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The Method of Data Collection Based on Multiple Mobile Nodes for Wireless Sensor Network

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ABSTRACT In traditional wireless sensor networks (WSN), data is transmitted to base stations through multiple-hop. However, multi-hop transmission will cause problems such as energy holes, uneven energy consumption, and unreliable data transmission. Aiming at the defects of traditional networks, this paper proposes a scheme for collaborative data collection using multiple mobile nodes (MN) as sink nodes. In this scenario, an important issue is how to reasonably plan the data collection path of each mobile node under a series of constraints such as energy. This paper studies routing strategy and path planning. Firstly, a dynamic clustering algorithm is used to cluster the randomly arranged sensor nodes, and then a sensor node with higher energy is manually arranged at the virtual cluster center generated by the clustering algorithm as a cluster head node to establish a data collection cluster. Then the monitoring area is divided into several parts according to the number of MN, so that the MN traverses the cluster head nodes in the respective monitoring areas for data collection. At the same time, in order to enable the MN to complete data collection within the energy limit and improve the path balance, a path-based path equalization algorithm (PEABR) is proposed to adjust the path of the MN, further reduce and equalize the path length of the MN to satisfy the constraint conditions, and optimize the path planning scheme. Finally, simulation was carried out by using Matlab simulator, and the simulation experiments which were performed in a laboratory environment verified the feasibility and effectiveness of the algorithm.

INDEX TERMS Wireless sensor network, mobile sink node, mobile data collection, path optimization.

I. INTRODUCTION

Wireless sensor network (WSN), a wireless network consisting of a large number of stationary or mobile sensors in a self-organizing and multi-hop manner, is widely used in military, medical health, smart home, building monitoring, environmental monitoring and other fields [1]–[5]. Since the location of the node is fixed, we also refer to it as the Static Wireless Sensor Network (SWSN) [6]–[12]. In SWSN, multi-hop communication and many-to-one communication modes of nodes often cause many problems, such as funnel/bottleneck effect and hotspot problems [13]–[17]. Simultaneously, nodes are mostly powered by batteries, and batteries are generally non-rechargeable or irreplaceable, so the limitation of network energy is also one of the main factors restricting the development of WSN [18]–[26].

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By introducing a mobile node (MN) into SWSN, the problems in SWSN can be overcome [27]–[32]. There have been some studies using mobile nodes as data collectors for mobile data collection. In reference [1], to solve the problems of poor scalability of farmland wireless sensor networks and uneven energy consumption of nodes, according to the characteristics of farmland sensor networks, a convergence tree set routing algorithm based on hop limit by dividing variable subnets is proposed to select routing algorithms, extending the life of the network. Literature [2] proposed a heuristic-list search algorithm (HLSA) for the problem of sensor node data aggregation and node energy imbalance during work, and the space problem that is often ignored. First select the appropriate backup anchor node, and then select the final anchor node according to the formula in the algorithm. The shortest path from the planning anchor node in spatial level to the mobile convergence node. The algorithm is applied to large warehouses in logistics transfer stations, which can effectively extend the life of the network and balance the energy between nodes. Literature [3] proposed a mobile sink data collection algorithm GMSDC based on genetic algorithm in order to improve the efficiency of node data collection. The GMSDC algorithm uses genetic algorithms to solve the best dwell points, and then builds a Sink movement path from these dwell points, which increases the amount of data collected. Reference [4], considering the Kinematic constraints of mobile nodes of similar models of vehicle type, proposes a mobile data acquisition algorithm based on clustering Dubins smooth curve. This algorithm takes into account the smoothness of mobile data collection and the optimization of node energy consumption and improve the energy efficiency of wireless sensor networks under moving path smoothness constraints. In reference [5], to reduce the energy hole and prolong the network life cycle, a combination of artificial immune algorithm and particle swarm optimization algorithm is proposed to find the approximate optimal solution for the path planning problem of mobile sink data collection. The proposed optimization algorithm can effectively reduce the energy consumption and shorten the traversal path. In reference [6], aiming at the problem of energy limitation of sensor nodes, a data collection method of maximizing the probability of minimum energy consumption is proposed by establishing the probability model of maximizing the probability of minimum energy consumption. The path length between the child nodes and sink nodes in the network is distributed optimized to maximize the lowest probability of the energy consumption of the entire network. The proposed algorithm is superior to similar algorithms in terms of energy consumption. In reference [7], a multi-objective optimization algorithm for mobile charging and data collection in wireless sensor networks is proposed. In reference [8], an optimal path strategy for data collection in mobile sink is proposed. In reference [13], a mobile data collection strategy based on tree cluster structure is proposed. Previous researches mostly focused on the path planning of a single mobile node. However, in reality, due to the energy limitations of the mobile node itself, it is difficult for a single mobile node to complete the task well in a large wireless sensor network. In this paper, a multi mobile node collaborative data collection scheme is proposed which is simple in principle and has high practicability and can provide some reference for such problems.

