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RESEARCH ARTICLE

Improved Sparrow Search Algorithm Optimized DV-Hop for Wireless Sensor Network Coverage

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ABSTRACT With the continuous improvement and development of wireless sensor network, it have been enriched to a great extent. Monitoring, processing and transmitting all kinds of sensing data is its main function, so their coverage issues have received widespread attention. Among them, the WSN coverage based on DV-Hop node positioning technology has low cost and power consumption with high scalability, and is extremely widely used. However, the current error control and WSN coverage of DV-Hop node positioning are not enough for practical applications. This research innovatively adopts an improved sparrow search pattern to optimise the DV-Hop localisation algorithm. The study introduces a deviation correction factor to adjust the minimum number of node hops and uses the minimum mean squared error criterion to correct the calculation error to reduce error. In addition, the study improved the sparrow search algorithm by means of a GPS optimisation population initialisation. In the algorithm performance comparison, GSSA showed the best convergence efficiency compared to other algorithms. The average error of the GSSADV-Hop localisation constructed in the study is 0.72 m, which is 77.71% less than the traditional DV-Hop error. The study provides a reference idea for the application of DV-Hop in WSN coverage, and offers a novel solution for the optimization of DV-Hop.

INDEX TERMS DV-Hop, node positioning, sparrow search algorithm.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are distributed sensor networks that transmit communication information wirelessly and therefore have the advantage of being flexible and convenient, and are widely used in the Internet of Things [1]. The process of urban intelligence has gradually accelerated, so the deployment of WSNs in urban environments has faced more challenges [2]. Many studies have addressed the deployment of WSNs at this stage, but WSN coverage is still one of the challenges that plague scholars [3]. In order to make data information transmission more efficient and stable, WSN coverage urgently needs to be improved, and the current WSN coverage based on DV-Hop node localization technique can no longer meet the practical needs [4]. WSN coverage needs to consider various factors such as node coverage, network connectivity, energy efficiency and minimum number of hops, and use various coverage techniques and strategies for optimization, so the DV-Hop optimization adopts bionic search with its unique performance [5]. This study uses an improved Sparrow Search Algorithm (SSA). The study ensures the initial distribution of the population is as uniform as possible by continuously optimizing the initialisation of the SSA population, thus reducing the search time and improving the search accuracy. Based on the optimised SSA, the study proposed the GSSADV-Hop model. To confirm the application of GSSADV-Hop in WSN coverage, the study selected several types of more mainstream bionic algorithm models for comparison tests. This study innovatively optimized the SSA algorithm from two aspects: population initialization and early warning position update, providing a novel solution for SSA algorithm optimization. More importantly, the research improves the positioning accuracy of DV Hop nodes, shortens the positioning time, and provides a valuable solution for the application of DV Hop in wireless sensor network coverage.

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II. RELATED WORK

As WSNs have matured over time, they have also become one of the most popular research subjects, and Kumar M and Ali J found that sensor nodes in wireless sensor networks are widely distributed and exposed to various risks. This study therefore proposes a new model for securing node communication and predicting various attacks. The model involves two panels: black hole attack checking and base station routing. The model outperformed other models in predicting risks [6]. A hierarchical data collection scheme was completed by lin C et al. for implementing a UAV-assisted industrial WSN. The study improved the linear programming formulation using an energy optimal formulation. By clustering nodes at different levels and using UAVs to collect data. The results show that the method is able to plan UAV paths at a lower cost [7]. Prabha M et al. found that energy limits the application of WSNs in their study of WSN overlays. The study therefore proposed an architecture incorporating compressed sensing to provide a more accurate and efficient data processing solution for clustered WSNs. The results showed that the system designed in the study provided a cost-effective solution with an energy efficiency of 70% and a prediction rate of 93% [8]. Lahane S R proposed WSNs lifetime extending model by extending the life cycle of message routing. The model was shown to outperform existing models [9]. Pedrycz W et al. noticed the lack of accuracy in the DV-Hop localization and proposed a new algorithm. The algorithm was improved on the evolution of differential simulated annealing. Recognising the importance of calculating jump distances, the study innovatively classified jump distances into three types, namely global monotonic mean jump distance, corrected mean jump distance between anchor nodes and corrected mean jump distance. Finally, experimental results indicated reduced error [10]. Liu J et al. created an involved DV-Hop founded by neural dynamics. The study constructed distance and coordinate variation with time using a model set in simulation experiments and constructed algebraic equations. In the experimental results, the algorithm possesses good accuracy and robustness in the localisation problem [11].

