Journal of Network Intelligence
Taiwan Ubiquitous Information
 ISSN 2414-8105
Volume **9**, Number **3**, August **2024**

Node Localization in Wireless Sensor Networks based on Improved Seagull Optimization Algorithm

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Received October 20, 2023, revised January 7, 2024, accepted March 25, 2024.

Abstract. *Traditional localization algorithms usually face the challenge of low accuracy and high computational complexity in complex environments. To solve this problem, a new positioning strategy based on improved gull optimization algorithm is proposed. Firstly, through in-depth analysis of the limitations of the traditional gull optimization algorithm, it is found that it has insufficient efficiency in the process of node initialization and search. Therefore, a tent chaotic mapping strategy is introduced to improve the initialization process of seagull population, so as to enhance the search ability and improve the convergence speed of the algorithm. The experiment demonstrates that the error of the original algorithm is about 31.23%, while the improved error decreases to 9.35%, a decrease of 21.88%. In practical applications, the average positioning error of the improved seagull algorithm in this study is 0.22 meters lower than traditional positioning algorithms and 0.16 meters lower than seagull algorithms. The experiment demonstrates that the improved seagull optimization algorithm greatly enhance the node localization in wireless sensor networks. This study provides a reference for the development and optimization of node positioning technology.*
Keywords: wireless sensor network; node positioning; seagull algorithm; tent chaotic mapping

1. **Introduction.** Wireless Sensor Network (WSN) is a Complex network that is interconnected through many sensor nodes (SN) through wireless communication [1]. These SN can capture and process various types of data, and then transmit the information to the data center through wireless networks. WSN have been extensively developed in various respects like intelligent transportation and health monitoring due to their wireless characteristics and wide coverage. In WSN, node localization (NL) technology plays a crucial role. This technology can ascertain the physical location of every node, thereby achieving accurate data acquisition and effective distribution. However, due to the fact that nodes in WSN are usually randomly deployed in a vast area, accurately determining the position of each node poses certain challenges. In addition, due to the restricted sources of wireless SN, such as power, storage, and computing power, it is necessary to fully consider their computational complexity and energy consumption (EC) issues when designing and implementing localization algorithms (LA). Although the node location problem of WSN has been widely studied, and a variety of optimization algorithms have been proposed and verified. However, most of the previous studies focused on the application of traditional optimization algorithms and their variants, while the innovation of the research lies in the specific improvement of Seagull Optimization Algorithm (SOA)

algorithms and the application of it to the WSN node location problem [2]. SOA is an optimization algorithm inspired by the behavior of seagulls searching for food, which has shown good performance on multiple problems [3]. However, the traditional SOA algorithm has some shortcomings in search ability and Rate of convergence. Therefore, this study aims to improve the SOA algorithm and utilize it to the problem of NL in WSN, for enhancing the NL. This study mainly consists of five. The first is an overview of the research; The second is a summary of relevant work at home and abroad; The third part is separated into two. The first introduces the NL technology in view of SOA algorithm, and the second introduces the improvement methods of SOA algorithm; The fourth is the analysis of experimental results on the improvement methods proposed in the study; The fifth is a summary of this study and prospects for the future. The main technical contributions of the research include the in-depth analysis of the limitations of traditional SOA, and the proposed improved SOA algorithm, which uses the tent chaos mapping strategy to optimize the initial population of the algorithm, effectively improve the search ability and convergence speed; Secondly, the weighted multipath radius method is introduced to estimate the distance between the unknown node and the beacon node more accurately, so as to significantly improve the positioning accuracy. In addition, a large number of experiments are conducted to verify the effect of the improved algorithm under different communication radii, which proves that the improved SOA is superior to the traditional method in positioning accuracy and has significant application value.

2. **Related Work.** WSN has become one of the important achievements in the process of human development in the last century, and many scholars have carried out a lot of research on the topic of energy consumption reduction of WSN node positioning. Karimi-Bidhendi et al. analyzed a heterogeneous two-layer wireless sensor (WS) and presented a relevant heterogeneous algorithm. On this basis, researchers explored the deployment of sensors and access points within the wired communication range. Through simulation experiments, the outcomes demonstrate that this algorithm is superior to methods such as minimum energy routing, clustering, and splitting clustering [4]. Prabha et al. proposed a new architecture combining clustering and compressed sensing using block Tridiagonal matrix for saving the EC of sensor and receiver nodes in environmental monitoring applications; This architecture can provide effective data processing when using clustered WSN. Researchers conducted instance simulation experiments, and the final results showed that this method improved the energy utilization efficiency of nodes and effectively reduced node EC [5]. Envelope proposes a data flow management method for WSN to maximize information collection and reduce data conflicts and power consumption between network nodes. The researcher detailed the working principle and experimental details of this method, and the experiment showcased that this method could markedly diminish EC while meeting the normal use of sensors [6]. Ri et al. presented a relevant energy-saving opportunity algorithm with time slot allocation utilizing the relevant network topology. This algorithm is utilized for reducing node EC. Researchers designed relevant tests, and the outcomes illustrate that relative to current methods, this method could markedly diminish network EC [7].

