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Wireless Sensor Localization Algorithm Based on Artificial Intelligence

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In order to improve the optimal selection ability of incremental wireless sensor self-localization nodes, an artificial intelligence-based wireless sensor self-localization node deployment algorithm is proposed. The method is comprised of the following steps: constructing an optimized topological structure model of a wireless sensor self-positioning node, performing output link conversion control of the wireless sensor self-positioning node by combining the channel equalization configuration method of an autonomous distributed wireless sensor network, establishing an optimized topological structure model of the wireless network, performing link conversion design of the wireless sensor self-positioning node by combining a channel adaptive equalization modulation method, energy feature extraction of the wireless sensor nodes in autonomous distributed wireless sensor networks which is carried out by combining the adaptive topology modulation method, adaptive selection and fusion clustering of wireless sensor self-positioning nodes that are carried out according to the energy clustering of wireless sensor nodes, extracting high-order spectral feature quantities of output information of wireless sensor self-positioning nodes, and realizing the optimal deployment and selection of wireless sensor self-positioning nodes according to fuzzy information clustering results, so that the wireless sensor self-positioning is complete. The simulation results show that the self-adaptive selection of localization nodes for wireless sensors using this method is improved, the output signal-to-noise ratio of wireless sensor network is higher, and the bit error rate is lower.

Keywords: Artificial Intelligence, Wireless Sensor, Self-Orientation, Fuzzy Information Clustering, Node.

1. INTRODUCTION

With the development of communication technology in autonomous distributed wireless sensor networks, a distributed sensor network design method is adopted to carry out transmission control of the autonomous distributed wireless sensor networks, a node optimization deployment model of the autonomous distributed wireless sensor networks is constructed, a node optimization design of the autonomous distributed wireless sensor networks is carried out by combining a network link equalization control method, and a route detection and node adaptive deployment model are combined (Chen et al., 2017). In order to improve the output performance, reduce the output error rate, and improve the output balance of the autonomous distributed wireless sensor network, the research on the optimal deployment method of the incremental wireless sensor self-positioning node has attracted great attention (Qiao et al., 2008).

The selection of wireless sensor self-positioning nodes for autonomous distributed wireless sensor networks is based on routing protocol design and path planning, and a wireless sensor self-positioning node selection model is established (Huang and Liu, 2016). Combined with a routing optimization design method, wireless sensor self-positioning node selection is carried out. Traditionally, the selection methods of wireless sensor self-positioning nodes include the grid clustering method, adaptive beam forming method and correlation constraint control method. The coverage model of a wireless sensor's self-localization node is established (Sun et al., 2014), and the optimal selection of a wireless sensor's self-localization node is carried out in

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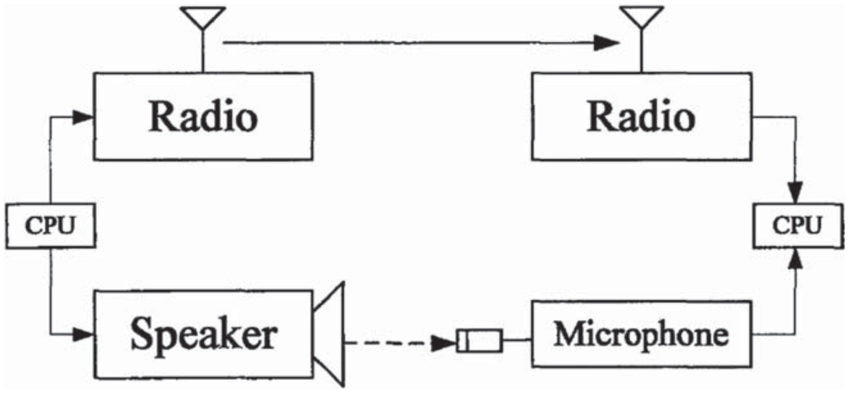

Figure 1 TOTA ranging schematic.

combination with the link equalization method. However, the traditional methods have poor self-adaptability and high computational cost in selecting a wireless sensor's self-localization node (Qasem et al., 2019; Dhi and Dedy, 2019; Rabia et al., 2020). To solve the above problems, this paper proposes an artificial intelligence-based wireless sensor localization node deployment algorithm. An optimized topological structure model of the wireless sensor self-positioning node is constructed, energy feature extraction of the wireless sensor nodes of the autonomous distributed wireless sensor network is carried out using an adaptive topological modulation method, self-adaptive selection and fusion clustering of the wireless sensor self-positioning nodes are carried out according to the clustering property of the energy of the wireless sensor nodes, high-order spectral feature quantities of output information of the wireless sensor self-positioning nodes are extracted, selection optimization of the wireless sensor self-positioning nodes is realized, and finally simulation test analysis is carried out to obtain an effective conclusion (Zhou et al., 2018).

2. BASIC DEFINITIONS

2.1 The Basic Principles of Node Positioning

2.1.1 Basic Concept of Wireless Sensor Node Location

(1) Anchor beacon node: A node with known position information prior to location. Anchor nodes are mainly used as reference nodes to locate unknown nodes in the positioning process.

(2) Unknown node: A node that cannot accurately obtain its own location information before positioning. Most of the nodes in the wireless sensor network are unknown nodes, and the unknown nodes need to be solved by combining the information of anchor nodes with certain algorithms.

(3) Neighbor Node: If the distance between the two nodes is less than the communication radius, the two nodes are called neighbor nodes.

(4) Jump: The number of nodes that the signal passes from one node to another.

(5) Jump distance: The distance between the two nodes in a network.