This paper mainly studies how to plan the path of multiple mobile nodes in the case of data collection, to achieve the shortest path under a series of constraints. The main work of this paper is as follows:

1)The node deployment is carried out in a way that the random arrangement and the manual arrangement are combined, the nodes are clustered by the improved K-means dynamic clustering algorithm, and the nodes with higher energy are arranged at the generated clustering center as the cluster head nodes.

2)The multi mobile node collaborative data collection scheme is proposed.

3)A path-based path equalization algorithm (PEABR) is proposed to further adjust and optimize the path of each mobile node.

4)Simulation was carried out by using the Matlab simulator, and the simulation experiments which were performed in a laboratory environment verified the feasibility and effectiveness of the algorithm.

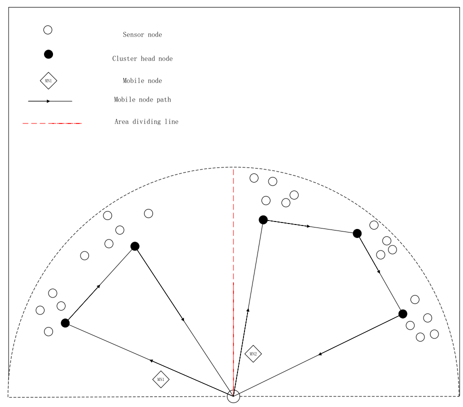


FIGURE 1. Network model.

II. EXPRESSION OF OPTIMIZATION PROBLEMS

The sensor network model consists of a base station, multiple sensor nodes, and multiple mobile nodes. As shown in Fig.1, the monitoring area is semi-circular and the network uses a cluster structure. The members in the cluster are randomly arranged sensor nodes and cluster head nodes which is an artificially arranged sensor node with higher energy. The nodes in the cluster first collect data and send it to the cluster head node. After receiving the data, the cluster head node performs simple processing and stores it in the buffer area to wait for the arrival of the MN. As a mobile data collector, MN traverses each cluster head node periodically to collect data.

Assume that there are N sensor nodes in the network, $N = \{1, \ldots, n\}$, Where, i $\neq j, i, j \in N$, node 1 represents a base station; V cluster head nodes $V = \{1 \ldots, v\}$; K mobile nodes, $K = \{1, \ldots, k\}$; The arc set of the cluster head node is $M = \{v(i, j), i \neq j\}$. d_{ij} to represent the Euclidean distance between two cluster head nodes, and the value of x_{ij}^{m} to indicate whether the path of the kth mobile node contains $v(i, j)$.

$$x_{ij}^{m} = \begin{cases} 1, & \text{line segment ij on the path of node k} \\ 0, & \text{others} \end{cases} \quad (1)$$

The energy consumption of MN is mainly composed of two parts: mobile energy consumption and receiving data energy consumption.

A. MOBILE ENERGY CONSUMPTION

The definition of mobile energy consumption is the total energy consumed by the MN from the base station, traversing the cluster head nodes of each cluster, and returning to the base station,

$$E_{Move} = \sum_{i=1}^{v}\sum_{j=1}^{v} x_{ij}^{k} d_{ij} e_d \tag{2}$$

where e_d is the energy consumption per unit moving distance, t_{ij} is the time required for MN to move from cluster head i to cluster head j, and v_{MN} is the moving speed of MN.

B. ENERGY CONSUMPTION OF RECEIVED DATA

The definition of energy consumption of received data is the total energy consumed when MN stays at the cluster head node of each cluster to receive the data from the cluster head,

$$E_{receive} = C_i e_{rx} \sum_{i=1}^{v}\sum_{j=2}^{v} x_{ij}^{k} \tag{3}$$

where e_{rx} is the energy consumption of receiving unit data.

Compared with mobile energy consumption, the energy consumption of received data accounts for a small proportion of the total energy consumption. Therefore, this paper ignores the energy consumption of received data and focuses on how to reasonably plan the path of multiple mobile nodes to ensure they can complete the data collection task with the minimum path under the premise of satisfying the constraints, and their energy limit is represented with the maximum endurance mileage.