In WSN, the DV-Hop localization algorithm has been optimized by different algorithms. Among them, various biomimetic optimization algorithms are most widely used. As one of the biomimetic optimization algorithms, SSA algorithm has been widely used in various fields due to its good search ability. Zhang L et al. noticed the phenomenon of homochromatic metamerism during color reproduction. In order to reconstruct spectral reflectance and reduce color reproduction errors, a backpropagation neural network was studied for optimization. In addition, in order to reduce the influence of initial values on the neural network and improve search accuracy. A new SSA algorithm has been proposed for research. Firstly, initialize the backpropagation neural network using the SSA algorithm, and then use sine chaotic mapping. In the final results, it was found that this method not only has more stable performance compared to other methods, but also can reconstruct spectral reflectance on small datasets [12]. Zhang S et al. found that the imaging performance of patterns is affected by the distortion of projection optical devices. Therefore, based on the SSA algorithm, a method for improving the distribution of aberration coefficients was proposed. The study first utilized the SSA algorithm's independence from initial values to obtain an improved aberration distribution, and then compared the simulated results with the algorithm. The experimental results show that the aberration improved by SSA is even better than the results under ideal conditions [13]. Hui X et al. used an SSA algorithm that is insensitive to initial values to constrain hypersonic reentry trajectory. By optimizing the SSA algorithm, the sensitivity of the initial values of control parameters was reduced and better initial values were obtained. The experimental results show that this calculation method has fast convergence speed and high robustness [14]. Liu T et al. proposed a new auxiliary system in the field of brain tumor detection. The system can be used for automatic diagnosis of brain tumor. The system consists of four steps, namely preprocessing, classification, extraction, and diagnosis. In addition, the study utilized SSA to optimize the search capability of the system. The results indicate that compared to the latest technology, this method is more efficient [15].

As mentioned in the review, research on WSN coverage has achieved certain results at this stage, and a large number of scholars have optimized WSN from aspects such as hardware security, node energy conservation, signal processing, and node positioning. However, in node localization, most research focuses on a relatively broad range of influencing factors such as distance and position, neglecting some details such as the impact of the minimum hop count of nodes on localization accuracy. In addition, it was discovered during the SSA method's optimization research that the algorithm has strong search performance and can lessen the sensitivity of initial values. The optimization capability and search mechanism of SSA can be used to limit the effect of DV-Hop on the initial distance measurement values between nodes, while ensuring stability and enhancing positioning accuracy, if node localization is changed into an optimization problem. The study optimized the initialization of the SSA population through a set of good points to ensure that the initial distribution of the population is as uniform as possible, thereby reducing search time and improving search accuracy. On the basis of optimizing SSA, DV-Hop was optimized and the GSSADV-Hop model was proposed.

III. RESEARCH ON THE DV-HOP OPTIMIZATION OF FOR WSNS LOCALIZATION METHOD

A. OPTIMIZED DV-HOP IN WSNS COVERAGE

WSNs coverage is a key technology in wireless sensor networks, which includes the location information of nodes [16]. The positioning of node directly affects the quality of data in the WSN coverage area. WSN coverage can be divided into three categories depending on the application scenario,

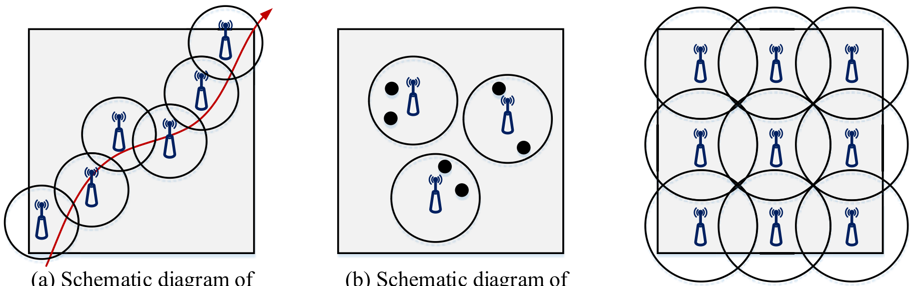


FIGURE 1. Schematic diagram of different types of WSN coverage.

as shown in Fig. Figure 2(a) shows a fence overlay, which identifies a path within the WSN coverage area and places sensors to ensure that moving target points are monitored. The fence overlay is used to monitor the area for trespass, where the curve indicates the path to be covered and the hollow circle indicates the sensor. Figure 2(b) shows the target coverage, where the sensor only needs to cover the target point. The solid black circle indicates the sensor and the diamond indicates the target point. Figure 2(c) shows area coverage, where area coverage is used for dead-end monitoring of the deployment area, where the black circle indicates the sensor and the disk indicates the sensing range. In WSNs, the nodes' locationis indispensable. DV-Hop is commonly used as a node localisation technique, which is widely adoptedfor the low costand high scalability [17]. Although the current DV-Hop has a number of advantages, there is still room for improvement in the error in WSN node localization. Therefore, this study investigates the optimization method of it with the main objective of reducing the localization error of WSN nodes, which is a distributed localization algorithm that divides the nodes in a WSN into two categories, namely anchor nodes (AN) and unknown nodes (UN). The AN have the ability to locate themselves, while the UN do not have the ability to locate themselves. In the localisation process of DV-Hop, it is first necessary to make all nodes get the minimum hops (MH) with the AN. When a neighbour node receives the data, it will record the AN information and plus the hop count by 1 bit, and then continue to propagate. If that neighbour node receives data from the same anchor node again, it will compare this time the tuning number with the stored hop count. The MHD of the AN is in equation (1).

$$HopSize_i = \frac{\sum_{i \neq j} \sqrt{(o_i - o_j)^2 + (z_i - z_j)^2}}{\sum_{i \neq j} h_{i,j}} \tag{1}$$

In equation (1), (o_i, z_i) and (o_j, z_j) denote the coordinates of AN i and j respectively, $HopSize_i$ denotes the MHD of AN i, and $h_{i,j}$ denotes the MH. The MHD of the UN is acquired from the data of the first AN and the distance of the AN. The expression for the AN distance is shown in equation (2).

$$d_{u,i} = HopSize_u \times h_{u,j} \tag{2}$$

In equation (2), $HopSize_u$ denotes the mean hop gap of the UN u and $h_{u,i}$ denotes the MH between the undirected node u and the AN i. After the estimated distances between different nodes are obtained by the above calculation, the UN can be assessed. The principles of the assessment methods are shown in Figure 1.