(6) Arrival time: The time a signal passes from one node to another.

(7) Arrival time difference: The difference in the time of two signals with different propagation speeds take to pass from one node to another.

(8) Angle of arrival: The angle at which a node receives a signal from another node relative to its own axis.

(9) Line of sight: If there are no obstacles between the two nodes, and they can communicate directly, these two nodes have a line of sight relationship.

(10) Non-line-of-sight relationship: If there are obstacles between two nodes that affect their direct communication, these two nodes have a non-line-of-sight relationship.

2.2 Common Node Positioning Methods

(1) TOA range

TOA ranging is used to find the distance between the two nodes according to the propagation speed of the signal and the propagation time between the two nodes. The ranging principle is shown in Figure 1.

Firstly, the two nodes synchronize the time through the radio module, then while the transmitter node sends the signal, the receiver node obtains the time through the radio module. When the receiver node receives the signal, the difference between the signal receiving time and the transmission time is the signal propagation time, and the propagation time multiplied by the propagation speed is the distance between the two nodes.

(2) TDOA range

TDOA ranging uses the time difference of different propagation speed of two signals to reach the receiver node, solving a column equation to determine the two node distance. The ranging principle is shown in Figure 2.

Two different kinds of signals, with different propagation speeds, are sent by the sending node, and the time of receiving the two signals is different.

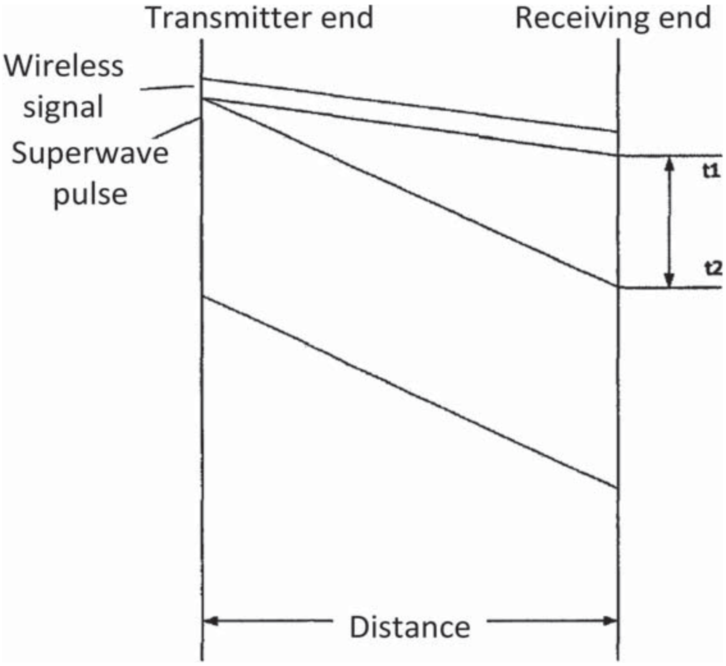

Figure 2 TDOTA ranging schematic.

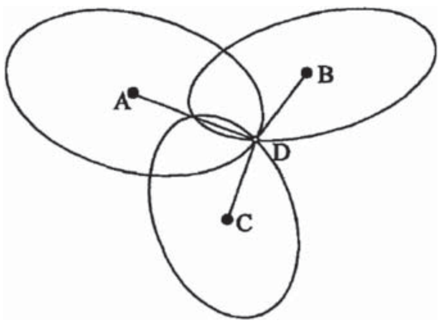

Figure 3 Schematic diagram of trilateral measurement.

2.3 Common Methods of Node Location Estimation

If the distance from the unknown node to three or more anchor nodes is determined, the trilateral measurement method can be used to locate the unknown node. As shown in Figure 3, d is the unknown node to be obtained, and A, B, C are the three paving nodes in the range of d communication, whose coordinates are $(x_1, y_1), (x_2, y_2), (x_3, y_3)$, and the distance from A, B, C to d are d_1, d_2, d_3.

The solution process is:

Let the coordinates of d be (x, y), column equations:

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2}=d_1 \\ \sqrt{(x-x_2)^2+(y-y_2)^2}=d_2 \\ \sqrt{(x-x_3)^2+(y-y_3)^2}=d_3 \end{cases} \tag{1}$$

Therefore:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2(x_1-x_3) & 2(y_1-y_3) \\ 2(x_2-x_3) & 2(y_2-y_3) \end{bmatrix}^{-1} \times \begin{bmatrix} x_1^2-x_3^2+y_1^2 & -y_3^2+d_3^2-d_1^2 \\ x_2^2-x_3^2+y_2^2 & -y_3^2+d_3^2-d_2^2 \end{bmatrix} \tag{2}$$

The result is the unknown node coordinates.

2.4 Topology Design of Wireless Sensor Self-Localization Node

In order to realize the selection of self-positioning nodes of wireless sensors based on artificial intelligence, it is necessary to first construct an optimized topological structure model of self-positioning nodes of wireless sensors, combine the channel equalization configuration method of autonomous distributed wireless sensor networks, carry out the self-adaptive selection of self-positioning nodes of wireless sensors, and establish a regional distribution model of autonomous distributed wireless sensor networks by adopting a fusion tag and multiple information reconstruction method (Zhang et al., 2019). Node deployment of the autonomous distributed wireless sensor network is carried out in a square area with an edge length of m, a total of n autonomous distributed wireless sensor network wireless sensor self-positioning nodes are located, the time delay compensation control method is adopted to carry out output node control of the autonomous distributed wireless sensor network, a distributed analysis model of output characteristics of the autonomous distributed wireless sensor network is established (Zhang et al., 2012), a multi-distributed fusion information

