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Application of Improved DV-Hop algorithm in Wireless Sensor Network

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Abstract: To improve the problem of inaccurate wireless sensor network positioning algorithm of DV-Hop node is proposed. Firstly, the optimization scheme of the anchor nodes is completed by calculating the triangle area of the anchor nodes. Furthermore, the particle group optimization algorithm combines the genetic chaotic particle group theory, and finally, the improved particle group algorithm is used to correct the node position obtained by the DV-Hop algorithm. The simulation experiments show that improving the DV-Hop algorithm compared with the traditional D V-Hop algorithm to monitor the underground leakage accident position more accurately.

Keywords: Particle swarm algorithm; Genetic algorithm; DV-Hop; Wireless sensor network.

1. Introduction

With the development of wireless communication technology, wireless sensor network (WSN) is increasingly used in coal mines.among DV-Hop[1-2]As a no-need ranging and positioning algorithm, it is very suitable for WSN node positioning under the mine. Many optimization algorithms have been improved to reduce localization error and improve localization accuracy [3-7]. document [3] The ant colony particle swarm algorithm is introduced into the unknown node computation stage of the DV-Hop algorithm to improve the localization accuracy. Document [4] The problem of collinear anchor nodes is removed by using the angle comparison principle of the multilateral measurement method. Document [5] The frog algorithm is introduced to solve the average per hop distance, thus reducing the node localization error and making it closer to the actual value. These algorithms contribute to some extent to optimize the performance of the DV-Hop algorithm, but they still have shortcomings. Based on the DV-Hop positioning algorithm, an anchor node optimization method avoids the problem that the nodes cannot be located, and proposes a DV-Hop improvement scheme based on the genetic chaotic particle swarm algorithm to reduce the average positioning error of downhole distribution network faults and improve the positioning accuracy.

2. Analysis and improvement of the DV-Hop algorithm

2.1. DV-Hop algorithm

The DV-Hop algorithm process is located as follows:

Step 1 anchor node will its own information (ID, coordinates, anchor receiving information node jump) through the flood, the initial value of jump is set to 0, each critical point received the information and update the minimum jump, and jump number plus 1, and continue to forward to the neighbor node, this rule to obtain the unknown node from each anchor node minimum jump value.

Step 2 takes the jumps of other anchor nodes and the average distance per jump of the anchor node is calculated according to Eq. (1).

$$d_{isa}=\frac{\sum_{i\neq j}\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}}{\sum_{i\neq j}hc_{ij}} \tag{1}$$

In this Eq.: (x_i, y_i) and (x_j, y_j) are the coordinates of anchor nodes i and j. hc_{ij} is the minimum number of jumps between anchor node i and node j.

Step 3: Using the three-sided measurement method, the distance between the unknown node A0 and the anchor nodes A1, A2, and A3, as shown in Figure 1, is calculated by Eq.(2).

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

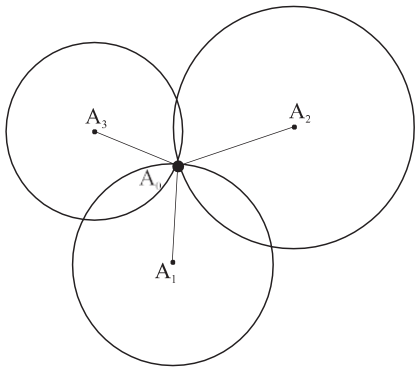

Figure 1. Schematic diagram of the trilateral measurement method

Convert Eq. (2) to the format of Eq. AX =P:

$$A=\begin{bmatrix}(x_1-x_k) & (y_1-y_k)\\ (x_2-x_k) & (y_2-y_k)\\ \vdots & \vdots\\ (x_{k-1}-x_k) & (y_{k-1}-y_k)\end{bmatrix} \tag{3}$$

$$X=\begin{bmatrix}x\\ y\end{bmatrix} \quad 4)$$

$$P=\frac{1}{2}\begin{bmatrix}x_1^2-x_k^2+y_1^2-y_k^2+d_k^2-d_1^2\\ x_2^2-x_k^2+y_2^2-y_k^2+d_k^2-d_2^2\\ \vdots\\ x_{k=1}^2-x_k^2+y_{k-1}^2-y_k^2+d_k^2-d_{k-1}^2\end{bmatrix} \tag{5}$$