In the DV-Hop, there are two types of error sources, the MH count error and the mean hop gap error. The MH count error arises because in the calculation, the DV-Hop records the hop counts of neighbouring nodes as integers. However, in practice, the distances between nodes are not the same, thus reducing the accuracy of node localisation. To minimise the MH error between nodes, some studies have used the dual communication radius algorithm to refine the minimum hop count [18]. However, this method still cannot avoid the MH count's influence between AN. Therefore this study introduces a deviation correction factor to make a secondary correction to the hop count between AN in WSNs. In the quadratic correction, the ideal hop count $H_{i,j}$ of WSN AN i and j needs to be defined first, and its expression is shown in equation (3).

$$H_{i,j} = \frac{d_{i,j}}{R} \tag{3}$$

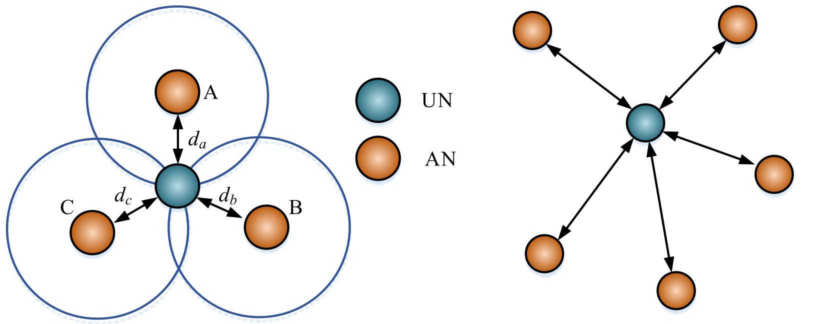
In equation (3), R denotes the node communication radius, $d_{i,j}$ denotes the Euclidean distance between AN $d_{i,j}$ and j, and $h_{i,j}$ denotes the minimum hop estimated by the dual communication radius, at which point the expression for the deviation correction factor is shown in equation (4).

$$\alpha_{i,j} = \frac{h_{i,j} - H_{i,j}}{h_{i,j}} \tag{4}$$

In equation (4), $\alpha_{i,j}$ is the deviation correction factor and the magnitude of $\alpha_{i,j}$ reflects the deviation error between the actual number of hops and the target number of hops; a larger value of $\alpha_{i,j}$ indicates a larger positioning error. The correction factor is obtained from the correction factor, as shown in equation (5).

$$w_{i,j} = 1 - \alpha_{i,j}^2 \tag{5}$$

In equation (5), $\alpha_{i,j}$ denotes the correction factor. The corrected minimum hop for the AN is therefore shown in



(a) Schematic diagram of trilateral measurement

(b) Maximum likelihood estimation method

FIGURE 2. Two unknown node estimation methods.

equation (6).

$$h'_{i,j} = w_{i,j} \times h_{i,j} \tag{6}$$

The MHD is calculated from the Euclidean distance of two nodes, and there is also a significant error between the Euclidean distance and the hop distance in the actual network, thus generating an mean distance error. Therefore the mean hop distance (MHD) in WSN also needs to be corrected. This study uses the minimum mean squared error for substitution, and the mean squared error is shown in equation (7).

$$f = \sum_{i \neq j} (\delta^2_{i \neq j} - h_{i,j} \times HopSize_i)^2 \tag{7}$$

On the basis of equation (7), the mean jump distance of the AN can be acquired by deriving $\frac{\partial f}{\partial HopSize_i} = 0$. The expression is shown in equation (8).

$$HopSize_i = \frac{\sum\limits_{i \neq j} h_{i,j} \times d_{i,j}}{\sum\limits_{i \neq j} h^2_{i,j}} \tag{8}$$

In equation (8), $HopSize_i$ is the MHD of AN i, on the basis of which the estimated distance between AN and the average error per hop can be calculated, as shown in equation (9).

$$\begin{cases} \hat{d}_{i,j} = HopSize_i \times h_{i,j} \\ \xi_i = \dfrac{\sum\limits_{i \neq j} (\hat{d}_{i,j} - d_{i,j})}{\sum\limits_{i \neq j} h_{i,j}} \end{cases} \tag{9}$$

In equation (9), $d_{i,j}$ denotes the Euclidean distance between AN i and of j. $\hat{d}_{i,j}$ denotes the estimated distance between AN i and j, and ξ_i denotes the average per-hop error of AN B. Thus the new MHD expression for the anchor node is shown in equation (10).

$$HopSize_{inew} = HopSize_i - \xi_i \tag{10}$$

This study introduces a normalised weighting factor to obtain more information about the AN for the MHD of the UN. The influence of distant AN on the positioning of UN is weakened by reassigning the weights of the MHD of each anchor node. The normalised weighting factor proposed in the study is shown in equation (11).