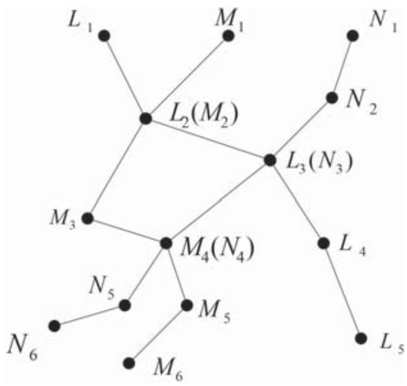

Figure 4 Optimal topology model of autonomous distributed wireless sensor network.

clustering method is adopted to carry out node deployment of the autonomous distributed wireless sensor network, and an optimized topology structure model of the autonomous distributed wireless sensor network is obtained as shown in Figure 4.

According to the optimized topology structure of the autonomous distributed wireless sensor network shown in Figure 4, the route relay node design of the autonomous distributed wireless sensor network is carried out, the route selection of the autonomous distributed wireless sensor network is carried out, the spatial deployment model is adopted, the multi-output conversion control of the autonomous distributed wireless sensor network is carried out (Mao et al., 2016), the candidate cluster head node is determined to carry out link adaptive allocation for one node. The transmission delay before the Source and Sink nodes of the autonomous distributed wireless sensor network is T_f, the intermediate area of the temporary cluster is selected, and the channel of the autonomous distributed wireless sensor network for L-bit data is expanded by combining the method of node transmission parameter adjustment to obtain a channel bandwidth of $T_s = N_f T_f$. Considering the clustering number of the autonomous distributed wireless sensor network, the bandwidth adaptive adjustment method is adopted to obtain cluster head nodes, and the residual energy of candidate cluster head transmitting nodes is:

$$NIntra_i(n) = NIntra_i(n) + 1, \text{ if } j \in N_i \cap t_{ij} < T_h \quad (3)$$

The method of ergodic equalization adjustment is adopted to obtain the communication coverage and calculate the sensor node of N_c chips. At this time, the original cluster head becomes the candidate cluster head, and the energy consumption of the node is obtained as follows:

$$T_c = ent(T_f/N_c) \quad (4)$$

Considering network connectivity, when $c_j T_c < T_f, \forall j \in [0, N_f - 1]$, is satisfied. Assuming that the dynamic difference characteristic quantity between the connection line of the wireless sensor self-positioning node A of the autonomous distributed wireless sensor network and the Sink node A is:

$$s(t) = \sum_i b_j \sum_{j=0}^{N_f-1} p(t - iT_s - jT_f - c_j T_c) \quad (5)$$

Wherein, b_j is the multipath channel loss of the incremental wireless sensor self-positioning node, T_s is the characteristic solution vector of each round of data collection, T_f is the sampling time of the autonomous distributed wireless sensor network, and T_c is the load balancing degree of the autonomous distributed wireless sensor network. Convergence tree routing protocol is adopted in the routing selection process of the autonomous distributed wireless sensor network, and the cluster head nodes of the autonomous distributed wireless sensor network are updated. The routing topology of autonomous distributed wireless sensor network is designed, the candidate cluster head nearest to Sink node is selected, and when $Nmax = 2$, the robust coefficients of neighbor nodes of the autonomous distributed wireless sensor network are calculated under different topology degrees, so as to realize the optimal design of topology structure of wireless sensor self-positioning nodes (Lin et al., 2016).

2.5 Optimization of Network Node Deployment

Node positioning refers to the communication between the unknown node and the adjacent beacon node or the unknown node that has obtained the position information, and has calculated its own position according to a certain location algorithm. A mobile beacon node is constructed by loading a node on a mobile robot or on an aircraft for node seeding, and the node is equipped with a GPS or other positioning device so it can get its current position information in real time even while moving. Suppose the communication radius of the node is R. As shown in Figure 5, the beacon node moves along the curve trajectory from position 1 and continuously broadcasts packets containing its current position information during the movement. In Figure 5(a), the unknown node of the beacon node moves from far and near, and the unknown node receives the broadcast packet of the beacon node only when the signal node moves in place; whereas in Figure 5(b), as the beacon node moves by, both near and far relative to the unknown node, the unknown node does not receive the broadcast packet of the beacon node until the beacon node moves in place to set n_1. In both cases, the distance from the position n to the unknown node can be considered as R. When the unknown node receives the position information of three (or more) and its distance is R, the position of

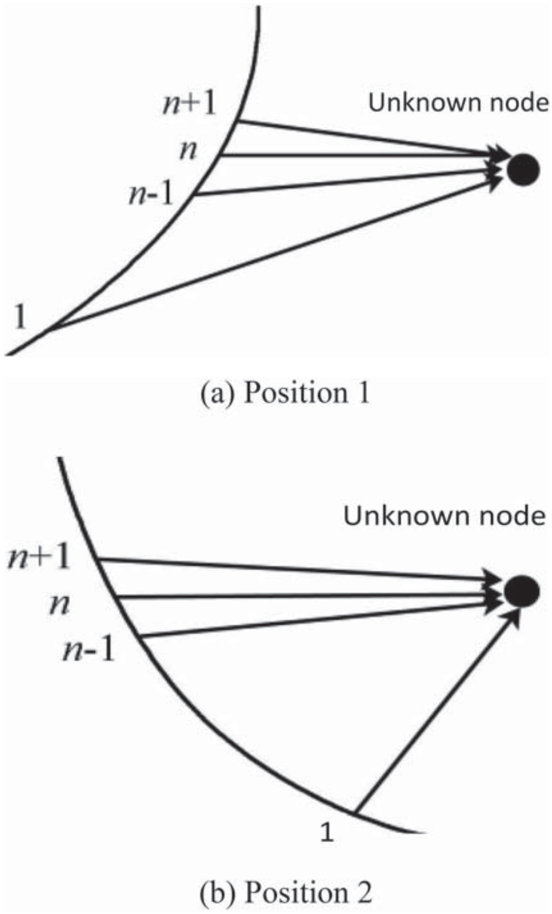

Figure 5 Map of beacon node movement.

the unknown node can be calculated using the trilateral measurement method.

