12).

$$P_i(t+1) = \begin{cases} P_i(t), \text{ if } f(X_i(t+1)) \geq f(P_i(t)) \\ X_i(t+1), \text{ if } f(X_i(t+1)) \leq f(P_i(t)) \end{cases} \tag{12}$$

In equation (12), $f(X)$ serves as the minimized objective function; t serves as the iterations' quantity. By calculating the optimal position of a single particle, the global optimal

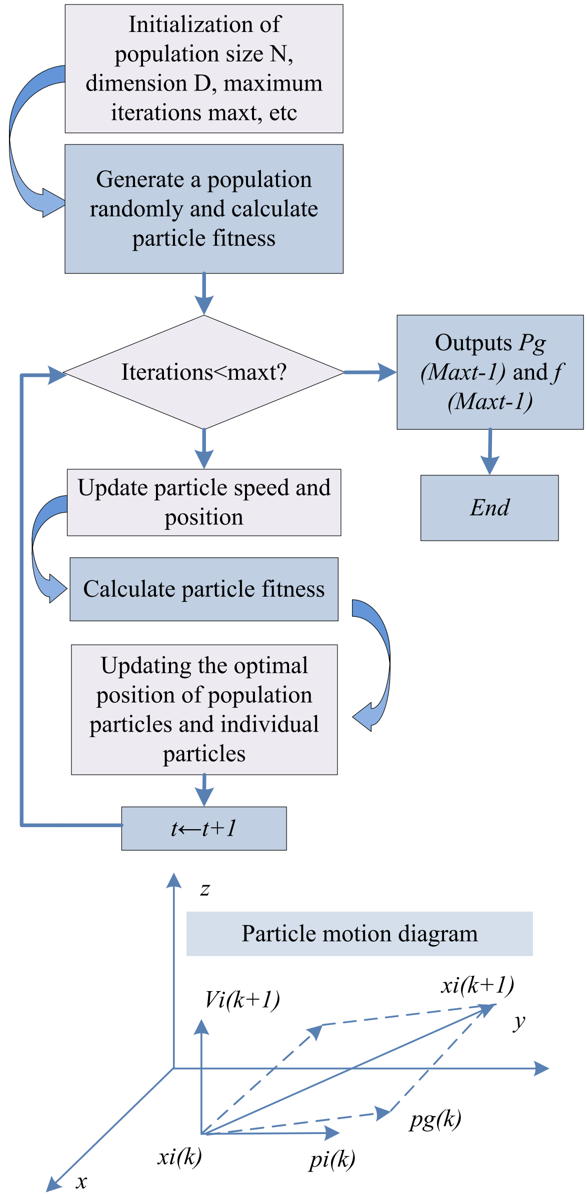


FIGURE 6. PSO algorithm flow.

position can be obtained as shown in equation (13).

$$\begin{aligned} P_g(t) &\in \{P_1(t), P_2(t), \ldots, P_N(t)\} \,|\, f\left(P_g(t)\right) \\ &= \min\{f(P_1(t)), f(P_2(t)), \ldots, f(P_N(t))\} \end{aligned} \tag{13}$$

The speed and position of the population gradually evolve with the number of iterations, and the initial process position and speed are shown in equation (14).

$$\begin{cases} x_{ij}(0) = rdft() \times (x_{\max} - x_{\min}) + x_{\min} \\ v_{ij}(0) = rdft() \times v_{\max} \end{cases} \tag{14}$$

In equation (14), $rdft()$ is a floating point number between 0 and 1; The search space of particles satisfies $v_{ij} \in [v_{\min}, v_{\max}], x_{ij} \in [x_{\min}, x_{\max}]$. However, the classic PSO algorithm has a tendency for particles to mature prematurely, leading to particles moving easily in a certain area and falling into local optima, resulting in unsatisfactory solution results. Sometimes, due to the complexity of solving problems, the dimensions of particles are large, resulting in computational overhead and unnecessary waste of energy. By adjusting the parameters in the algorithm, such as weight factors, learning factors, and other important parameters, the calculation can be preliminarily simplified. So a particle swarm optimization algorithm based on linear decreasing weights was used, and the improved algorithm is abbreviated as the DV-HOP-PSO algorithm. The linear decreasing weight formula is shown in equation (15).