Using least squares estimation:

$$X = (A^T A)^{-1} A^T P \tag{6}$$

2.2. Deficiency of the D V-Hop algorithm

(1) The topological relationship of anchor nodes will directly affect the positioning accuracy of wireless sensor nodes. Figure 2 shows the distribution of wireless sensor nodes in the underground coal mine power grid [8]. Due to the long and narrow geographical environment of the underground coal mine, the sensors in the distribution network cannot meet the requirements of uniform layout during installation, which will produce the sensor node collinear or approximate collinear situation, neither of which can achieve the node positioning. Therefore, the removal of collinearity and the selection of suitable anchor nodes becomes a key problem.

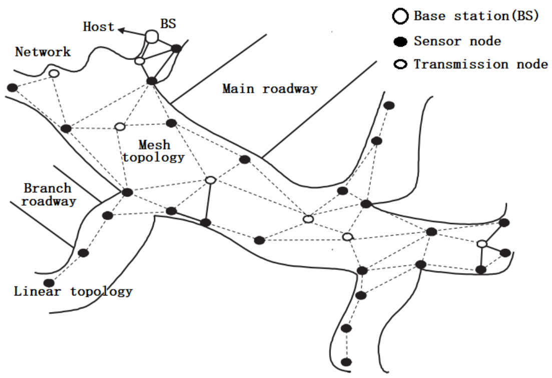

Figure 2. Distribution diagram of wireless sensors in underground coal mine power grid

In the DV-Hop algorithm, the average distance often errors with the actual value due to the influence of environment and communication. And once the error occurs, it will be cumulative to affect the subsequent calculation, and eventually lead to greater calculation errors. Therefore, the calculation error must be reduced by correcting for the unknown node coordinates.

3. Improvement of the DV-Hop algorithm

3.1. Anchor node preferred scheme

In this paper, the area of anchor node by calculating whether the anchor node is collinear:S_n

$$S_n = \begin{vmatrix} x_i & y_i & 1 \\ x_j & y_j & 1 \\ x_k & y_k & 1 \end{vmatrix} \tag{7}$$

Assume that (x_i, y_i) , (x_j, y_j) and (x_k, y_k) are the coordinates of 3 anchor nodes randomly distributed,$S_n$is the triangle area composed of anchor nodes.If $0 \le S_n \le \delta$, then these three anchor nodes are considered to be in an approximate line, so another anchor nodes are needed to assist in positioning.

3.2. Particle swarm optimization DV-Hop

The particle swarm optimization algorithm PSO (Particle Swarm Optimization) shows its unique advantages in handling optimization problems due to its excellent global search performance and fast convergence ability [9]. PSO starts from the random solution, for the n -dimensional optimization problem, randomly generates the initial population of m particles, and substitutes the flight speed V_i and position X_i of the ith particle into the optimization objective function to obtain the fitness value. After updating V_i and location X_i and iteration, the optimal solution is found. The optimal solution obtained by the ith particle search is recorded as p_i, and the current optimal solution obtained by particle swarm search is recorded as p_b, and V_i and X_i are updated by using Eq. (8) and Eq. (9).

$$X_{in}(k+1) = X_{in}(k) + V_{in}(k+1) \tag{8}$$

$$V_{in}(k+1) = \omega V_{in}(k) + c_1 r_1 (P_{in} - X_{in}(k)) + c_2 r_2 (P_{bn} - X_{in}(k)) \tag{9}$$

In the equation, c_1 and c_2 are shrinkage factors, and ω is inertia weight.