2.5.1 Design of Moving Trajectory

If the beacon node can move three (or more) times from far to near or from near to far in the range of the node, the unknown node can obtain the position information of three (or more) distances of R. Figure 6 shows the moving trajectory designed in this paper. The beacon node starts from monitoring the central position of the region with a square uniform outward expansion. The periodic broadcast during the movement contains the grouping of its current position information. As long as the beacon node can reach the area, the unknown node can be located.

2.5.2 Location Information Grouping Selection

In theory, as long as the unknown node obtains three packets of noncollinear position information each with a distance of R, it can accurately determine its position: the center of the outer circle of the triangle composed of these three positions. In practice, however, beacon nodes can only broadcast packets periodically. Therefore, it is considered that the distance between the unknown node R and the unknown node is actually R′, then R′Φ R, so there is an error ΔR: $\Delta R = R - R'$, ΔR is random, so the effect of mutual offset on location when choosing the location involved must be considered. By comparing the two graphs in Figure 7, the error between the two is obvious. Obviously, the triangle formed by selecting the three locations involved in the localization should contain unknown nodes.

2.5.3 Node Deployment

The network node deployment optimization is combined with the channel equalization configuration method of the autonomous distributed wireless sensor network, the output link conversion control of the wireless sensor self-positioning node is carried out (Zhou et al., 2014), the optimized topology structure model of the wireless network is established, the influence of the autonomous distributed wireless sensor network on the utility degree of the wireless sensor self-positioning node is expressed by a weight coefficient, the network output link equalization design is carried out in a regular area and an irregular area, and the transmission matrix SN * L of the network is obtained (Qi et al., 2014). The load of the autonomous distributed wireless sensor network on the cluster head ni is as follows:

$$candidate = \{n_j | d(n_i, n_j) < d_0 \cup d_j < d_i,\ n_j \in CH\} \quad (6)$$

By adopting a load balancing design method, the output utility function of the incremental wireless sensor self-positioning node is obtained as follows:

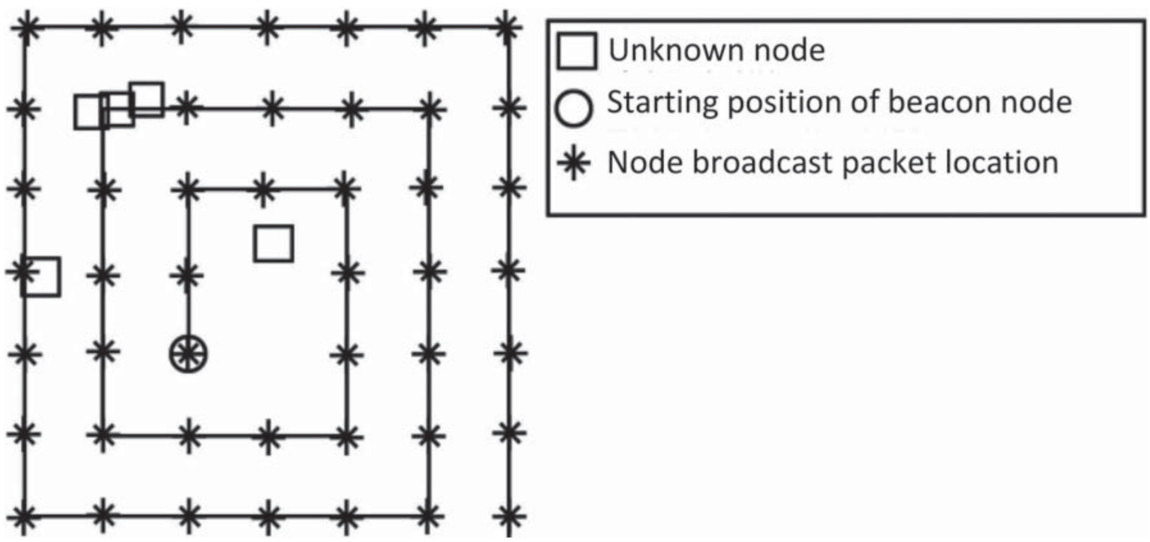

Figure 6 Schematic diagram of the moving trajectory of the beacon node.