$$w = w_s - (w_s - w_e)\,(MaxIt/N) \tag{15}$$

In equation (15), the initial inertia weight w_s is set to 0.9, and the final inertia weight w_e is set to 0.4. When using a PSO algorithm in view of linear decreasing weights to calculate the coordinates of a node to be located, the range from the node to a KN is taken as the target problem. If the distance between each particle in the PSO algorithm and each KN is the closest, then the coordinates of this particle are close to the node's estimated coordinates to be located. The study uses root mean square error as a measure of the difference between the estimated coordinate value and the actual value. The objective function relationship is demonstrated in equation (16).

$$f(x, y, z) = \sqrt{\frac{1}{m}\sum_{i=1}^{w}\left(\sqrt{(x-x_i)^2+(y-y_i)^2+(z-z_i)^2}-d_i\right)^2} \tag{16}$$

By continuously iterating and optimizing the objective function, the final position information of the tested node is obtained. The improved final node localization algorithm is shown in Figure 7.

Based on the above operations and the positioning algorithm based on MCR, this study introduces a hop threshold to discard AN with larger errors and calculate the AHD of AN. Then, the HCMSPSO-DV-HOP is obtained by replacing the MLE algorithm with the PSO algorithm based on linear decreasing weights.

IV. PERFORMANCE ANALYSIS OF HCMSPSO-DV-HOP NODE LOCALIZATION ALGORITHM

To evaluate the performance of the designed algorithm in terms of accuracy and stability, the MATLAB R2016a simulation software of the Windows 10 system was used to simulate the network experimental environment. Study setting WSN coverage area to 100m × 100m × A 100m three-dimensional space is randomly distributed with nodes in this environment for simulation analysis of related experiments.For testing the optimization effect of the research on the PSO algorithm, the experiment compares the improved PSO algorithm (I-PSO) designed by the research institute with other commonly used optimization algorithms.

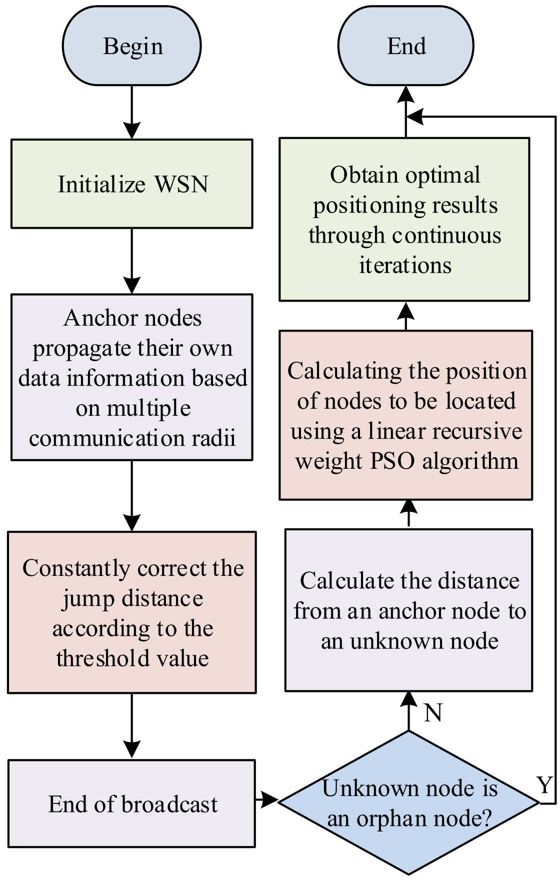


FIGURE 7. DV-HOP-PSO algorithm flow based on hop distance correction for multiple communication radii.

Including ant colony optimization algorithm (ACO), chaotic wolf swarm algorithm (WSA), traditional particle swarm optimization algorithm (PSO), and dragonfly optimization algorithm (DA). Under the same simulation environment, 5 algorithms were iteratively trained, and the training results were recorded in Figure 8.