3.3. Genetic chaos particle swarm algorithm

This paper presents a genetic chaos particle swarm algorithm called GCPSO (Genetic Chaos Particle Swarm Optimization) by introducing the chaos principle and the dynamic weight adaptive regulation method.

3.3.1. Genetic algorithm

The genetic algorithm GA (Genetic Algorithm) is a development law that simulates the continuous evolution of living organisms in nature [10]. In this paper, a new generation of elites is formed by introducing the crossover and variation of GA algorithm in the PSO algorithm, and finally the optimal solution of the optimization problem is obtained.

(1) Select the crossover

Select N even individuals, then pair the selected individuals in pairs, perform cross operation, and generate offspring particles. Suppose that particle a and particle b are selected for cross operation, and the corresponding positions $X_a(t)$ and $X_b(t)$ are replaced by the following descendants:

$$X_1^k = rX_1^k + (1-r)X_2^k \tag{10}$$

$$X_2^k = rX_2^k + (1-r)X_2^k \tag{11}$$

Corresponding speed:

$$V_1^k = rV_1^k + (1-r)V_2^k \tag{12}$$

$$V_2^k = rV_2^k + (1-r)V_1^k \tag{13}$$

2) Variant operation

After crossing particles with probability P, perform the following mutation operations:

$$x_i^{k+1} = \begin{cases} x_i^k + c_i & if\ f_{itness}(x_i^k + c_i) > f_{itness}(x_i^k) \\ x_i^k & others \end{cases} \quad 14)$$

$$V_i^{k+1} = V_i^k \tag{15}$$

In the equation, c_i is the interval $\left[x^L - x_i^k, x^U - x_i^k\right]$ uniformly distributed random number, x^L and x^U are the upper and lower limits of search respectively.

3.3.2. Adaptive parameter adjustment

Chaos is a nonlinear motion which is very sensitive to initial conditions and can traverse all states. In this paper, the chaos principle is used to optimize the velocity V_i and position X_i of particles by adaptively adjusting the parameters of particle swarm optimization algorithm. Create a chaotic sequence as follows:

$$\beta^{k+1} = \lambda \beta^k (1 - \beta^k) \tag{16}$$

When $\lambda = 4$, the system will enter into a chaotic state, and the chaotic variable $\beta^t (t = 1,2,\cdots)$ will traverse all the states in the system without repetition. After that, r_1 and

r_2 are dynamically adjusted to generate an excellent population, and then lead the particles to the optimal solution through equations (8) and (9). Chaotic optimization is as follows:

$$\begin{cases} r_i^{k+1} = 4.0 \times r_i^k(1 - r_i) \\ r_i^k \in (0,1), i = 1,2 \end{cases} \tag{17}$$

Inertial weights ωplay a role in maintaining algorithmic balance in optimization. This paper chooses the dynamic weight adjustment method, and the weight update Eq. is:

$$\omega(k) = \omega_{max} - \frac{(\omega_{max} - \omega_{min})\times k}{k_{max}} \tag{18}$$

In the equation, ω_{max} and ω_{min} are the upper and lower limits of inertia weight; k is the current iteration number; k_{max} is the maximum number of iterations.

3.4. DV-Hop improvement based on genetic chaos particles

DV-Hop algorithm (GCPSO-Hop) and DV-Hop algorithm based on genetic chaos particle swarm algorithm have the same communication energy consumption, but GCPSO-Hop algorithm has slightly more computing energy consumption than DV-Hop algorithm. Since the energy consumption of the wireless sensor network is mainly generated by the communication energy consumption, so the energy consumption of the GCPSO-Hop positioning algorithm meets the application conditions. This paper targets f_i as the minimum localization error:

$$f_i = \sum_{i=1}^{n} d_k - \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{19}$$

In the equation, (x, y) is the coordinate of the unknown node, (x_i, y_i) is the coordinate of the anchor node, and d_k is the actual measured distance. The fitness function is: The fitness function is:

$$f_{itness}(x) = \sum_{i=1}^{n} \alpha_i f_i(x, y) \tag{20}$$

In the equation, α_iA is the inverse ratio of the number of hops of unknown node and anchor node i; n is the number of unknown nodes. In this paper, we use the GCPSO algorithm to correct the coordinates of unknown nodes found in the later part of the DV-Hop algorithm. The specific optimization steps are as follows:

Step 1 The average hop distance d_{isa} and the minimum hop number h_{cij} are obtained through step 1 and Step 2 of the DV Hop algorithm.