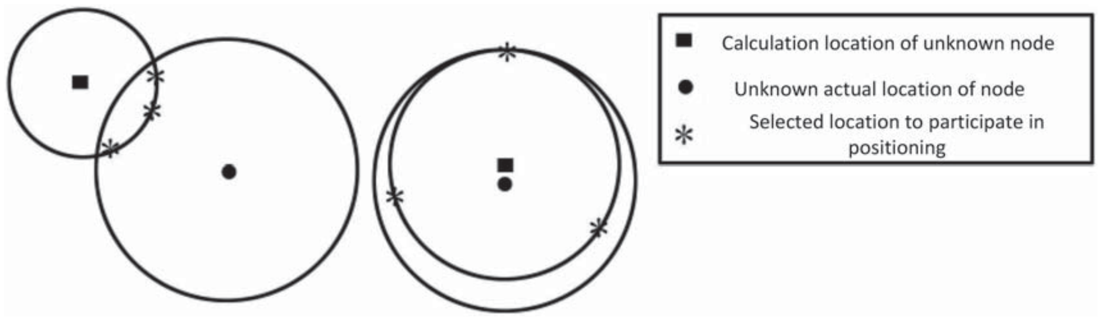

Figure 7 Effect of location information selection on location calculation.

$$\begin{aligned} E &= E_{Tx}(l, d(n_i, n_j)) + E_{Rx}(l) + E_{Tx}(l, d_j) \\ &= l(E_{elec} + \varepsilon_{fs} d^2(n_i, n_j)) + lE_{elec} + l(E_{elec} + \varepsilon_{fs} d_j^2) \\ &= 3lE_{elec} + l\varepsilon_{fs}(d^2(n_i, n_j) + d_j^2). \end{aligned} \tag{7}$$

According to the distribution characteristics of cluster heads and data between clusters, spatial deployment is carried out, and the output energy characteristic of the autonomous distributed wireless sensor network is E_{res} (Mohan et al., 2013), and the distance between E_{res} and Sink is:

$$T(n) = \begin{cases} \dfrac{P}{1 - P[r \bmod (1/P)]} \cdot \left\{ c \left[\dfrac{E_{res}}{E_{init}} + \left(r_u div \dfrac{1}{p} \right) \left(1 - \dfrac{E_{res}}{E_{init}} \right) \right] \times + (1 - c) \dfrac{d_{\max} - d_i}{d_{\max} - d_{\min}} \right\} & n \in G \\ 0 & \text{else} \end{cases} \tag{8}$$

Under the given threshold probability, r_u is set to 0, the candidate cluster head will broadcast its own node number, and the neighboring nodes will obtain the energy consumption factor matrix $B_{N\times 1}$ according to the principle of proximity. The calculation formula is as follows:

$$\begin{aligned} r(t) &= \sum_i \sum_{j=0}^{N_f-1} \sum_{l=0}^{L-1} b_i \alpha_l p(t - iT_s - jT_f - c_j T_c - \tau_l) + \omega(t) \\ &= \sum_i \sum_{j=0}^{N_f-1} b_i p_h(t - iT_s - jT_f - c_j T_c - \tau_0) + \omega(t) \end{aligned} \tag{9}$$

The channel equalization distribution matrix $S_{N\times L}$ of the autonomous distributed wireless sensor network is fused with the energy data of the l bits data received by the nodes, and the optimal design of network node deployment is carried out (Kimmett et al., 2015).

3. OPTIMIZATION OF LOCALIZATION NODE SELECTION FOR WIRELESS SENSOR

3.1 Fusion Clustering of Localization Nodes of Wireless Sensor

On the basis of constructing the optimal topology model of wireless sensor self-localization nodes, the optimal design of wireless sensor self-localization node selection is carried out. In this paper, the deployment algorithm of wireless sensor self-localization node based on artificial intelligence is proposed. The link conversion design of the wireless sensor self-positioning node is carried out by combining the channel adaptive equalization modulation method (Yang et al., 2018), and the load model of the autonomous distributed wireless sensor network node is obtained by combining the adaptive topology modulation method as follows:

$$\begin{aligned} r(t) &= \sum_{i}\sum_{j=0}^{N_f-1}\sum_{l=0}^{L-1} b_i\alpha_l p(t - iT_s - jT_f - c_jT_c - \tau_l) + \omega(t) \\ &= \sum_{i}\sum_{j=0}^{N_f-1} b_i p_h(t - iT_s - jT_f - c_jT_c - \tau_0) + \omega(t) \end{aligned} \tag{10}$$

Wherein

$$p_h(t) = \sum_{l=0}^{L-1} \alpha_l p(t - \tau_{l,0}) \tag{11}$$

In addition, $\omega(t)$ is the weight coefficient of the data that is initially randomly selected, and the energy consumed by the incremental wireless sensor self-positioning node to send l bits data is also used. The diversity equalization method is adopted to optimize the balanced deployment of cluster head nodes in autonomous distributed wireless sensor networks, and the route detection design of sensor nodes is carried out by combining the full network energy equalization method, and the column vector is defined as:

$$P = E[d_kX_k] = E\begin{bmatrix} d_kx_{0k} \\ d_kx_{1k} \\ \vdots \\ d_kx_{Lk} \end{bmatrix} \tag{12}$$

Each node receives the energy overhead sent by the cluster head as follows:

$$P_{\text{AOMDV}} = (1-P_d)^2\{1-[1-(1-P_e)^n(1-P_d)^{n-1}]^m\} \tag{13}$$

According to the shortest path optimization method, the output conversion control of the wireless sensor self-positioning node of the wireless network is carried out, the incremental wireless sensor self-positioning node self-adaptive selection is then carried out using the fractional interval equalization design method, and the mean square error is set to be as follows:

$$\begin{aligned} MSE = \xi &= E\left[\varepsilon_k^2\right] \\ &= E\left[d_k^2\right] - 2W^TP + W^TRW \end{aligned} \tag{14}$$

Considering the load of the autonomous distributed wireless sensor network and the output characteristics of the nodes located by the wireless sensors themselves, the broadcast information of the adjacent cluster heads is extracted and received, and the weight graph increment control is carried out (Fan and Li, 2018).