$$W_i = \frac{1/h_i}{\sum\limits_{j=1}^{k} 1/h_j} \tag{11}$$

In equation (11), h_i denotes the number of hops between AN i and the UN, and i denotes the number of hops between all AN and UN. Therefore, the final per-hop distance of the unknown node u is shown in Equation. (12)

$$HopSize_u = \sum_{i=1}^{k} W_i \times HopSize_{inew} \tag{12}$$

B. RESEARCH ON OPTIMIZED DV-HOP LOCALIZATION WITH IMPROVED SPARROW SEARCH ALGORITHM

In the previous section, the study optimised the application of the DV-Hop localisation to WSN overlays. Although the effects of errors in node localisation were optimised, the over-reliance on the initial value of inter-node ranging could still not be avoided. This resulted in the accuracy of the optimised DV-Hop localisation algorithm not being significantly improved. To address this problem, this research transforms node localisation into an optimisation problem. In the optimization problem, the SSA has a good search ability, is insensitive to the inter-node distance, and is able to improve the localization accuracy while maintaining good stability [15]. Therefore, this study uses SSA to optimise the DV-Hop localisation algorithm so as to localise the UN. The SSA process is shown in Figure 3.

As shown in Figure 3, the SSA algorithm first initializes population parameters to determine the number of individuals in the population. Update the positions of discoverers and joiners, and then randomly select sparrow individuals who are aware of danger to update their positions. Finally, obtain the current population position and record the best fitness value, and judge whether the termination condition is met. If the termination condition is met, the current population position and the best fitness value will be output; If not satisfied, return to step 2 of the process. SSA is a probability-based

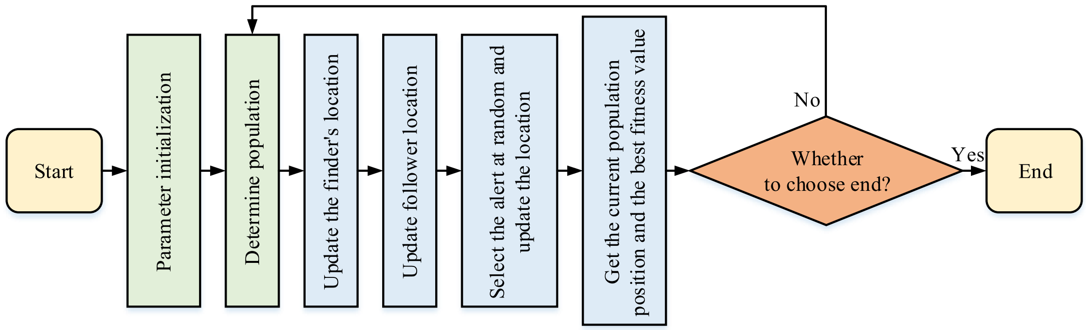


FIGURE 3. Sparrow search algorithm flow chart.

stochastic search method that is mainly applied to solve unrestricted optimal problems. The method employs a method that mimics population habits by randomly selecting a best population in the existing ones and adding the corresponding information to the existing population to guide the population search [19]. The population in SSA mainly consists of discoverers and joiners, with the discoverers and joiners in an adversarial relationship. The joiners monitor the discoverers and will compete to become new discoverers. SSA improves the exploitation of the search space and, with the help of early warners, the local search space is well exploited. However, SSA still suffers from slow convergence and insufficient accuracy. So for further improving the localisation accuracy, the study improves SSA in terms of both population initialisation and early-warning agent position update, and the improved algorithm is named GSSA. when executing SSA, the population position needs to be initialised. As the distribution of the population is random and may not cover all solutions, which affects the accuracy and time of the search, it is necessary to ensure that the initial distribution is as uniform as possible. The study uses a GPS to optimise the initialisation of the population. In the good point set (GPS), G_s is assumed to be a cube in a s-dimensional Euclidean space, the point set is denoted as $r = \{r_1, r_2, \ldots, r_s\}$, and the set has element $r_k = \left\{2\cos\frac{2\pi k}{p}, 1 \le k \le s\right\}$. If the table of p is the smallest prime satisfying $\frac{(p-s)}{2} \ge s$, then r is a good point at this point. The expression of the GPS is equation (13).

$$p_n(i) = \{\{r_1 \times i\}, \{r_2 \times i\}, \ldots, \{r_s \times i\}, i = 1, 2, \ldots, n\} \tag{13}$$

The deviation equation for the GPS is shown in equation (14).

$$\phi(n) = C(r, \varepsilon)n^{-1+\varepsilon} \tag{14}$$

In equation (14), ε denotes an arbitrarily small constant and $C(r, \varepsilon)$ denotes a constant associated with r, ε, at which point $p_n(i)$ is the best set. The upper limit of the spatial dimension of the solution is set to BB and the lower limit is set to u. The set of good points can be mapped to the search space by equation (15).

$$x_k(i) = l_k + P_n(i)_k(u_k - l_k) \tag{15}$$

The value of the first sparrow in the first dimension can be obtained by using equation (15). The sparrow population size setting is 16 and is distributed in a square area with upper and lower limits of 50m and 0m. The random distribution with a good set of points to initialise the population distribution is shown in Figure 4.