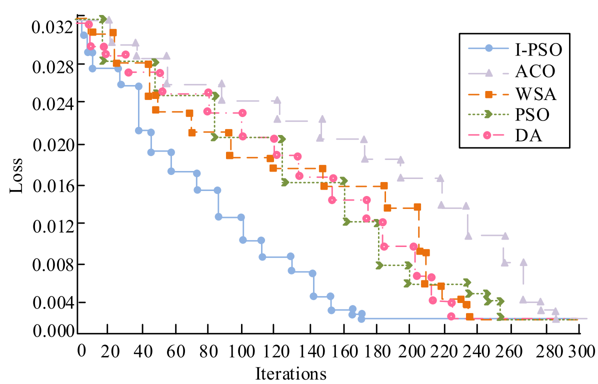
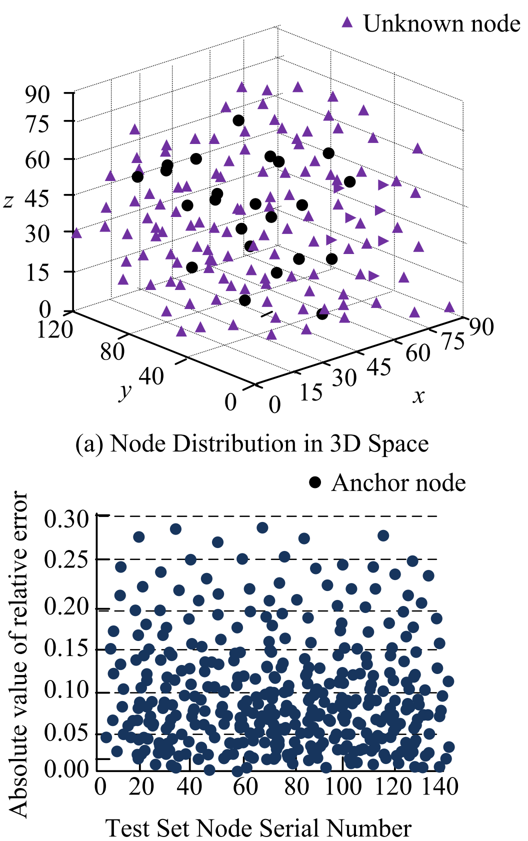


FIGURE 8. Comparison of iterative training of five optimization algorithms.

In Figure 8, as the number of iterations continues to increase, the iteration losses of each algorithm gradually decrease. The I-PSO only iterated 172 times to achieve the target loss value of 0.0036; ACO achieved the target loss value at 288 iterations, 116 more than I-PSO; WSA iterated 232 times to reach the target value, 60 more iterations than I-PSO; PSO iteration reached the target value 246 times, 74 more iterations than I-PSO; DA iteration reached the target value 229 times, which is 57 more iterations than I-PSO. Based on the content in Figure 8, it can be seen that the optimized PSO algorithm has better convergence.

For testing the performance of the node localization algorithm designed by the research institute, the improved HCMSPSO-DV-HOP was used to locate nodes in TDS. Then it records the error data of node positioning in this space in the form of a scatter plot in Figure 9.



(a) Node Distribution in 3D Space

(b) Algorithm positioning error

FIGURE 9. Error results of HCMSPSO-DV-HOP algorithm for locating nodes in 3D space.

Figure 9 (a indicates that the distribution of WSN nodes in this space is not uniform, with a distribution range within the $x \in \{0, 90\}$, $y \in \{5, 120\}$, and $z \in \{0, 72\}$ intervals. In Figure 9 (b), the positioning error of nodes is mainly concentrated between 0.00 and 0.15, with less distribution of error points above 0.15. The average relative error absolute value of algorithm positioning is 0.048. Based on the content of Figure 9, the conclusion that the positioning error of HCMSPSO-DV-HOP can remain within a small range and meet the positioning requirements can be obtained.

This study optimizes and improves the DHA through skip distance correction. To test the effectiveness of the renovation, DHA, HCMSPSO-DHA, and genetic algorithm modified wireless SN localization algorithm (GA-DV-HOP) were selected for research. Under the same experimental environment, the positioning error was analyzed in equation (17).

$$\delta = \sqrt{(x - x')^2 + (y - y')^2} \tag{17}$$

In addition, other experiments use errors represented by normalized positioning errors. The node positioning error results are indicated in Figure 10.