3.2 Incremental Control of Weight Graph and Optimal Selection of Nodes

The self-adaptive selection and fusion clustering of the wireless sensor self-positioning nodes are carried out according to the clustering of the energy of the wireless sensor nodes, and the high-order spectrum characteristic quantity of the output information of the wireless sensor self-positioning nodes is extracted, so that the shortest path for node deployment is obtained as follows:

$$T_{l1} = \sqrt{{F_{p1}}^2 + {F_{q1}}^2} \tag{15}$$

The Euclidean distance from the Sink node is defined and the incremental characteristics of the weight graph are obtained as follows:

$$m = \begin{cases} 1, DS \le R \\ \left\lfloor \dfrac{DS}{R} \right\rfloor, DS > R \end{cases} \tag{16}$$

Wherein, the interval distance of nodes in the cluster is expressed, and the output response characteristic quantity of the nodes in the autonomous distributed wireless sensor network is obtained through cooperation with common nodes, and is expressed as follows:

$$L = \sqrt{(\overline{p_0s'})^2 + (\overline{p_0s_j})^2 - 2(\overline{p_0s'}) \times (\overline{p_0s_j}) \times \cos\angle s_jp_0s'} \tag{17}$$

$$\varphi = \arccos\left(\frac{(\overline{p_0s_j})^2 + (\overline{s_js'})^2 - (\overline{p_0s'})^2}{2(\overline{s_js'}) \times (\overline{p_0s_j})}\right) \tag{18}$$

The energy coefficient of the wireless sensor nodes of the autonomous distributed wireless sensor network is obtained by adopting a clustering compressed sensing method as follows:

$$(\overline{ps'})^2 + (\overline{pp_1})^2 - 2(\overline{ps'}) \times (\overline{pp_1}) \times \cos\angle s'pp' = (\overline{p_1s'})^2 \tag{19}$$

According to the topology change of the network connectivity domain, the optimal deployment of network nodes and channel design are carried out, and the evaluation results of the optimal deployment parameters are as follows:

$$\overline{ps'} = \overline{pp_1} \times \cos\angle s'pp' + \sqrt{(\overline{p_1s'})^2 + (\overline{pp_1})^2 \times \sin^2\angle s'pp'} \tag{20}$$

$$\overline{p_0s'} = \overline{ps'} + \overline{p_0p} \tag{21}$$

The energy feature extraction of the wireless sensor nodes of the autonomous distributed wireless sensor network is carried out by combining an adaptive topology modulation method, and is as follows:

$$\begin{aligned} R_w(l) &= E[w(k)w^H(k+l)] \\ &= \int_{-\pi}^{\pi}\left[\delta_l.\frac{1}{\Delta\sqrt{2\pi}}e^{-(\theta-\theta_0)^2/2\Delta^2}\right]a(\theta)a^H(\theta)d\theta \end{aligned} \tag{22}$$

In the formula, θ_0 and Δ respectively represent the bandwidth and time delay of the incremental wireless sensor self-positioning node, and by adopting a distributed clustering structure reorganization method, the weight distribution coefficient of the incremental wireless sensor self-positioning node is obtained as follows:

$$x(t) = \mathrm{Re}\left\{a_n(t)e^{-j2\pi f_c\tau_n(t)}s_l(t - \tau_n(t))e^{-j2\pi f_ct}\right\} \tag{23}$$

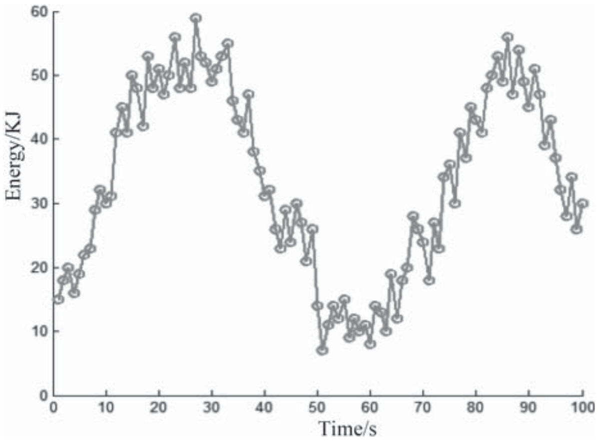

Figure 8 Energy distribution of wireless sensor self-localization node.

Extracting the high-order spectral feature quantity of the output information of the self-positioning node of the wireless sensor to obtain the cluster first round commutation feature distribution of the self-positioning node of the wireless sensor is as follows:

$$c(\tau, t) = \sum_{n} a_n(t) e^{-j2\pi f_c \tau_n(t)} \delta(t - \tau_n(t)) \tag{24}$$

The candidate cluster head closest to the Sink node is selected, and the self-positioning node selection of the wireless sensor is realized by utilising a clustering equalization method.

4. SIMULATION TEST ANALYSIS

In order to test the application performance of the method in realizing incremental wireless sensor self-positioning node risk intelligent evaluation, and in order to verify the application performance of the method in realizing wireless sensor self-positioning node optimal selection, simulation test analysis is carried out where the number of wireless sensor self-positioning nodes is set to 20, 60 and 120 respectively, and set the number of receiving nodes to be 20, 60 and 120 respectively, the bandwidth for symbol transmission between nodes is 60 Baud.

The wireless sensor self-positioning node selection optimization is carried out according to the above parameters, and the energy distribution is obtained as shown in Figure 8.