Inspired by seagulls populations in nature, intelligent algorithm scholars have proposed a new SOA to simulate the migration and attack behavior of seagulls. In order to improve the accuracy of WSN NL, there are many studies that refer to and improve SOA algorithms to WSN NL problems. Balasubramanian and Govindasamy used meta-heuristic optimization algorithm to solve the NL problem in order to determine the exact location of unknown nodes in the network. Enhanced NL based on Gull Optimization (ESGOBNL) technique is used in the study.The ESGOBNL method determines the location coordinates of the sensor nodes by introducing the idea of Levy Motion (LM) in the Sorting Gull Optimization (SGO) algorithm.The experimental results of the ESGOBNL method show that it is good with a minimum Mean Localization Error (MLE) of 0.12.Compared to other techniques Compared to other techniques, Elephant Herding Optimization (EHO), Hybrid Elephant Herding Optimization (HEHO) and Tree Growth Algorithm (TGA) have a maximum MLE of 0.79, 0.33, and 0.28 respectively [8]. Dhiman et al. proposed a special version of the SOA. This algorithm utilizes technologies such as dynamic archiving concepts and network mechanisms. It utilizes a special method for finding the corresponding archived solution. In WSN NL, this method has higher positioning accuracy. The experiment demonstrates that this optimization algorithm outperforms other algorithms [9]. Ewees et al. found that the global optimization search space of current SOA is linear; This leads to the underutilization of the global search function of SOA. Therefore, researchers have presented an improved SOA utilizing lsamvy flight operator as well as mutation operator. Experiments are designed to verify the effectiveness of the improved algorithm in WSN NL. The final experiment showcases that the model is superior to other methods in global optimization, Feature selection, etc. [10].

In summary, scholars have explored a variety of optimization strategies to enhance node deployment, reduce node energy consumption, improve data processing efficiency, and improve network lifetime and connectivity performance. What is particularly striking is that SOA inspired by the behavior of seagulls in nature has been validated in a variety of application scenarios [11]. Recent studies focus on using this algorithm to accurately determine the location of unknown nodes in the network, and the enhanced NL technology based on Seagull optimization shows superior location results [12]. In addition, in order to improve the performance of the algorithm, scholars have also carried out improvements and innovations to SOA, such as introducing the concept of dynamic archiving, using specific flight and mutation operators. However, the above studies seldom pay attention to the balance between efficiency and cost. In order to further optimize the NL technology in WSN and improve efficiency and positioning accuracy while controlling costs, this study takes DV-Hop (DH) positioning algorithm as the base point to improve the calculation method of jump point and node spacing, and introduces SOA to replace the distance calculation method in the original step. Improve the accuracy of positioning algorithm. On this basis, the tent chaotic mapping (TCM) strategy is introduced to solve the problem of uneven population distribution in SOA, in order to further improve the accuracy and efficiency of the positioning algorithm, and provide more scientific suggestions for WSN NL technology.

3. **Research on improved SOADH positioning technology.** For obtaining higher precision WS positioning technology, this study introduces SOA into the commonly used DH positioning algorithm. Meanwhile, a TCM strategy is introduced to address the issue of uneven population distribution in SOA. For addressing the insufficient positioning accuracy of the traditional DH algorithm, the multi path radius is introduced for refining the minimum hop value, and the weighted Minimum mean square error is added for calculating the relevant distance.

3.1. **Design of DH positioning technology in view of SOA.** Before diving into an improved SOA, it is essential to understand the basic concepts and operational mechanisms of traditional SOA. As a heuristic optimization algorithm, SOA is inspired by the migration and foraging behavior of seagulls, and seeks the optimal solution by simulating these behaviors. SOA was presented by Professor Dhiman in 2019, and the proposed approach is seagulls' relevant behavior [13]. The SP migrates between different places to obtain food according to seasonal changes, and the predation process includes two stages: migration and predation. Figure 1 demonstrates that in the migration, seagulls will maintain the independence of individual flight according to the law, avoiding collisions with other seagulls. In the predation phase, seagulls will attack their prey in a spiral flight pattern.

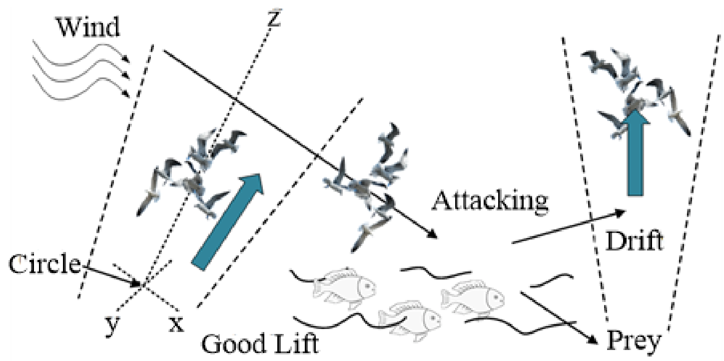

Figure 1. Schematic diagram of seagull predation behavior

The application of seagull migration behavior in algorithms can be divided into three stages, namely avoiding collisions, determining the relative direction (RD) with the optimal individual (OI), and determining the relative distance with the OI [14]. In the collision avoidance stage, the algorithm updates individual positions by introducing an additional variable value, as shown in Equation (1).

$$C_s(t) = A \times P_s(t) \tag{1}$$

In Equation (1), t serves as the current number of iterations; $C_s(t)$ serves as a new location that does not conflict with other seagulls; $P_s(t)$ serves as the current position of the seagull; A serves as the movement behavior of seagulls in a designated space; The calculation method is shown in Equation (2).

$$A = f_c(1 - t/\mathrm{Max}_{\mathrm{iteration}}) \tag{2}$$

In Equation (2), f_c serves as the control factor, usually set to 2; $\mathrm{Max}_{\mathrm{iteration}}$ is the maximum number (MAN) of iterations. Seagulls will determine their RD with the current OI while avoiding collisions, as shown in Equation (3).

$$M_s(t) = B \times (P_{b_s}(t) - P_s(t)) \tag{3}$$

In Equation (3), $M_s(t)$ represents the RD to the OI; $P_{bs}(t)$ represents the position of the OI; B is a random number (RN) that balances global search and local search, and the relevant expression is demonstrated in Equation (4).