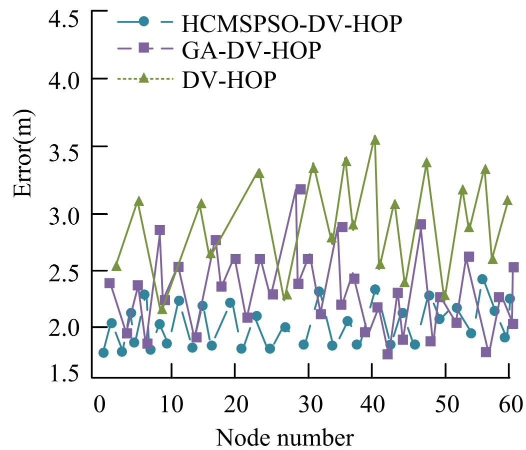


FIGURE 10. Change curve of sensor node positioning error for different algorithms.

In Figure 10, the DHA has the highest node positioning error, with a fluctuation range of 2.16 to 3.62; The error fluctuation range of the GA-DHAexisting between 1.89 and 3.25; The error fluctuation range of the HCMSPSO-DHA is 1.62-2.51. The HCMSPSO-DHA, which utilizes PSO for skip distance correction, has the optimal localization comparing the three algorithms. This can achieve relatively accurate positioning.

To analyze the actual effect of SN localization using different algorithms, this study records the node localization results of the three algorithms in the form of scatter plots in Figure 11.

Figure 11 shows that genetic algorithm and PSO algorithm have corrected the ranging error of wireless SN. Therefore, the positioning performance of wireless SN is significantly better than traditional DHA. In Figure 10 (b), the algorithm finds that the aggregation direction of nodes is more concentrated on a certain AN; The node distribution of the HCMSPSO-DHA in Figure 10 (c) is closer to the true node distribution and overcomes the drawback of GA-DHA being prone to falling into local optima.

To further test the effect of HCMSPSO-DHA, the research compares it with the traditional DHA, HCMCDHA, 3D hyperbola DHAin view of error weighting (3D-DV-HOP-BEW) and Weight GWO DHA. Under the influence of different AN ratios, communication radii, and total nodes,

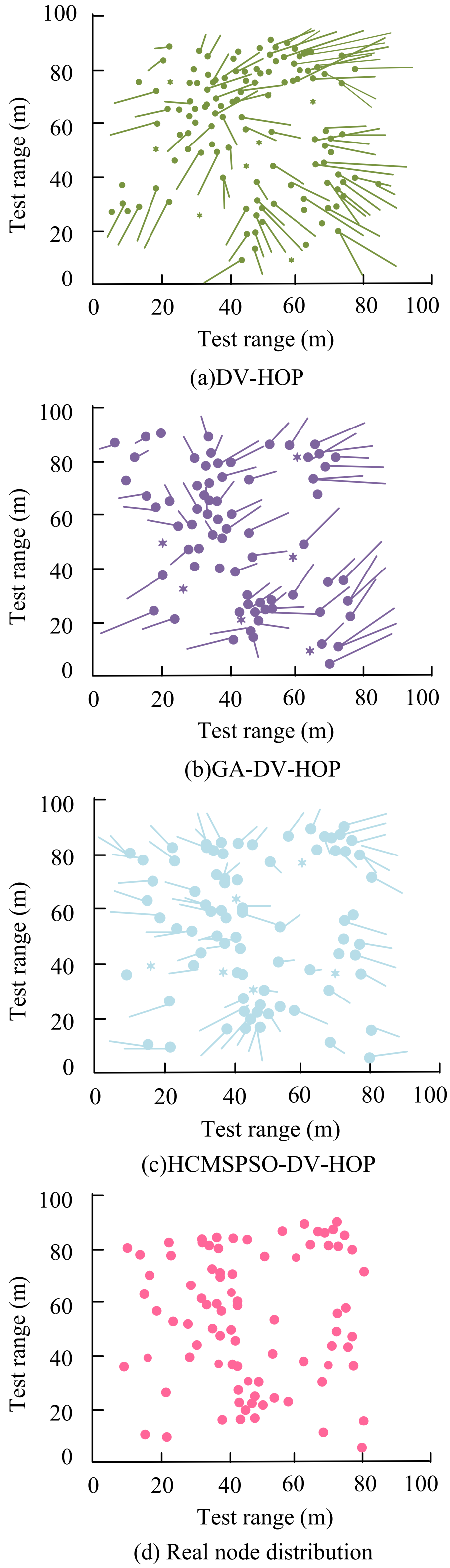


FIGURE 11. Actual positioning results of nodes using different algorithms.