According to the energy distribution characteristics, the high-order spectral feature quantity of the output information of the positioning node of the wireless sensor is extracted, the node is optimally selected according to the fuzzy information clustering result, the transmission power is tested, and the comparison result is shown in Figure 9.

Analysis of Figure 9 shows that the transmission power of the wireless sensor self-positioning node selection using the method in this paper is relatively large, which improves the output performance of the network and tests the output bit error rate. The comparison results are shown in Table 1. Analysis of Table 1 shows that the method in this paper has higher signal-to-noise ratio, lower delay and lower bit error rate of the network output.

The simulation curves of Figures 10 and 11 show the comparison of the traditional algorithm with the present algorithm in terms of location accuracy and packet delivery when the number of nodes is 100, the radius of node emission is 5m, and the connectivity of the network is 3, 6 and 9, where the abscissa represents the percentage of beacon nodes, the ordinate represents the location error or packet delivery, the solid line represents the traditional algorithm, and the dashed line represents the present algorithm. Figure 12 and Figure 13 show the comparison of positioning errors and traffic between traditional algorithms and this algorithm for different connectivity when beacon nodes account for 20% of the total number of nodes. Table 2 lists the number of threshold hops n for each connectivity and the percentage of corresponding beacon nodes. Where "con" means connectivity. (In this paper, dv-hop represents the algorithm and ldv-hop represents the traditional algorithm.)

It can be seen from the simulation curve that the positioning accuracy of this algorithm is obviously higher than that of traditional ones when the percentage of beacon nodes is relatively low. The data traffic of this algorithm is related to the selection of the threshold N, and when the threshold N is small, the data traffic of this algorithm is obviously lower than that of the traditional algorithm under the same conditions. This is because when a gate N is given, an unknown node communicates only with nodes in the bounded hop range and does not extend to the entire network, which reduces network traffic. Therefore, in the wireless sensor network with limited node energy, this algorithm can meet the requirements of low energy consumption in the network. When the proportion of beacon nodes is certain (e.g. 20%) and the connectivity is relatively small, the location error of this algorithm is obviously smaller than that of traditional algorithm, and the traffic is lower than that of traditional algorithm with the increase in connectivity. It can be seen that this algorithm can effectively improve the positioning accuracy and reduce the packet delivery.

5. CONCLUSION

A node optimal deployment model of an autonomous distributed wireless sensor network is constructed, and the

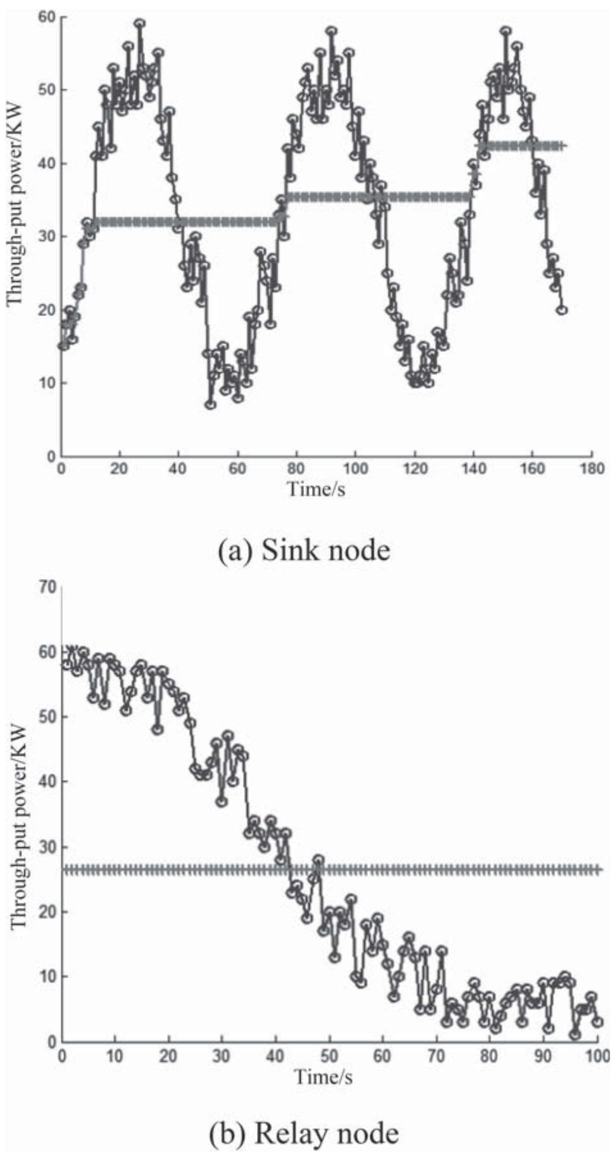

Figure 9 Transmission power test of nodes.

Table 1 Comparison of network performance.

Number of Nodes	This Method		Traditional Method	
	Time delay/ms	BER	Time delay/ms	BER
20	1.23	0.015	3.43	0.121
60	2.45	0.012	4.67	0.112
90	2.55	0.005	5.68	0.134
120	3.44	0	7.99	0.054

Table 2 Threshold List.

Percentage Beacons	0.1	0.2	0.3	0.4
Threshold con = 3	14	10	8	6
Threshold con = 6	8	6	5	5
Threshold con = 9	6	6	6	2

node optimal design of an autonomous distributed wireless sensor network is carried out by combining the balanced control method of network links. This paper proposes a node deployment algorithm for wireless sensor self-localization based on artificial intelligence. Link conversion design of wireless sensor self-positioning nodes is carried out by combining a channel adaptive equalization modulation method. Energy feature extraction of wireless sensor nodes of an autonomous distributed wireless sensor network is carried out by adopting an adaptive topology modulation method.