$$B = 2 \times A^2 \times rd \tag{4}$$

In Equation (4), rd represents a RN uniformly distributed within $[0, 1]$. When the seagull successfully determines the relative distance to the OI, it enters the stage of determining the relative distance to the OI. The calculation method for distance $D_s(t)$ is showcased in Equation (5).

$$D_s(t) = |C_s(t) + M_s(t)| \tag{5}$$

During the predatory attack phase of seagulls, when they discover prey, the SP gathers into a spiral shape (SS) and hunts by continuously improving the angle and speed of the attack. In the Cartesian coordinate system, this motion behavior could be expressed by Equation (6).

$$\begin{aligned} r &= u \times e^{av} \\ x &= r \times \cos(\alpha) \\ y &= r \times \sin(\alpha) \\ z &= r \times \alpha \end{aligned} \tag{6}$$

In Equation (6), r serves as the radius of motion of the seagull's spiral flight; α represents the attack angle of the seagull, which is a RN in the $[0, 2\pi]$ interval that follows a uniform distribution; u and v are constants in the SS, usually taken as 1; xyz represents the three axes of the coordinate system, from which the final attack position $P_s(t)$ of the seagull could be drawn as shown in Equation (7).

$$P_s(t) = D_s(t) \times x \times y \times z + P_{bs}(t) \tag{7}$$

Through the above calculation, the design of SOA can be summarized into five steps. Firstly, it initializes the frequency f_c and spiral parameters u, v, etc., and initializes the position of each individual in the initial SP. Secondly, it calculates the fitness value (FV) of each one and finds the optimal location through sorting. Next, it performs a cyclic iteration to update the seagull position, recalculates the fitness of each one, and selects the optimal location by comparing with the previous one. Finally, it loops to the MAN of iterations to end the algorithm. In view of SOA, this study selects the DH LA as the basic algorithm for WSN NL. By gradually improving the problems in this algorithm, better network NL techniques are obtained [15]. The DH LA is separated into three. Firstly, the minimum number (MN) of hops between nodes is obtained, and then the average hop (AH) distance of each beacon node (BN) is calculated in view of the coordinates of the BN. The relevant expression is indicated in Equation (8).

$$HopSize_i = \frac{\sum_{i \neq j} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i \neq j} h_{ij}} \tag{8}$$

In Equation (8), $HopSize_i$ serves as the AH distance of BN i; (x_i, y_i) and (x_j, y_j) serve as the coordinates of BN i and BN j; h_{ij} is the MN of hops between two BN. The unknown node (UN) determines its own hop distance in view of the nearest BN, and the distance d_{iu} between the two is obtained by the number of hops with the BN. The calculation method is shown in Equation (9).

$$d_{iu} = HopSize_i \times h_{iu} \tag{9}$$

In Equation (9), h_{iu} is the MN of hops between the UN and the BN. Finally, the UN are located using a special method. This study replaces the step of calculating the position coordinates of UN in the DH LA with SOA, and obtains an improved DH LA in view of SOA. The relevant details are illustrated in Figure 2.

The estimated distance in each BN and an UN is demonstrated in Equation (10).

$$dis_i = HopSize_i \times h_i \tag{10}$$

Assuming that there are a total of n BN in the monitoring environment, namely $B_1, B_2, \cdots, B_n$; The corresponding coordinates are $(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)$, then the distance in the UN (x, y) and each BN is $dis_1, dis_2, \cdots, dis_n$. If the error in the estimated

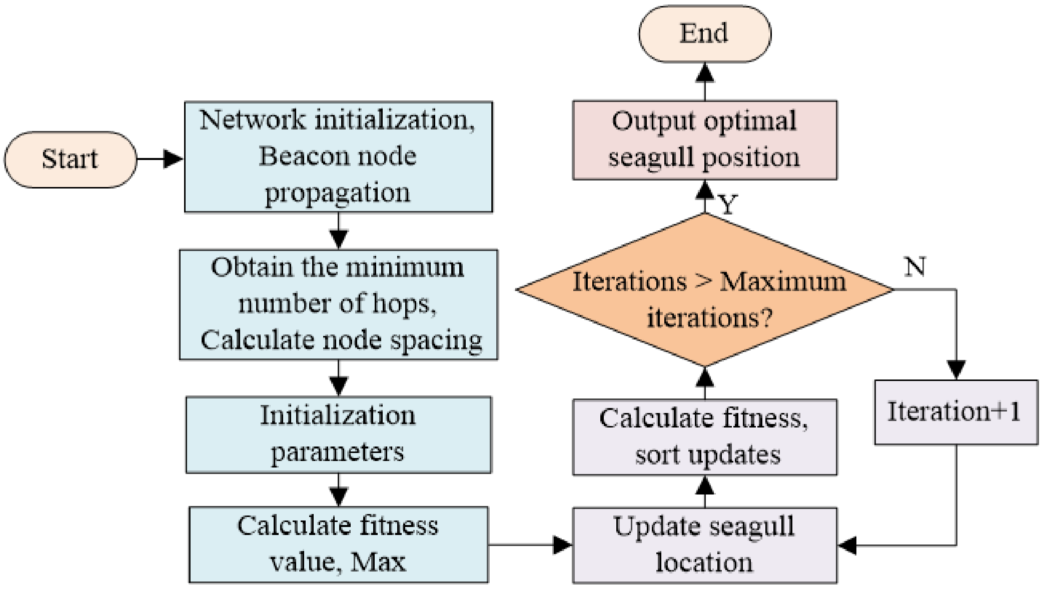

Figure 2. Flow chart of DH improved LA in view of SOA

distance and the actual distance in the UN and any BN m is set to e_m, the calculation method is illustrated in Equation (11).

$$e_m = |(x - x_m)^2 + (y - y_m)^2 - dis_m^2| \tag{11}$$

In Equation (11), (x_m, y_m) is the coordinate of BN m. The sum of errors at each point is calculated as the fitness function in SOA, and Equation (12) is obtained.

$$F = \sum_{m=1}^{n} e_m \tag{12}$$

By incorporating the fitness function into the calculation of Figure 3 SOA, the UN position coordinates could be drawn, which completes the localization of WSN nodes.