Step 2 Initialize particle swarm. Initialize particle velocity V_i and position X_i, and set the number of iterations $k = 0$.

Step 3 Calculate the fitness value f_{itness} according to equation (20).

Step 4 Compare the fitness of each particle. The individual optimal solution in the group is set as P_i, and the global optimal solution is set as P_b.

Step 5 Update the velocity V_i and position X_i of particles according to Formula (8) and Formula (9).

Step 6 Determine whether the algorithm is terminated. If the maximum number of iterations is reached, the optimal solution will be output; otherwise, go to Step 7.

Step 7 Randomly select M individuals according to the fitness value, and perform cross operation on them to obtain M new individuals.

Step 8 Perform mutation operation on all individuals, select N individuals with high fitness from $M + N$ to enter the next generation, and return to Step 3.

4. Experimental Simulation and Results analysis

To verify the effectiveness of the improved algorithm, sensor nodes are randomly generated in a simulation region of 100 m×100 m. Simulation experiments using MATLAB for GCPSO-Hop, DV-Hop, GA-Hop and Posho, and analyze the results were analyzed. The absolute positioning error is:

$$e = \sqrt{(x - x_e)^2 + (y - y_e)^2} \tag{21}$$

Relative definition error is:

$$\hat{e}_{err} = \frac{\sum_1^n e_{err}}{R} \tag{22}$$

In the equation, (x, y) is the actual coordinate of the unknown node, (x_e, y_e) is the estimated coordinate, and R is the communication radius. Set $c_1 = c_2 = 2.0$, $\omega_{max} = 0.9$, $\omega_{min} = 0.4$, genetic crossover probability $P = 0.85$, population size of each generation $N = 40$, and iteration number $k = 200$.

communication radius. Setting, genetic crossing probabilities, size of the population per generation, number of iterations.

Because the coal mine underground roadway is narrow and slender and the open space is limited. In order to reduce the error of the node communication, reducing the distance between the deployment paving nodes and adding the redundant nodes is adopted to ensure the communication between the nodes. In addition, a denser single-chain deployment mode is adopted in the narrow width lanes to ensure the communication quality between nodes. In order to test the performance of this algorithm, the experimental platform of simulated ZigBee wireless sensor distribution network is built. A schematic diagram of the experimental platform is shown in Figure 3. The power supply is a three-phase current source, the single-phase output current is 1 A~100 A, the isolation transformer ratio is 1:1, R is the protection resistance, A, B and C are three-phase upper current sensors. Once the circuit in the grid ground fault, the three-phase line loses balance will appear zero order component. After the signal adjustment circuit, the 0~3.3V voltage signal is output, and then converted into a digital signal by the A / D converter, and ultimately conducive to the ZigBee wireless technology transmission to the terminal. Table 1 shows the zero-order current of the measured alignment lines.

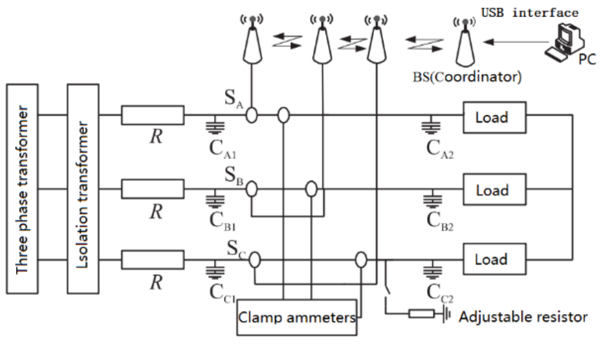

Figure 3. Schematic diagram of the experimental platform structure

Figure 4 is a random distribution plot of the nodes. The asterisk is the unknown node, and the cross symbol is the anchor node. At this time, the anchor node is approximately collinear with the underground coal mine. Figure 5 shows the localization effect of undetecting collinearity and excluding cololllinearity. As shown in Figure 5 (a) and Figure 5 (b), the localization effect after excluding collinearity scheme is better, which can effectively reduce the average localization error of nodes.