Figure 4(a) and Figure 4(b) show the random distribution and the GPS initialised population distribution respectively. The figures make it obvious that the initialized population distribution for favorable points is more uniform and covers a larger area. Therefore, GPSs can be used to improve the quality of the traversal and settlement. GSSA algorithm's objective function also needs to be established when using GSSA to estimate the position of UN in the third stage of the DV-Hop localisation. At this point the distance error of the UN and AN needs to be obtained, which is calculated as shown in equation (16).

$$\varepsilon = \sum_{i=1}^{N} \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i\right) \tag{16}$$

In equation (16), (x, y) denotes the true coordinates of the UN, (x_i, y_i) denotes the true coordinates of the AN, d_i denotes the estimated distance between them, and N denotes the total AN number. When the error and the gap between the UN and all AN is minimized, the fitness function of GSSA is obtained, as equation (17).

$$fitness(x, y) = \sum_{i=1}^{N} \left|\left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i\right)\right| \tag{17}$$

The fitness function in equation (17) converts the localisation phase of the DV-Hop localisationinto an optimisation problem. The study solves the GSSA by solving for the minimum of the fitness function. Based on the above analysis, the flow of the GSSA improved with optimised DV-Hop localisation algorithm (GSSADV-Hop) is shown in Figure 5.

As shown in Figure 5, in the workflow of GSSADV-Hop, the sensors are first expanded and the estimated distance between the anchor node and the unknown node is calculated. Then initialize the SSA parameters and calculate the fitness value. The position of searcher, joiner and alerter in the population is updated by the fitness value. Finally, recalculate the fitness value and determine whether the maximum number of

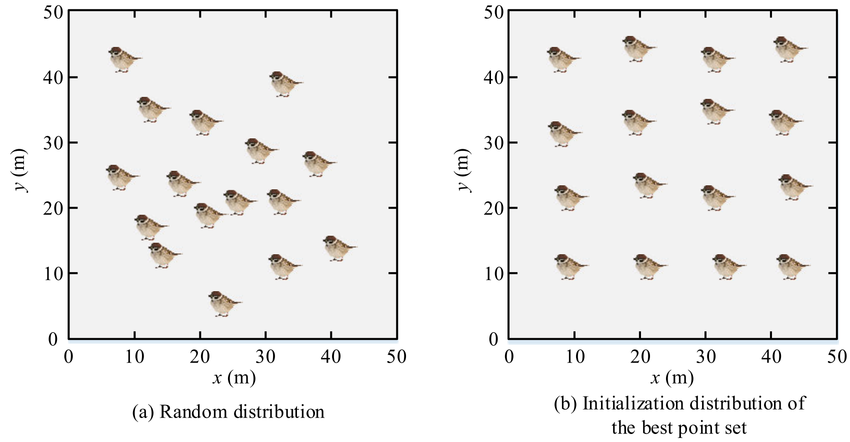


FIGURE 4. Random distribution and GPS initialization population distribution.

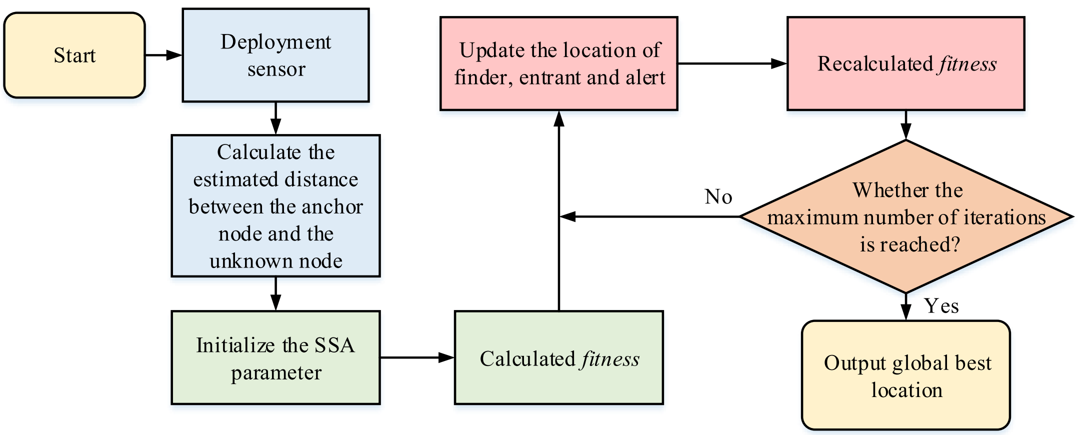


FIGURE 5. Flowchart of GSSADV-Hop.

iterations is met. If it is met, the global optimal position will be output. If not, the position update step will be returned.

IV. EXPERIMENTAL RESULTS OF GSSADV-HOP LOCALIZATION ALGORITHM IN WSN OVERLAY

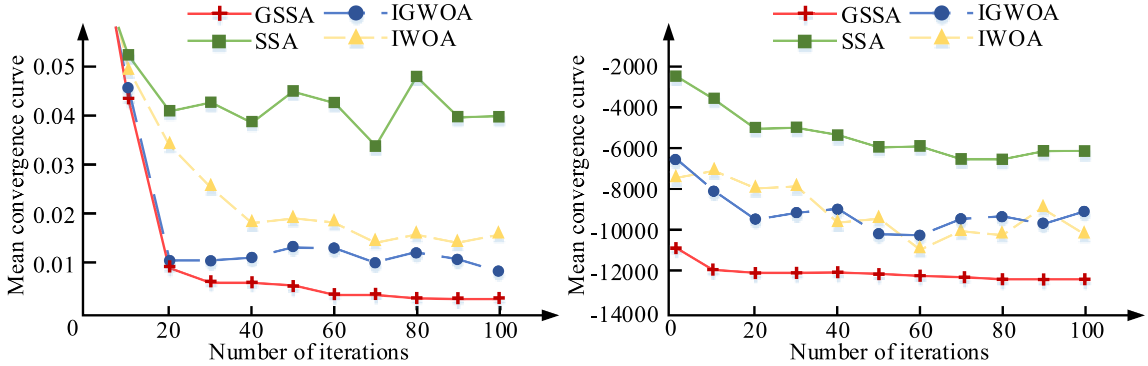
In order to verify the performance of GSSA, two benchmark functions were selected for simulation experiments, namely the unimodal benchmark and the multimodal benchmark. The GSSA was compared with the basic SSA, the Improved Grey Wolf Optimization Algorithm (IGWOA), and the Improved Whale Optimization Algorithm (IWOA). To ensure that the computer equipment does not generate errors, the same computer equipment was used for the simulations. The information on the computer equipment used is Table 1.