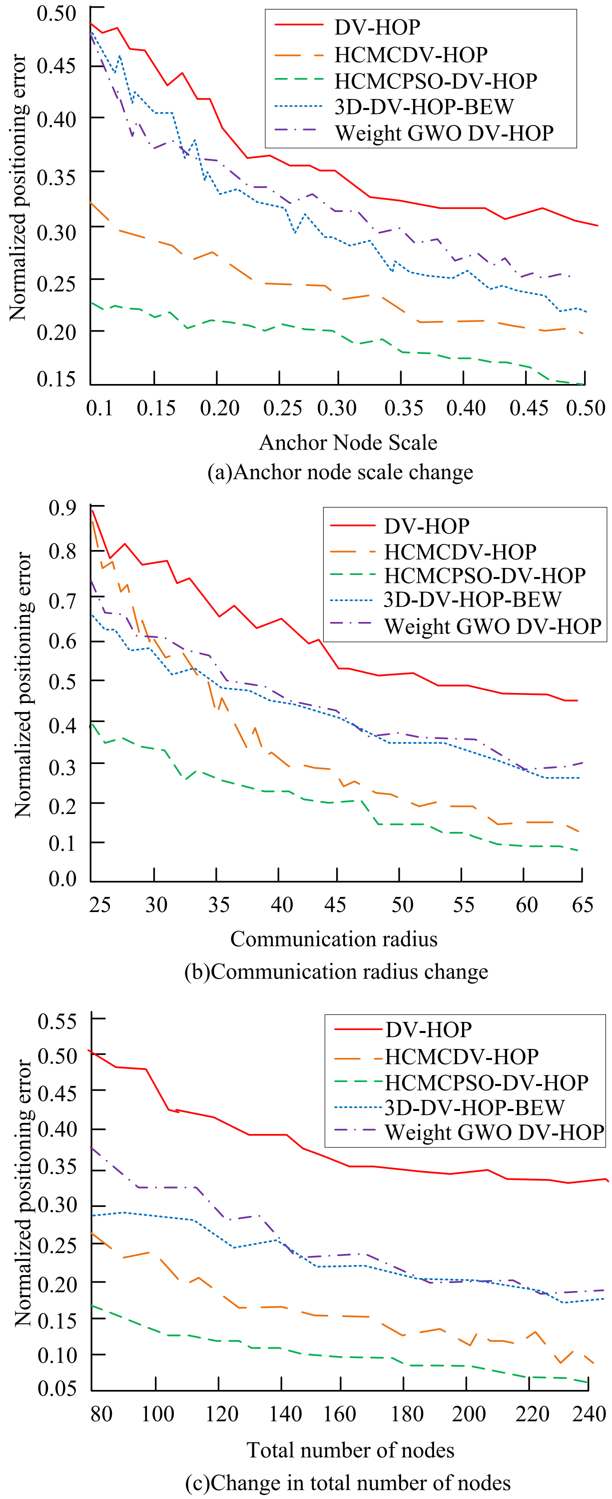


FIGURE 12. Error changes of five positioning algorithms under different influencing factors.

the relevant error of each algorithm is compared, as shown in Figure 12.

In Figure 12 (a), as the AN's ration increases, the positioning effect of the algorithm also grows. When the AN's ration increases, the relevant performance of 3D-DV-HOP-BEW algorithm and Weighted GWO DHA is much better than that of 3D DHA. The positioning performance of the HCMCPSO-DHA is much better than the other four algorithms, with an average error of 0.12. In Figure 12 (b), as the CRgrows, the