Table 1. Zero-order current error of transmission line measured by wireless sensor network

Order number	Line zero-order current / A	WSN detects zero-order current / A	Error /%
1	1.00	1.03	3.00
2	3.00	3.14	4.67
3	5.00	5.24	4.80
4	7.00	7.36	5.14
5	9.00	9.58	6.44
6	11.00	10.46	4.91
7	13.00	13.46	3.54
8	15.00	15.63	4.20
9	17.00	16.60	2.35
10	19.00	18.71	1.53
11	20.00	20.85	4.25
average error	-	-	4.08

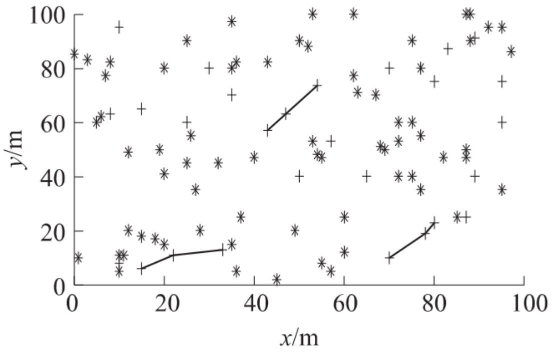

Figure 4. Random distribution of the nodes

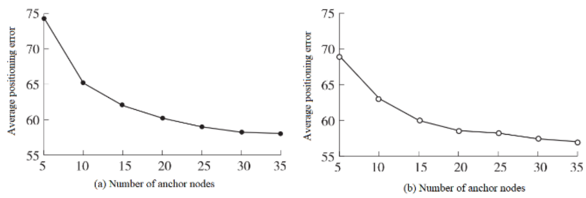

Figure 5. excluded the localization mean error comparison before and after being approximately collinear

Figure 6 shows the change curve of the average total number of anchor nodes between 5% and 35%. It can be seen from the figure that the average localization error of the four localization algorithms is constantly decreasing as the proportion of anchor nodes increases, and the localization performance of the GCPSO-Hop algorithm shows obvious advantages. At the anchor node ratio of 35%, the GCPSO-Hop algorithm has the smallest average localization error and was 11.16% lower than DV-Hop. It show that GCPSO-Hop algorithm can improve node localization accuracy and reduce localization error.

Figure 7 shows the relationship of the average localization error with the number of nodes with the same proportion of anchor nodes. As the number of nodes increases, the average localization error all decreases and gradually stabilizes. The average localization error of both the GA-Hop algorithm and the PSO-Hop algorithm was smaller than that of the DV-Hop algorithm, but it did not reach the optimization. Since the GCPSO-Hop algorithm is more accurate on the location correction obtained from the localization, the average localization error is smaller.

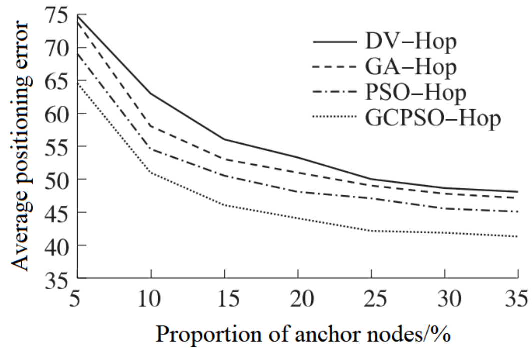

Figure 6. The average localization error changes with the proportion of the anchor nodes