For the simulated optimisation algorithms involved in the comparison, it was set with the same population and iterations, and each algorithm was run individually. The average convergence curve over 100 iterations was obtained as shown in Figure 6.

Figure 6(a) shows the convergence curve of the single mode benchmark test function. In 100 iterations, GSSA showed the best convergence performance compared to other algorithms. In the first 20 iterations, only the optimal values of IGWOA and GSSA were close. After 20 iterations, the GSSA iteration results are significantly better than other algorithms and have more stable performance. The average convergence value of GSSA after stabilization is 0.002; The average convergence value of IGWOA is 0.012; The average convergence value of IWOA is 0.017; The average convergence value of SSA is 0.041. The experimental results validate the superiority of the GSSA algorithm. Figure 6(b) shows the convergence curve of the multimodal benchmark test function. The multimodal benchmark test function is generally used to evaluate the exploration ability of algorithms. From the graph, it can be seen that the optimal value of GSSA is significantly better than the other three types of algorithms. In 100 iterations, the optimal value of GSSA is -1.22×10^{-4}; The optimal value of IWOA is -1.09×10^{-4}; The optimal SSA value is -0.61×10^{-4}; The optimal value of IGWOA is -1.02×10^{-4}. The experimental results demonstrate that the study improves SSA from two aspects: population initialization and early warning position

TABLE 1. Computer equipment.

Item	Configuration
Video card	GTX 1080ti
CPU	Inter Xeon E5
Gpu-accelerated library	CUDA 10.0
Memory	64 GB
Operating system	Windows 10
Deep learning framework	TensorFlow 1.8



(a) Single-mode benchmark function (b) Multimodal benchmark function

FIGURE 6. The average convergence curve.

update, promoting GSSA to move towards global optimization, thereby improving search accuracy and reducing time spent, verifying GSSA's excellent exploration ability.

For confirming the optimization effect of the GSSA algorithm on WSN coverage, the study conducted a coverage comparison experiment with a 100m×100m monitoring area as an example. The pixels in the area was 100 × 100, and nodes was 40. The communication radius was 20 m, and radius of sensing was 10m. The average coverage curve was obtained as shown in Figure 7.

From Figure 7, the evaluation coverage obtained by GSSA increased and gradually approached the optimal value with increasing iterations. the best average coverage of GSSA over 500 iterations reached 98.23%. the best average coverage of SSA over 500 iterations reached 86.67%. The best average coverage of IGWOA over 500 iterations reached IWOA achieved a best average coverage rate of 88.76% over 500 iterations. Although IGWOA outperformed GSSA in terms of maximum coverage in the first 50 iterations, GSSA still outperformed the other algorithms in terms of overall coverage. This is because the initialization of the optimal point set has a more uniform population distribution, more comprehensive coverage of the space, and improves the ergodicity and quality of the search space. The experimental results verify that GSSA has higher application value in WSN coverage.

To verify the GSSADV-Hop localisation algorithm, the study compared DV-Hop, IPSODV-Hop and IGWODV-Hop. Firstly, for the optimisation of GSSADV-Hop on the localisation error, the study set the deployment area as a 50m × 50m square. Figure 8 is the localisation error.

Figure 8(a) shows the localisation effect of DV-Hop, while Figure 8(b) is the localisation effect using the GSSADV-Hop. The yellow line indicates the connection between the algorithm and real actual position of the UN. Its length indicates the size of the positioning error, with longer lines indicating larger positioning errors. Figure 8(a) shows that the yellow lines are all present, indicating that most of the UN have a large error in their location. The error of GSSADV-Hop node positioning is reduced by 77.71%. The results validated that the GSSADV-Hop can significantly reduce the node localisation error and improve the accuracy of unknown node localisation. For further verifying the localisation effect of GSSADV-Hop under different parameters, a total of 100 total nodes and 20 AN were set up for this experiment. 20 to 50m is the communication radius. The effect of communication radius on localisation error was first obtained, as shown in Figure 9.

The variation of the positioning error of each algorithm with increasing communication radius can be seen in Figure 9. Overall, the average error value of each algorithm goes downwithincreasing radius. The average positioning error of GSSADV-Hop is 0.87m, IPSODV-Hop is 2.11m, IGWODV-Hop is 2.08m, and DV-Hop is 3.62m. When the communication radius of the node is 50m, the positioning error of GSSADV-Hop is 0.62m; The positioning error of IPSODV-Hop is 2.61m; The positioning error of IGWODV-Hop is 2.37m; The positioning error of DV-Hop is 3.17m. Compared to IPSODV-Hop, GSSADV-Hop reduces positioning error by 58.17%; Compared to GWODV Hop, GSSADV Hop reduces positioning error by 58.77%; Compared to DV Hop, GSSADV Hop reduces positioning error by 75.97%.