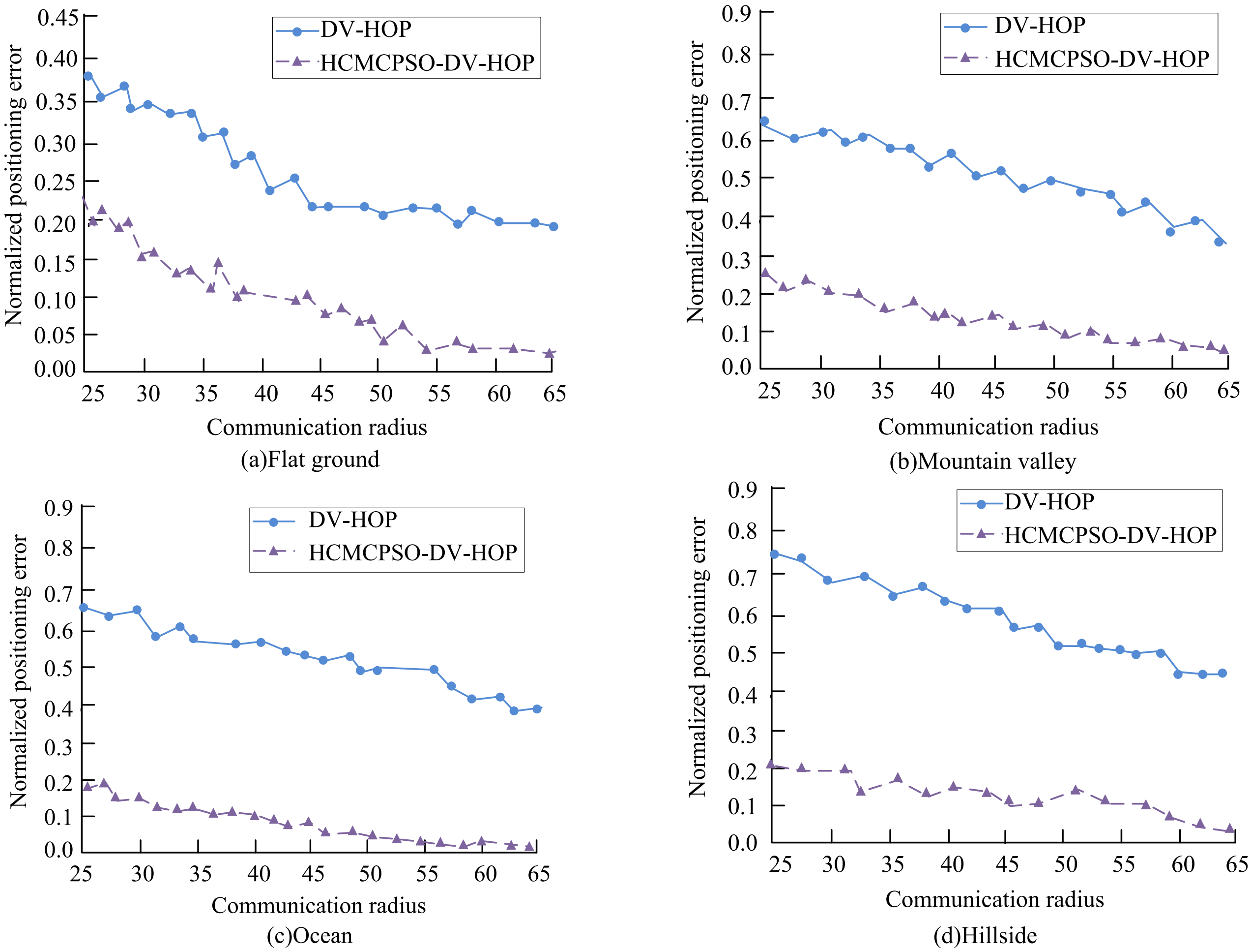


FIGURE 13. Comparison of positioning error changes of DV-HOP algorithm before and after improvement in different three-dimensional terrain types.

positioning error of the algorithm gradually diminishes. The error transformation amplitude of the HCMCPSO-DHA is the smallest under different radii. This is because in situations where the CR is small, the algorithm can promote information transmission between nodes by increasing their connectivity, ensuring positioning accuracy (PA). In Figure 12 (c), under different network scales, the related accuracy of the algorithm gradually increases; The average error value of the HCMCPSO-DHA is 0.09, which is greatlysuperior to other algorithms and has the smallest variation. This is because the algorithm, after replacing the MLE method with the PSO algorithm based on linear decreasing weights, overcomes its disadvantage of large errors in the case of matrix irreversibility.

To further verify the positioning effect of the algorithm in 3D models, comparative experiments will be conducted on the DHA before and after improvement. In the experiment, different 3D terrain types were selected for WSN node localization, and the variation of the algorithm's localization error with the increase of CR was recorded. The final positioning result is shown in Figure 13.