3.2. **Design of weighted DH LA for improving SOA.** Although SOA has shown excellent performance in many applications, in dealing with the complex and dynamic problems in WSN, it faces the problem of population diversity and reduced optimization speed caused by the uneven distribution of seagull populations. In order to overcome these limitations and further improve the effectiveness of SOA, we studied the introduction of tent chaos mapping strategy to improve the initialization of seagull population. It is demonstrated in Figure 3 [16].

The relevant expression is shown in Equation (13).

$$x_{t+1}^i = \begin{cases} 2x_t^i, & 0 \le x_t^i \le 0.5 \\ 2(1 - x_t), & 0.5 \le x_t^i \le 1 \end{cases} \tag{13}$$

In Equation (13), $i = 1, 2, \cdots, n$, it serves as the size of the population. $t = 1, 2, \cdots, d$, it serves as the spatial dimension [16]. It selects d initial values to obtain d chaotic sequences x_i^t, and initializes the population through inverse mapping. The calculation method is shown in Equation (14).

$$y_i^t = lowbound_i + (upbound_i - lowbound_i)x_i^t \tag{14}$$

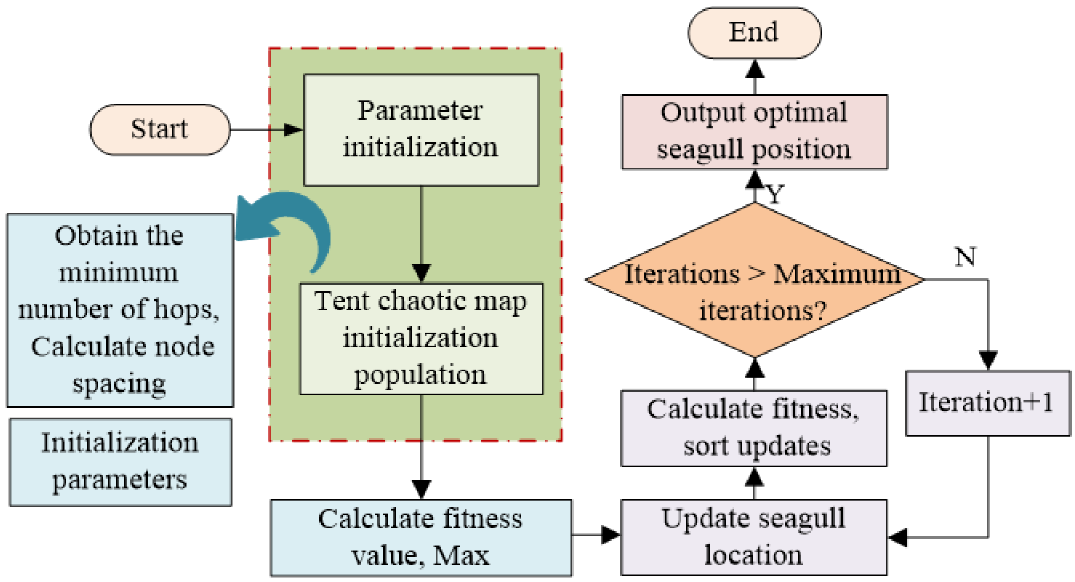

Figure 3. Algorithm flow after introducing TCM strategy

In Equation (14), $lowbound_i$ and $upbound_i$ are the lower and upper boundaries for the search of chaotic sequence x_i^t. Secondly, after improving the SOA, to further obtain more accurate positioning coordinates, this study obtained an improved weighted DH positioning algorithm in view of multiple communication radii by improving the minimum hop count and AH distance calculation methods of DH. To improve the calculation method of minimum hop count, this study introduces multiple communication radius (CR) refinement to reduce errors. The hop count calculation formula is demonstrated in Equation (15).

$$h = \frac{i}{n}, \frac{(i-1)R}{n} < d < \frac{iR}{n}, i = 1, 2, \cdots, n \tag{15}$$

In Equation (15), h serves as the quantity of inter-node hops; n serves as the quantity of concentric circles in the CR; R is the CR, usually 3. After refining the hop count, the study utilizes a correction factor for performing a secondary correction on the hop count of the BN. The correction method is indicated in Equation (16).

$$h' = 1 - \left(1 - \frac{d}{R \times hop}\right)^2 \times h \tag{16}$$

In Equation (16), d represents the distance between BN; hop serves as the estimated hop count after refining the multiple communication radii [17]. The second improvement to the DH LA is the improvement of the AH distance. Research has shown that the AH distance between nodes follows Gaussian distribution characteristics; In view of Equation (8), the research introduces Minimum mean square error for addressing the AH distance, and uses the weighting method for reducing the positioning error (PE) between UN and BN. It is demonstrated in Equation (17).

$$avgHopSize = \sum_{i=1}^{n} w_i \times \frac{\sum_{j=1}^{n} h_{ij} \times d_{ij}}{\sum_{j=1}^{n} h_{ij}^2} \tag{17}$$

In Equation (17), w_i represents the weight, and the closer the distance in UN and BN, the greater the weight [19]. d_{ij} is the distance in two BN, calculated utilized a special method. The overall process of the improved SOA based weighted DH LA is indicated in Figure 4.