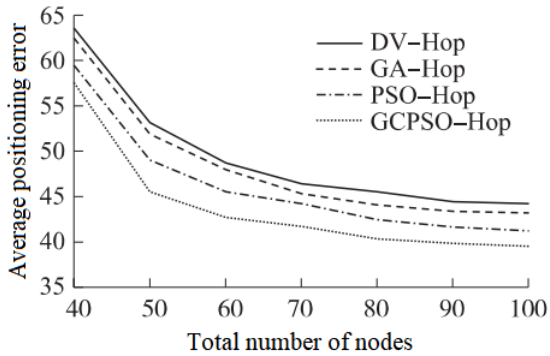

Figure 7. Changes of the average localization error with the number of nodes

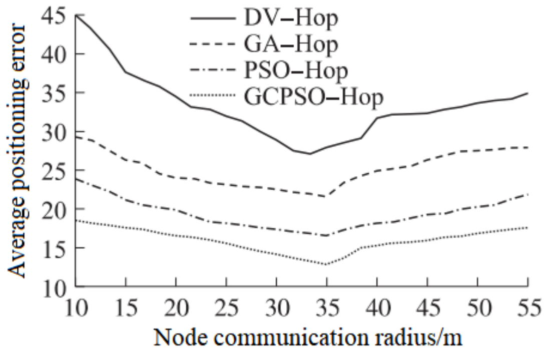

Figure 8. Average localization error along with the node communication radius relationship

For a more comprehensive analysis of the performance of the GAPSO-Hop algorithm. Figure 8 shows the average localization error change curve of the nodes at different communication radii when the anchor node ratio is 20%. It can be seen from the simulation results that when R hours as the communication radius increases, the average localization error begins to decrease.

For example, at R = 10 m, the average localization error of the nodes of the GCPSO-Hop algorithm was reduced by 23.8% compared with that of the DV-Hop algorithm. When R is greater than 35m, although the connectivity change of the network increases the localization error as the communication radius increases. But then the GAPSO-Hop algorithm is still the best of all the algorithms. To verify the effectiveness and accuracy of the GCPSO-Hop algorithm, six positioning nodes were selected in the underground coal mine for the validation experiment, and the experimental data are shown in Table 2. In Table 2, the actual coordinates of nodes are (x, y) and the measured coordinates are (x_e, y_e) . From the actual measurement results, we can see that the GCPSO-Hop algorithm is closer to the actual value than other algorithms, and thus has smaller localization error and higher accuracy.

Table 2. Actual measurement results

panel point	Actual coordinates (x, y) / m	Measured coordinates (x_e, y_e) / m		
		GA-Hop	PSO-Hop	GCPSO-Hop
1	(3.22, 1.14)	(4.10, 2.10)	(3.92, 1.73)	(3.32, 1.41)
2	(5.53, 2.11)	(4.6, 3.23)	(6.10, 1.64)	(5.90, 2.51)
3	(6.34, 3.21)	(7.12, 4.62)	(5.84, 4.27)	(5.93, 3.44)
4	(10.01, 9.8)	(12.12, 10.61)	(11.25, 8.83)	(9.53, 9.41)
5	(11.28, 3.56)	(11.69, 4.28)	(13.45, 3.32)	(11.69, 4.15)
6	12.98, 9.53)	(12.35, 10.83)	(13.68, 9.95)	(12.45, 9.08)

5. Conclusion

An improved DV-Hop algorithm is proposed for the identification of underground leakage accidents. Firstly, through the anchor node optimization scheme, the defect of the anchor node combination is avoided. On the basis of the particle swarm optimization algorithm, a genetic chaotic particle swarm optimization algorithm (GCPSO) is proposed to correct the estimated position of DV-Hop. Experimental simulations show that GCPSO-Hop algorithm has a better optimization effect than DV-Hop algorithm in reducing the average positioning error and improving the positioning accuracy, which proves the feasibility and effectiveness of GCPSO-Hop algorithm in the underground safety supervision process in coal mines.

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