In Figure 13, the PA changes of the two algorithms are also different under four different terrain conditions. Among them, in flat terrain conditions, the PA of the improved DHA is the highest among the four terrains. The PA of the HCMCPSO-DHA in the four terrains is basically the same, with a variation amplitude of no more than 0.02. The DHA's average related erroris 0.56, while the HCMCPSO-DHA's average related error is 0.12. It is 0.44 less than before the improvement.

To comprehensively test the performance of the localization algorithm designed by the research institute, the experiment compares the node localization algorithm (Method 1) designed by the research institute with excellent node localization algorithms in recent years. It includes the node location algorithm based on improved Quasi radiative transformation optimization proposed in [14] (method 2), the node location algorithm based on signal phase search and Kalman filter proposed in [18] (method 3), the node location algorithm based on reverse learning social spider optimization proposed in [20] (method 4), and the node location algorithm based on multiple communication radius and

TABLE 1. Comparison of positioning performance of various positioning methods.

Project	Test 1		Test 2		Test 3	
	Running time (s)	Positioning accuracy (%)	Running time (s)	Positioning accuracy (%)	Running time (s)	Positioning accuracy (%)
Method 1	0.48	96.42	0.51	96.43	0.49	96.36
Method 2	1.02	84.71	1.00	84.69	1.03	84.72
Method 3	0.74	90.12	0.75	90.20	0.72	90.17
Method 4	1.94	72.86	1.92	72.91	1.93	72.88
Method 5	1.32	80.30	1.31	80.32	1.29	80.29

sparrow search proposed in [21] (method 5). Five positioning methods are used to locate WSN nodes with different numbers of nodes to be located, as shown in Figure 14.

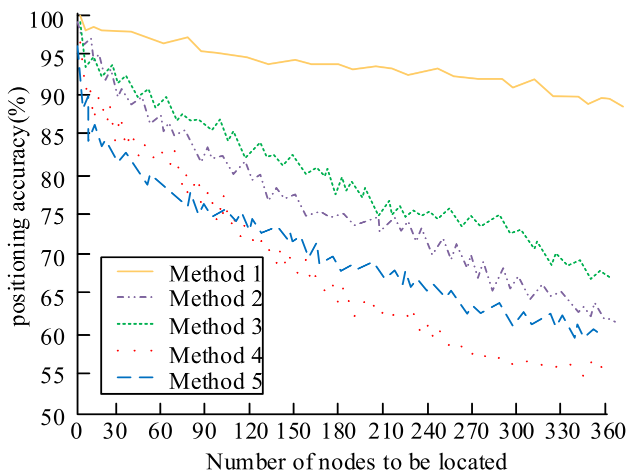


FIGURE 14. Changes in positioning accuracy of five positioning methods under different number of nodes to be positioned.

In Figure 14, the positioning accuracy of the five positioning methods gradually decreases with the increase of the number of nodes to be located. Among them, Method 1 has the smallest change amplitude, only reducing by 4.2%, and its average positioning accuracy is 96.8%. When the data size is 30, the average positioning accuracy of Method 1 is 98.7%. When the data size reaches 360, the average positioning accuracy is 94.4%; When the data size of Method 2 is 30, the average positioning accuracy is 91.2%. When the data size reaches 360, the average accuracy is 66.4%, a decrease of 24.8%; Method 3 has an average positioning accuracy of 94.7% when the data size is 30, and 68.9% when the data size is 360, a decrease of 25.8%; When the data size is 30, the average positioning accuracy of Method 4 is 84.7%. When the data size reaches 360, the average accuracy is 55.2%, a decrease of 29.5%; Method 5 has an average positioning accuracy of 81.5% when the data size is 30, and 59.8% when the data size is 360, a decrease of 21.7%. Based on the content in Figure 14, it can be seen that the positioning accuracy and performance of Method 1 are significantly better than the other four methods.

To further compare the performance of the algorithms, three testing experiments were conducted and the positioning results of each method were recorded in Table 1.