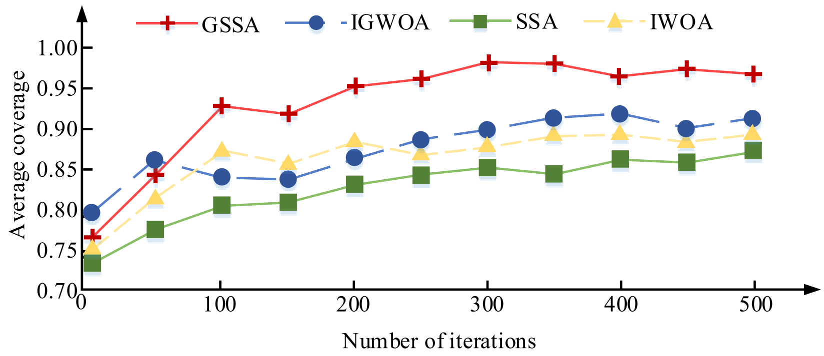


FIGURE 7. Average coverage curve.

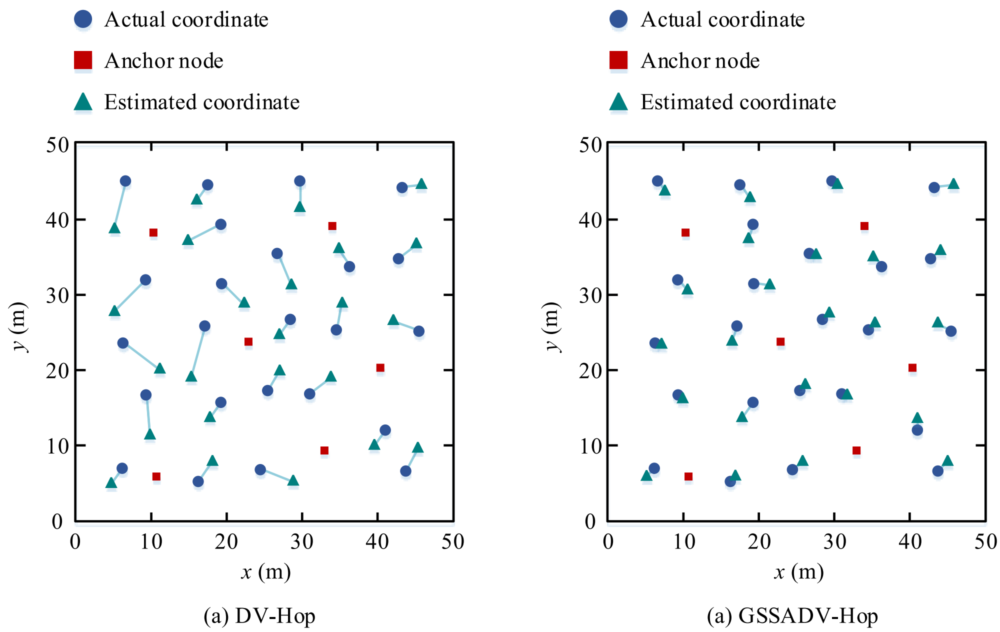


FIGURE 8. Location error of UN and AN.

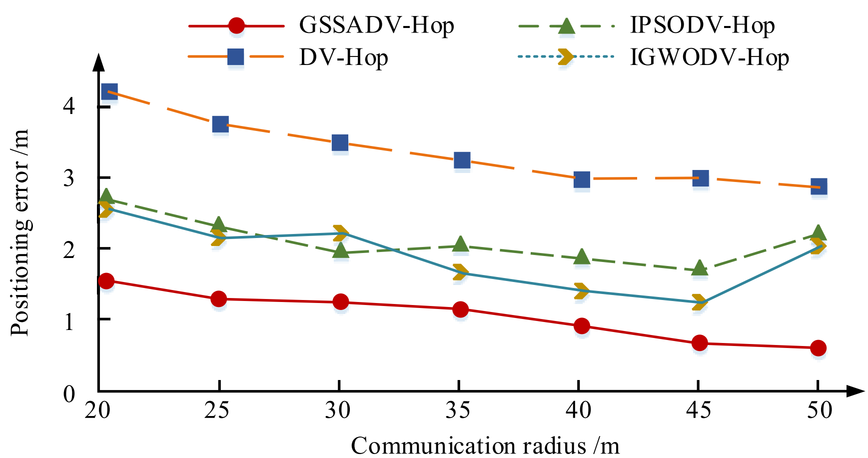


FIGURE 9. Positioning error influenced by communication radius.

The results validated that there was a significant improvement in GSSADV-Hop positioning accuracy. Total number of nodes' effect on the localisation error was obtained experimentally and is shown in Figure 10.