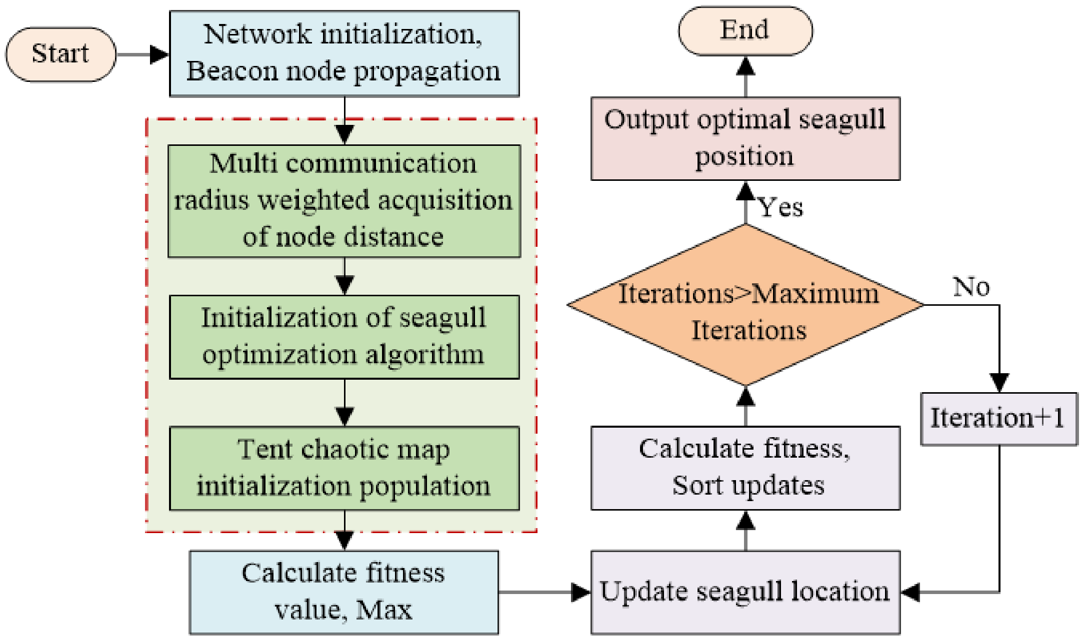

Figure 4. Flow chart of weighted DH LA in view of multiple communication radii and improved SOA

In Figure 4, the overall improved LA can be separated into 7 steps. Firstly, the method of multiple communication radii is utilized for refining the MN of hops in nodes. It sets the quantity of concentric circles in the CR to 3, and propagates the data of each BN to the sensor through broadcast packets. Second, according to Equation (17), the distance in UN and BN is counted using the improved weighted Mean squared error. Fourthly, through early experiments, in order to ensure that the algorithm has sufficient search ability and computational efficiency balance, the number of seagulls is set at 30. The frequency f_c is chosen as 2 to provide the stability of the algorithm and avoid overfitting. The spiral parameter uv is uniformly set to 1 to simplify the model and enhance the stability of the algorithm, while ensuring similar results in different runs. Fifthly, it calculates the FV of each seagull in view of the fitness function and ranks it to obtain the optimal seagull position. Sixth, it calculates the position of seagulls after updating their predatory behavior through SOA, and determines whether the updated position is within the search range through a judgment function. Seventh, it iteratively iterates the seagull position until the MAN of iterations is achieved, and outputs the result. For evaluating the WS positioning algorithm used in this research institute, the indicator PE was used for evaluation, and its calculation method is shown in Equation (18) [20].

$$error = \frac{\sum_{i=1}^{N} \sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2}}{NR} \tag{18}$$

In Equation (18), N serves as the quantity of UN; $(\hat{x}_i, \hat{y}_i)$ serves as the estimated coordinate value of UN; (x_i, y_i) is the actual coordinate value of the UN. To ensure the fairness and objectivity of algorithm evaluation, the PE evaluation of the method will be compared by removing the average value after multiple iterations.

4. **Performance experimental analysis of improved SOA weighted DH LA.** In order to ensure the stability and effectiveness of the experiment, the experiment is carried out in the software MATLAB R2021b version, which provides a rich mathematical toolbox and powerful numerical calculation ability to support complex algorithm testing. In order to simulate the real wireless sensor network environment, a square area with a side length of 100m is set as the experimental search environment, and the space is large enough to make the node layout and search practical. The population size is set at 30 to strike a balance between computational complexity and search power; The maximum number of iterations of 500 ensures that the algorithm has a sufficient chance of approaching or reaching an optimal solution without prematurely terminating or consuming computing resources excessively. Dimension 5 is based on the actual needs of the problem, ensuring that the algorithm can accurately estimate the location of unknown nodes; The number of weighted multiple communication radii is set to 5 in order to divide the minimum number of hops between nodes more carefully and enhance the accuracy of positioning. The experiment sets the quantity of BN, the quantity of UN, and the CR as independent variables. Through changing the variable values, the influence of experimental variables on PE is analyzed, and the algorithm's function is estimated. When using an improved SOA for calculation, data such as the search history of the SP, the movement trajectory, and the average FV will be obtained, as well as the initial, mid-term, and later stages of the iteration will be selected for comparison; The initial situation is shown in Figure 5.