In Table 1, the average running time (ART) of Method 1 reaches 0.49 seconds, and the average PA is 96.40%; The running time of Method 2 reaches 1.02 seconds, which is 0.53 seconds longer than Method 1, with an accuracy of 84.71% and 11.69% less than Method 1; The running time of Method 3 is 0.74 seconds, which is 0.45 seconds longer than Method 1, with an accuracy of 90.16% and 6.24% less than Method 1; The running time of Method 4 is 1.93 seconds, which is 1.44 seconds longer than Method 1, with an accuracy of 72.88% and a decrease of 23.52% compared to Method 1; The running time of Method 5 is 1.31 seconds, which is 0.82 seconds longer than Method 1, with an accuracy of 80.30% and 16.10% less than Method 1. Table 1 showcases that the WSN node localization algorithm designed by the research institute can quickly and accurately locate the positions of each node in TDS.

V. CONCLUSION

The nodes in WSN are used to perceive, collect, and process information about various environments and monitoring objects when the network is distributed in complex and dangerous areas. If the node location cannot be determined, the various detection information collected will be meaningless. To this end, research is conducted on 3D DV-HOP positioning algorithm'srelevant analysis, and then combined with MCR. This study optimizes the HC and HD by setting a HC threshold, and finally introduces a PSO algorithm based on linear decreasing weights to optimize localization. Finally, it obtained the optimized HCMSPSO-DV-HOP localization algorithm. Through experiments, it was found that the optimized PSO algorithm achieved the target loss value of 0.0036 after only 172 iterations, demonstrating good convergence. HCMCPSO-DV-HOP is least affected by different AN ratios, communication radii, and total number of nodes, and the algorithm has high stability. The average positioning error of the HCMCPSO-DHA is 0.12. It reduces the error by 0.44 compared to before improvement, and the improvement effect is relatively obvious. The ART of the algorithm reaches 0.49 seconds, and the average PA is 96.40%. It can quickly and accurately locate the positions of various nodes in TDS. There is still great room for progress in research at this point. In future work, it should be considered for enhancing the PA while further reducing the data volume of algorithm operations to reduce time complexity. The research only focuses on algorithms for fixed nodes, and further exploration can be conducted on the movement of nodes.

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YI WU was born in Guangdong, China, in 1986. He received the B.S. degree in industrial design from the University of Jilin, China, in 2009, and the M.S. degree in vehicle engineering from Chongqing Jiaotong University, Chongqing, China, in 2012.

Since 2012, he has been with Guangzhou Toyota, BAIC New Energy, and GAC Research and Development Center. He has participated in the preparation of books on vehicle human factors engineering. He is the author of more than six articles. His research interests include vehicle information security, communication encryption, V2X technology, and forward-looking technology development management.

CAN ZHANG was born in Hunan, China, in 1989. She received the B.S. degree in applied international economic and trade from Hunan Normal University, Hunan, in 2011, and the M.S. degree in applied e-commerce and logistics technology from The Chinese University of Hong Kong, Hong Kong, China, in 2012.

From 2012 to 2021, she was an Internet Product Manager with E-Commerce Company, Guangzhou, Guangdong, China. Since 2022, she has been an Vehicle Cloud System Engineer with the Department of Intelligent Connected Vehicles, GAC Research and Development Center, Guangzhou. Her works include vehicle cloud system designing and vehicle connected data mining and analysis. Her research interests include information management systems, data mining, mathematical modeling, and machine learning.

LIN TONG was born in Fujian, China, in 1987. She received the B.S. degree in control technology and instruments and the M.S. degree in control science and control engineering from the Harbin Institute of Technology, China, in 2007 and 2010, respectively.

From 2011 to 2013, she was a SW Engineer with ZTE Mobile Communications Company Ltd., Shenzhen, China, and with the Samsung Mobile Research and Development Center, Guangzhou, Guangdong, China, from 2013 to 2019. Since 2019, she has been a Project Management Manager with the GAC Research and Development Center, Guangzhou. Her work includes the management of the forward project.

XIAOSHENG SHI was born in Hubei, China, in 1991. He received the B.S. degree in communication and information engineering from the University of Electronic Science and Technology of China, China, in 2013, and the M.S. degree in electrical and electronic engineering from the University of Glasgow, Glasgow, Scotland, U.K., in 2014. He is currently pursuing the Ph.D. degree in cyberspace security with the Huazhong University of Science and Technology.

Since 2015, he has been engaging in the research and development of automotive electronic systems with the GAC Research Institute and Bosch Group. He has published more than ten patents and copyrights. His research interests include IoT information security, autonomous driving, and the Internet of Vehicles.