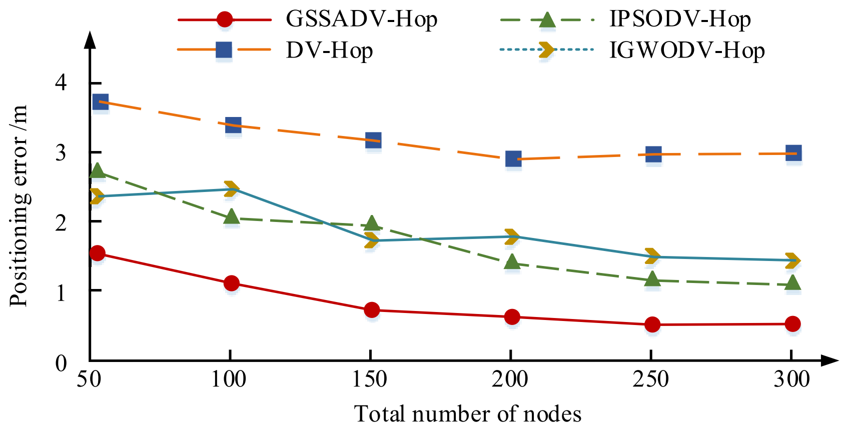


FIGURE 10. The influence on positioning error.

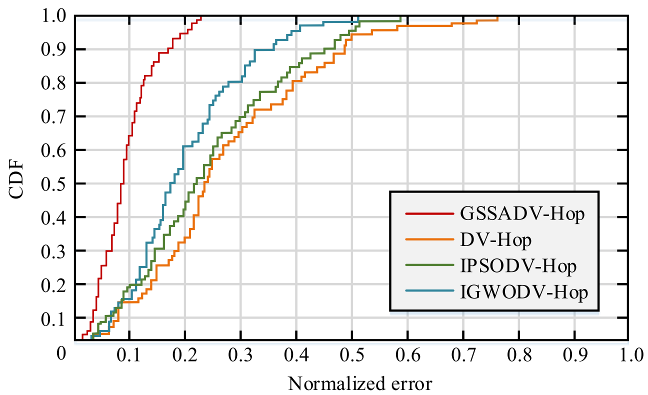


FIGURE 11. CDF of the total positioning error of each algorithm.

From Figure 10, the average positioning error of each algorithm reduced as thenodes goes up. When the total number of nodes is 300, the positioning error of GSSADV-Hop is 0.44m; The positioning error of IPSODV-Hop is 1.32m; The positioning error of IGWODV-Hop is 1.64m; The positioning error of DV-Hop is 3.27m. The average positioning error of GSSADV-Hop is the lowest, only 0.87m; The average positioning error of IPSODV-Hop is 1.84m; The average positioning error of IGWODV-Hop is 1.89m; The average positioning error of DV-Hop is 3.41m. Compared to the other three algorithms, the GSSADV-Hop positioning error has decreased by 52.72%, 53.97%, and 74.49%, respectively. The experiments validate that the GSSADV-Hop can effectively reduce the node errors in different environments.

To further verify the superiority of GSSADV-Hop, the study evaluates the performance of GSSADV-Hop by the Cumulative Distribution Function (CDF) of the node-normalized localization error. As can be seen in Figure 11, when the CDF is 0.1, 60.04% of the nodes of GSSADV-Hop are in range, while 19.94%, 16.34% and 15.12% of the nodes of the other algorithms are in range at this time, respectively. When the CDF was 0.2, GSSADV-Hop had 96.19% nodes in range, at which time the other algorithms had 60.09%, 45.21% and 34.07% nodes in range, respectively. The experimental results showed that the vast majority of node localisation errors of GSSADV-Hop were smaller than those of the other algorithms, and the overall robustness was superior.

V. CONCLUSION

In wireless sensor networks, both node localisation and coverage are key issues to improve the effectiveness of network usage. With the various optimization algorithms proposed, the DV-Hop can no longer meet the needs of practical applications. The majority of the present node localization research concentrates on elements like distance and position, while ignoring some aspects like the effect of the minimum hop count of nodes on localization accuracy. In addition, it was discovered during the SSA method's optimization research that the algorithm has strong search performance and can lessen the sensitivity of initial values. The optimization capability and search mechanism of SSA can be used to limit the effect of DV-Hop on the initial distance measurement values between nodes, while ensuring stability and enhancing positioning accuracy, if node localization is changed into an optimization problem. Therefore, this research uses an GSSA to optimise DV-Hop and proposes the GSSADV-Hop node localisation algorithm in WSN coverage technology. The results showed that in the experiment on the impact of communication radius on positioning error, compared to IPSODV Top, IGWODV Top, and DV Top, GSSADV Top reduced positioning error by 58.17%, 58.77%, and 75.97%, respectively. In the experiment on the impact of total number of nodes on positioning error, compared to IPSODV Top, IGWODV Top, and DV Top, GSSADV Top reduced positioning error by 52.72%, 53.97%, and 74.49%, respectively. From the evaluation of GSSADV Hop performance by CDF, it can be seen that when CDF is 0.1, 60.04% of GSSADV Hop nodes are within the range, while other algorithms are 19.94%, 16.34%, and 15.12%, respectively. When the CDF is 0.2, 96.19% of nodes in GSSADV-Hop are within the range, while other algorithms are 60.09%, 45.21%, and 34.07%, respectively. It has been verified that the positioning error of GSSADV-Hop is smaller than other algorithms, and the overall robustness is better. Although this study has achieved certain results, due to limited experimental conditions, no comparative experiments were conducted under more influencing factors. In addition, in the improved method, research is conducted to weaken the influence of distant anchor nodes on the localization of unknown nodes by redistributing the weight of the average hop distance of each anchor node. But this impact has not been completely eliminated. The above issues will become the main research directions in the future.

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