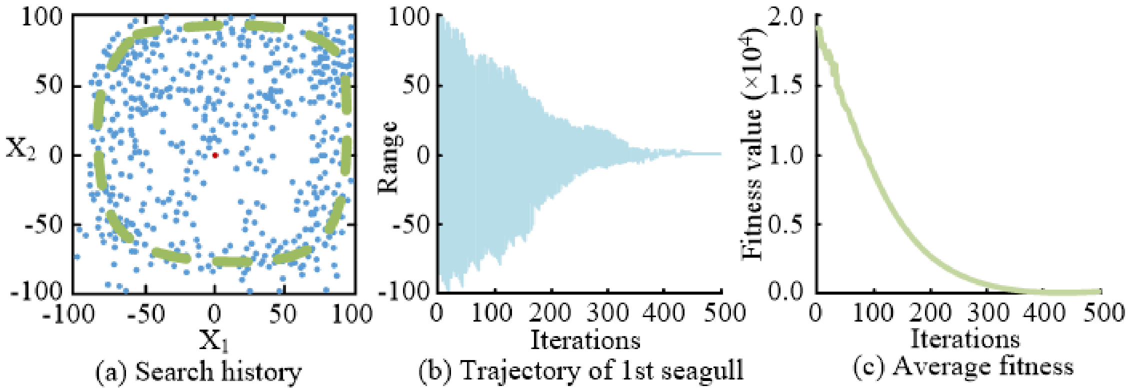

Figure 5. Improving the initial iteration pattern of SOA

In Figure 5, the center of the 200 meter search range is taken as the coordinate origin; At the beginning of the iteration, the SP showed no obvious spiral distribution trend within the search range and showed a random distribution state. Figure 6 (b) clearly shows that with the quantity of iterations grows, the trajectory tends towards the center of the search range. As the iterations' quantity is between 300 and 400, the motion trajectory tends to stabilize. The average FV of the SP gradually decreased from the initial 4 * 104. The mid-term iteration pattern is shown in Figure 6.

Figure 6 (a) shows that in the middle of the iteration, the entire SP exhibits a circular distribution trend and gradually begins to spiral towards the optimal seagull individual. The iterative motion trajectory of the optimal seagull is shown in Figure 7 (b). The individual seagull basically moves within a radius of 1m, maintaining the basic position of the entire SP. As the iterations' quantity reaches 300, its motion trajectory tends to

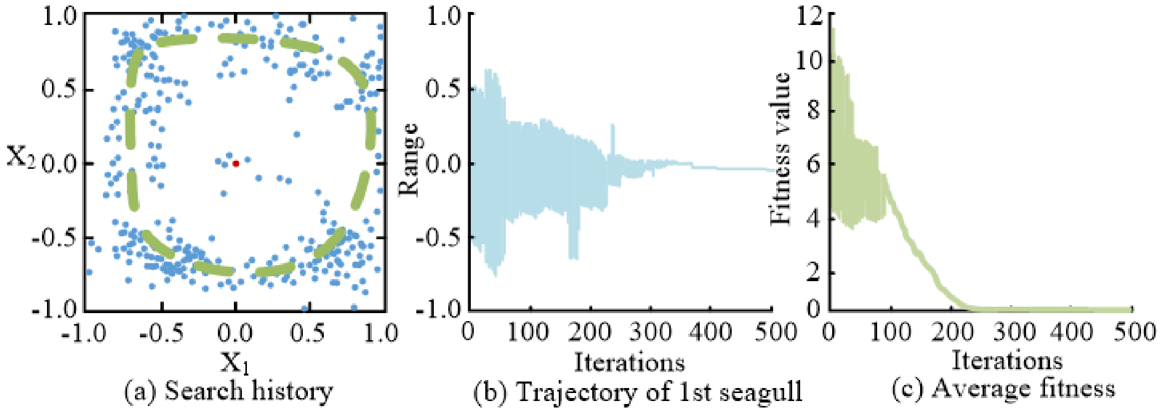

Figure 6. Improving the mid-term iteration pattern of SOA

stabilize. The average FV remains between 4 and 12 within 100 iterations and shows a decreasing trend; After 100 iterations, the average FV tends to 0. The pattern of the later iteration is shown in Figure 7.

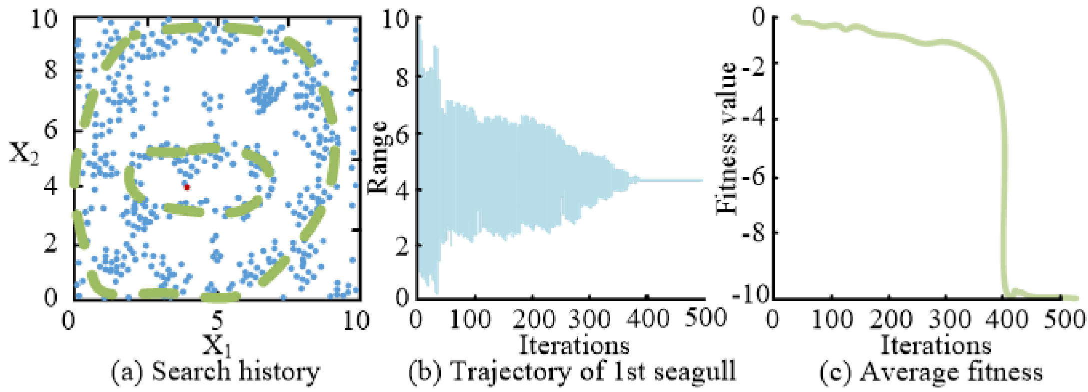

Figure 7. Improving the post iteration pattern of SOA

Figure 7 shows that in the later stages of the iteration, the entire SP exhibits a spiral distribution state. At this point, the average FV of the SP is shown in Figure 7 (c). As the iterations' quantity approaches 400, the FV rapidly diminishes from 0 to around -10. Meanwhile, the experiment used the original DH algorithm, the improved Three CR DH algorithm (3DH) The improved Multi CR weighted DH algorithm (W-DH) and the SOA based DH algorithm (SOA-DH) were analyzed with the improved SOA based Multi CR weighted DH algorithm (SOA-WDH) proposed at the end of the experiment. When exploring the influence of the quantity of BN in positioning technology on the algorithm, the experiment set the CR to 80m, the quantity of summary points (SPO) to 200, and the initial quantity of BN to 10, increasing by 10 intervals until it reaches 40

In Figure 8, all five algorithms show a downward trend as the quantity of BN increases. The original DH algorithm has the largest PE, while the weighted multi CR DH positioning algorithm in view of improved SOA has the smallest PE. Before the quantity of BN grows to 20, the trend of PE in each algorithm shows a rapid decline, and the PE show a slow decline trend between 20 and 80 intervals. The average error (AE) values of different algorithms under the quantity of BN are demonstrated in Table 1.