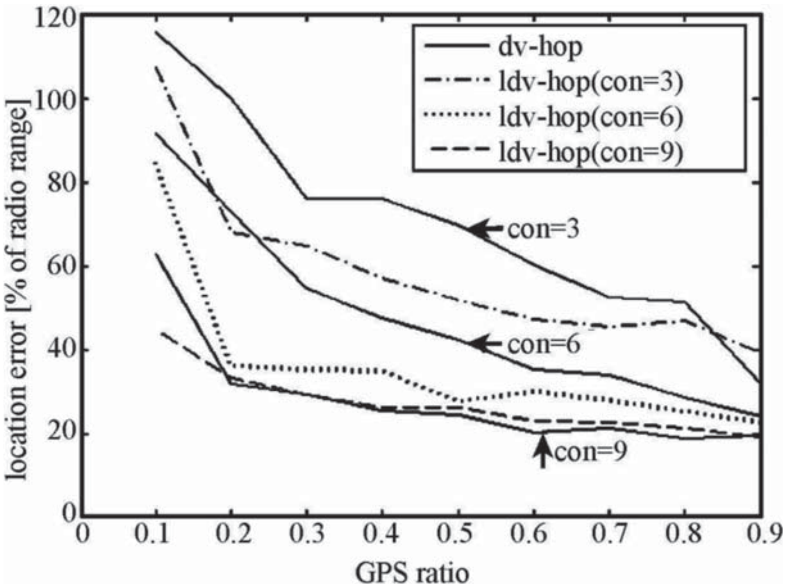

Figure 10 Comparison of positioning accuracy.

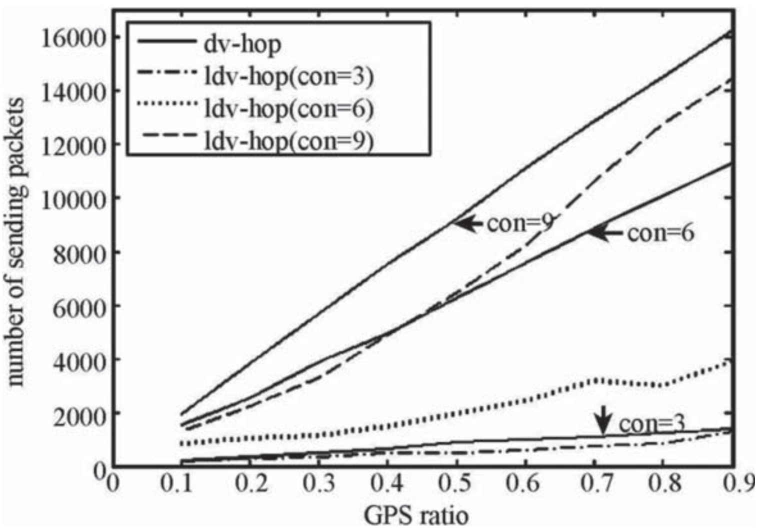

Figure 11 Comparison of packet delivery.

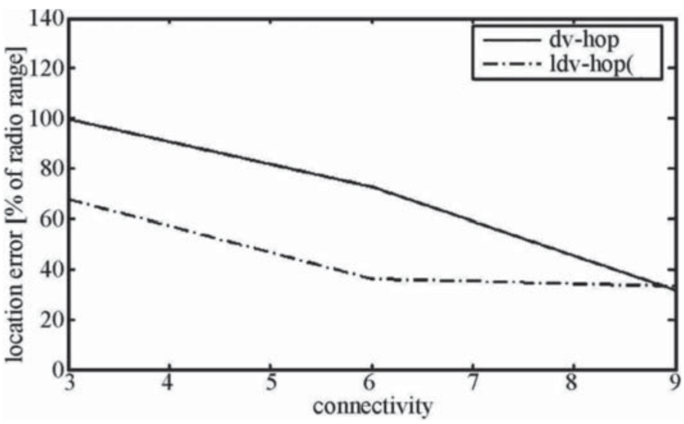

Figure 12 Comparison of positioning errors under different connectivity.

Optimal and balanced deployment of cluster head nodes of the autonomous distributed wireless sensor network is carried out by adopting a diversity equalization method. Route detection design of sensor nodes is carried out by combining a full-network energy equalization method. Optimal deployment and selection of wireless sensor self-positioning nodes are

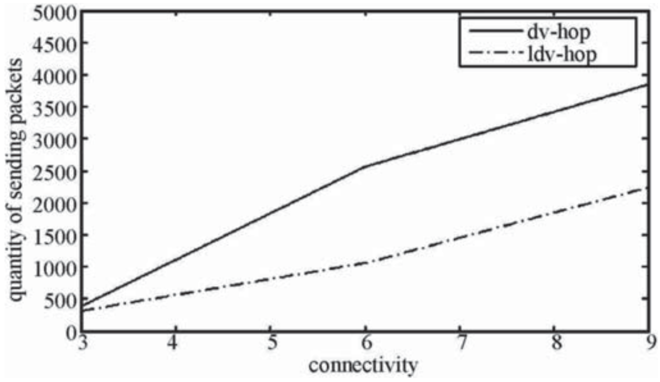

Figure 13 Comparison of package delivery at different connectivity.

realized according to fuzzy information clustering results, and wireless sensor self-positioning and node optimal selection are completed. Analysis shows that this method can improve the output performance of the network, optimize the deployment of nodes and reduce the output error rate.

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