In Table 1, the average PE of the five algorithms is ranked from high to low as DH (0.3081m)¿SOA-DH (0.2231m)>3DH (0.1823m)>W-DH (0.1054m)>SOA-WDH (0.0847m).

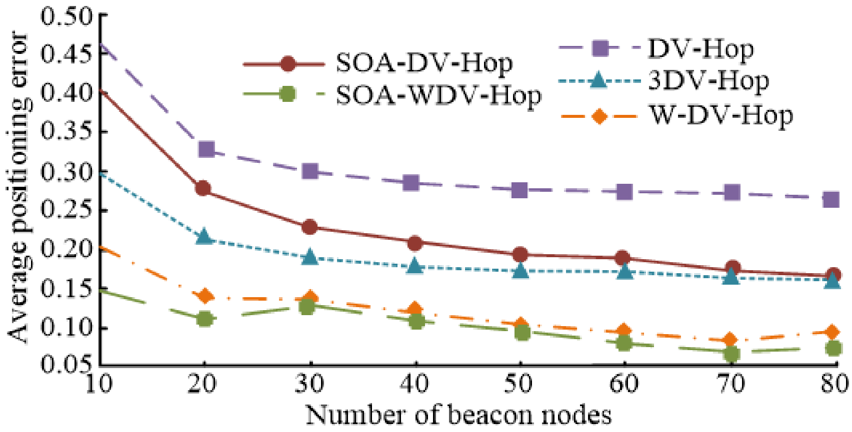

Figure 8. The influence curve of the number of BN on PE under different algorithms

Table 1. The Quantity of BN Corresponds to the AE of Each Algorithm

Number of BN	**DV-Hop (m)**	**3DV-Hop (m)**	**W-DV-Hop (m)**	**SOA-DV-Hop (m)**	**SOA-WDV-Hop (m)**
10	0.4752	0.2958	0.2085	0.4130	0.1332
20	0.3276	0.2016	0.1210	0.2713	0.0939
30	0.2998	0.1786	0.1007	0.2229	0.1144
40	0.2827	0.1661	0.0906	0.2005	0.0923
50	0.2750	0.1592	0.0845	0.1838	0.0788
60	0.2717	0.1591	0.0818	0.1787	0.0605
70	0.2695	0.1502	0.0799	0.1614	0.0480
80	0.2629	0.1478	0.0762	0.1533	0.0562
Mean	0.3081	0.1823	0.1054	0.2231	0.0847

The average PE of the SOA-WDH algorithm is 0.2234m below the original DH positioning algorithm. When exploring the impact of SPO on algorithms in positioning technology, the experiment sets the initial SPO to 100, increasing by 50 intervals until reaching the maximum value of 450. The quantity of BN is set to 10% of the total number of points, and the CR is set to 50m. The average PE trend presented by the five algorithms in the experimental results is shown in Figure 9.

In Figure 9, the total of summarized points for the five positioning algorithms is inversely proportional to the PE, with the original DH algorithm having the highest PE. Before the total number of nodes increased to 200, the trend of the PE of each algorithm showed a rapid decline, and after 200, the PE showed a slow downward trend. As the calculation methods of UN spacing vary, the PE difference among the three distance calculation methods increases as the SPO's quantity grows. The AE values of each algorithm under different SPO are indicated in Table 2.

In Table 2, the PE of adding SOA is about 0.1 below the original DH algorithm, and the average PE of the improved SOA-WDH algorithm in view of SOA is 0.195m lower than that of the original DH algorithm. This clearly indicates that the improved SOA proposed in the study has higher positioning accuracy. When exploring the impact of BN CR on the algorithm in positioning technology, the experiment sets the quantity of SPO to 200, the quantity of BN to 20, and the initial CR is 50m, increasing at intervals

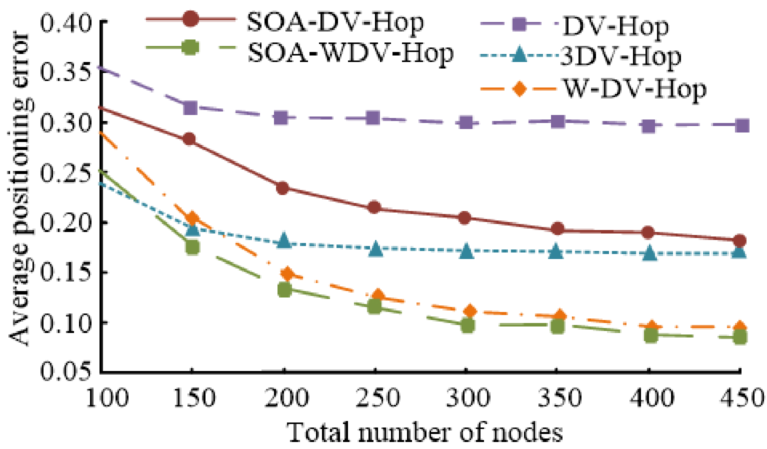

Figure 9. The influence curve of summarizing points on pe under different algorithms

Table 2. Summarize the AE Values of Each Algorithm Corresponding to the Quantity of Points

Total number of nodes	**DV-Hop (m)**	**3DV-Hop (m)**	**W-DV-Hop (m)**	**SOA-DV-Hop (m)**	**SOA-WDV-Hop (m)**
100	0.3375	0.2100	0.2672	0.2950	0.2258
150	0.2965	0.1642	0.1667	0.2589	0.1446
200	0.2862	0.1483	0.1137	0.2086	0.0977
250	0.2847	0.1429	0.0862	0.1861	0.0791
300	0.2791	0.1392	0.0739	0.1757	0.0600
350	0.2818	0.1384	0.0663	0.1633	0.0597
400	0.2779	0.1356	0.0544	0.1542	0.0487
450	0.2776	0.1356	0.0542	0.1511	0.0459
Mean	0.2902	0.1518	0.1103	0.1999	0.0952

of 10m until the radius increases to 120m. The average PE trend presented by the five algorithms in the experimental results is shown in Figure 10.

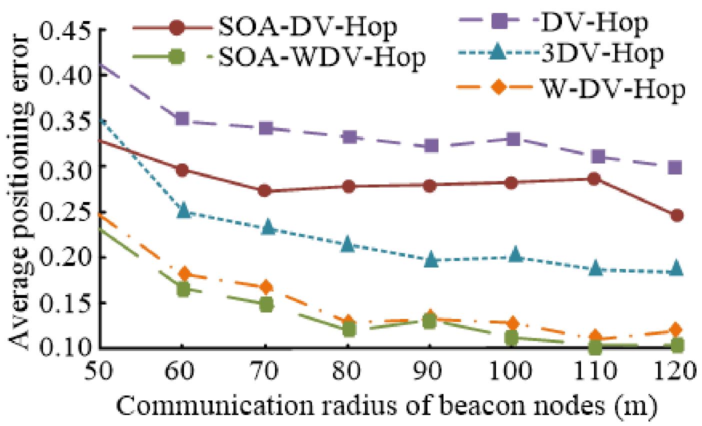

Figure 10. The impact curve of CR on PE under different algorithms

Figure 10 showcases that the total number of summarized points for the five positioning algorithms is inversely proportional to the PE. The original DH algorithm has the highest PE, ranging from 0.3m to 0.42m. The multi-path weighted DH algorithm for improving SOA has the smallest PE, ranging from 0.1m to 0.25m. The AE values of different algorithms under different communication radii are demonstrated in Table 3.

Table 3. The AE Value of Each Algorithm Corresponding to the CR

CR (m)	**DV-Hop (m)**	**3DV-Hop (m)**	**W-DV-Hop (m)**	**SOA-DV-Hop (m)**	**SOA-WDV-Hop (m)**
50	0.4119	0.3448	0.2910	0.3234	0.2131
60	0.3454	0.2369	0.1743	0.2904	0.1417
70	0.3373	0.2140	0.1344	0.2668	0.1245
80	0.3261	0.1938	0.1135	0.2735	0.0938
90	0.3135	0.1768	0.0953	0.2733	0.1058
100	0.3239	0.1811	0.0927	0.2771	0.0842
110	0.3017	0.1660	0.0841	0.2805	0.0740
120	0.2877	0.1633	0.0805	0.2384	0.0724
Mean	0.3309	0.2096	0.1332	0.2779	0.1137

In Table 3, the PE of adding SOA is 0.12m smaller than the original DH algorithm. The average PE of the improved SOA-WDH algorithm in view of SOA is 0.2172m lower than the original DH positioning algorithm, and 0.1642m lower than the original positioning algorithm incorporating SOA. This indicates that the multi path weighted DH LA in view of improved SOA possesses higher localization and better localization in WSN.

5. **Conclusion.** WSN has become an important component of environmental monitoring, health monitoring, and many other fields. In WSN, NL is the key technology, as it directly influences its performance and application. This study proposes a solution in view of an improved SOA algorithm for NL in WSN. This study will introduce improved SOA into LA and construct a multi path weighted DH LA in view of improved SOA; In the simulation experiment, when analyzing the influence of the total of nodes on the algorithm, the total of SPO for the five positioning algorithms is inversely proportional to the PE; The PE of SOA-DH is 0.12m smaller than the original DH algorithm; The average PE of the SOA-WDH algorithm is 0.22m below the original DH positioning algorithm. When analyzing the influence of BN CR on the algorithm, the original DH algorithm has the largest PE, ranging from 0.3m to 0.42m. The SOA-WDH algorithm has the smallest PE, ranging from 0.1m to 0.25m. These results fully prove the significant advantages of improved SOA (ISOA) in improving the positioning accuracy of WSN nodes. Applying ISOA to practical scenarios, such as indoor positioning of large buildings, emergency response at disaster sites, and even agricultural monitoring, will significantly improve the performance and reliability of WSN. In these applications, ISOA is able to locate each node more precisely, thus optimizing the data collection and distribution process of the network and improving the overall network efficiency.

Although this research has achieved remarkable results in improving the precision of wireless sensor network node positioning, there are still some important problems that cannot be covered. First of all, the research mainly focuses on the theoretical improvement and simulation experiment verification of the algorithm. The impact of complex factors in the actual physical environment, such as multipath effect, node failure and environmental noise, on the performance of the algorithm has not been fully discussed. Future work will focus on testing and optimizing ISOA algorithms in more diverse and uncertain real-world application environments. In addition, the performance of the algorithm in terms of energy efficiency and network scale scalability is also a key direction for future research. With the continuous expansion of the application range of WSN, how to effectively manage energy consumption and adapt to the needs of large-scale networks while maintaining high positioning accuracy will be an important topic to promote the development of this field.

Acknowledgment. The research is supported by Supported by Scientific and Technologial Innovation Programs of Higher Education Institutions in Shanxi, Practical Operation Platform for Simulating Electrical Control System in Intelligent Manufacturing, (No. 2020L0766).

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