The path optimization problem of MN can be described as follows:

$$Minimize \sum_{k=1}^{k}\sum_{i=1}^{v}\sum_{j=1}^{v} x_{ij}^{k} d_{ij} \tag{4}$$

$$\sum_{i=1}^{V}\sum_{k=1}^{K} x_{ij}^{k} = 1, \quad j \in v,\ j \neq 1 \tag{5}$$

$$\sum_{j=1}^{V}\sum_{k=1}^{K} x_{ij}^{k} = 1, \quad i \in v,\ i \neq 1 \tag{6}$$

$$\sum_{i=1}^{v} x_{ip}^{k} - \sum_{j=1}^{v} x_{pj}^{k} = 0, \quad k \in K,\ p \in V,\ p \neq 1 \tag{7}$$

$$\sum_{j=2}^{v} x_{1j}^{k} = 1, \quad k \in K \tag{8}$$

$$\sum_{i=2}^{v} x_{i1}^{k} = 1, \quad k \in K \tag{9}$$

$$\sum_{i=1}^{v}\sum_{j=1}^{v} x_{ij}^{k} d_{ij} e_d + C_i e_{rx} \sum_{i=1}^{v}\sum_{j=2}^{v} x_{ij}^{k} \leq W \tag{10}$$

$$u_1^k = 1, \quad k \in K \tag{11}$$

$$u_i^k - u_j^k + 1 \leq (N-1)(1 - x_{ij}^k), \quad k \in K, i, j \in V, i, j \neq 1 \tag{12}$$

Constraints (5) and (6) ensure that each sensor node is accessed only once per round by one mobile node. For example, if mobile node K reaches node j from node i, $(j \in v, j \neq 1)$, that is $x_{ij}^k = 1$, and due to $\sum_{j=1}^{v}\sum_{k=1}^{k} x_{ij}^k = 1$, mobile nodes except K starting from other nodes will not be able to access j, and from constraints (5), it can be seen that after mobile node K leaves node j, only the nodes in V will be accessed; constraint (7) ensures the continuity of the path, once a mobile node reaches a sensor node, it will certainly leave from the same sensor node. Specifically, when the mobile node K reaches the sensor node P from the sensor node i, there is $x_{ip}^k = 1$, and then there must be $x_{pj}^k = 1$, that is the mobile node leaves from the node p to another one in V Node j; constraint (8) ensures that the mobile node starts from the base station to any other sensor node; constraint (9) ensures that the final location of the mobile node is the base station; constraint (10) is the energy limit of each round of mobile node, and its energy consumption includes mobile energy consumption and data collection energy consumption, and constraint (10) ensures the energy of the mobile node in a task cycle cannot exceed the maximum energy that value W carried by the mobile node. From the previous analysis, the energy consumption is mostly concentrated in the mobile energy consumption part, so the energy constraint can also be simplified as the maximum endurance mileage; constraint (11) and (12) ensures that there is no sub-loop in the path loop of the mobile node, specifically, the u_i^k represents the number the mobile node K visited sensor when it reaches the sensor node i, when $x_{ij}^k = 1$, $u_i^k \leq u_j^k - 1$ can be obtained from constraints (11) and (12), which ensures that there is no sub-loop in the path [24]. The goal of the problem is to design a closed-loop that sequentially accesses a set of vertices to minimize the total path length. This problem has both a traveling salesman problem and a knapsack problem, so it's a hard problem of NP.

III. MULTI-MN PATH PLANNING

A. ESTABLISHMENT OF DATA COLLECTION CLUSTER BASED ON DYNAMIC CLUSTERING

In order to evenly divide the nodes in the network into clusters, and to balance the network energy consumption and energy consumption of each cluster head, we use a dynamic clustering algorithm to cluster the nodes in the monitoring area [32], [33]. In practical applications, compared with neighbor clustering and fuzzy clustering, the K-means algorithm is simple, practical and higher efficiency.

The K-means algorithm is based on minimizing the clustering function. For the J-th clustering set, the clustering function is defined as:

$$J_{\mathrm{j}} = \sum_{i=1}^{N_j} \left\| X_i - Z_j \right\|^2, \quad X_i \in S_j \tag{13}$$

where S_{j} is J-th cluster set, Z_{j} is the cluster center, N_j is the number of samples contained in cluster set S_{j}, and the selection of the cluster center should make J_{j} extremely small [1], then $\frac{\partial J_j}{\partial Z_j} = 0$ shown as formula (14):

$$\frac{\partial}{\partial Z_{\mathrm{j}}} \sum_{\mathrm{i}=1}^{N} \| X_i - Z_{\mathrm{j}} \|^2 = 0 \tag{14}$$

then,

$$Z_{\mathrm{j}} = \frac{1}{N_{\mathrm{j}}} \sum_{i=1}^{N_j} X_i \tag{15}$$

The algorithm flow is as follows:

(1) Select K initial cluster centers: $Z_1(1), Z_2(1), \ldots\ldots, Z_k(1)$;

(2) Allocating the remaining samples to one of the K cluster centers according to the principle of minimum distance (Euclidean distance);

(3) Obtaining $Z_j(k+1)$, j = 1, 2, ... k of each cluster center;

(4) If $Z_j(k+1) \neq Z_j(\mathrm{k})$, return to step (2) reclassify the sample, repeat iterative calculation until $Z_j(k+1) = Z_j(\mathrm{k})$, the algorithm converges, the calculation is completed, and the result is recorded;

However, the final clustering result of the K-means algorithm will be affected by the position and number of the initial clustering center, and it will easily converge to the local optimum rather than the global optimal. For this reason, we adopt the binary K-means algorithm, which can overcome the convergence of the K-means clustering algorithm to the local optimum. The basic idea is: Firstly consider all points as a cluster and perform clustering (K = 2), then select the cluster that can minimize the sum of squared errors (SES) and continue to divide (K = 2), and repeated this it until the number of clusters is equal to the number we specify [34].

After the clustering of the previous step, the nodes are clustered to generate k categories (clusters), and k virtual cluster centers are generated at the same time. Because inter-cluster communication mostly uses single-hop transmission, the single-hop distance is the main factor affecting energy consumption. In each cluster generated by the clustering algorithm, the sum of the squares of the distances between the member nodes and these virtual centers is the smallest, that is, the distance between these points and the virtual cluster center is the smallest. Then the nodes are manually arranged to the positions of these virtual cluster centers as cluster head nodes, which can reduce the energy consumption of communication within the cluster. After the cluster head node is arranged, it sends a broadcast to the members in the cluster to determine itself as the cluster head node.

B. MN PATH PLANNING

In order for mobile nodes to work more collaboratively, each node needs to be reasonably allocated with work tasks. For this reason, the article divides the fan-shaped monitoring area according to the number of mobile nodes. During the division process, there may be a large difference in the length of the path that the mobile node has to traverse, which may cause the problem that path length of some nodes exceeds the maximum cruising range. This paper proposes a path equalization algorithm based on ratio (PEABR) to solve this problem, and proposes a maximum deviation rate to characterize the path length balance between mobile nodes.

The larger the maximum deviation rate indicates that the path length between mobile nodes is more unbalanced. On the contrary, the paths between mobile nodes are more balanced, as follows:

$$\beta = \frac{max\{L_1, \cdots, L_k\} - min\{L_1, \cdots, L_k\}}{min\{L_1, \cdots, L_k\}} \tag{16}$$

where L_k, $k = \{1, 2, \cdots, K\}$ is the shortest path of the mobile node in its respective area. The algorithm step is as follows:

(1) According to the number of MN, it is divided into k sectors with angles of π/k, and determine the fan-shaped area to which the cluster head belongs as the area of the entire cluster;

(2) Calling the ant colony algorithm to obtain the order in which each MN accesses the cluster head nodes of each cluster in its sector and the length of each node in its region is $L_1, L_2, \ldots\ldots L_k$;

(3) Take the ratio of the path length of each MN in its area to get the deviation value ∂, that is

$$\partial_{\mathrm{j}} = \frac{L_{j+1}}{L_j}, \quad \mathrm{j} = 1,2,\ldots\ldots,\mathrm{k} \tag{17}$$

(4) According to the deviation value and the relationship between the path length of each area and the maximum cruising range, there are four cases:

1) If any $L_i < L_{\max}$, $i = 1, 2, \cdots, k$, and $1-\gamma < \partial_j < 1+\gamma$, then the path is considered to be reasonable, and the shortest path of each MN is output, where γ is a given constant called deviation rate, $0 < \gamma < 1$;

2) If any $L_i < L_{\max}$, $i = 1,2, \cdots, k$, but $\partial_j < 1 - \gamma$ *or* $\partial_{\mathrm{j}} > 1 + \gamma$, it is considered that the path division has the possibility to improve, and enters the path adjustment stage. If the maximum deviation rate can be reduced while keeping the total path length unchanged or reduced after adjustment, the adjustment is considered reasonable and the adjusted path is output. If after adjustment, the total path length cannot be maintained constant or reduced in the case of reducing the maximum deviation rate, the original division result is directly output;

3) If there is $L_i > L_{max}$, $i = 1, 2, \cdots, k$ and $\partial_j < 1 - \gamma$ *or* $\partial_{\mathrm{j}} > 1 + \gamma$, it is considered that the path division is unreasonable and the adjustment process starts. If the requirements cannot be met after adjustment, the number of mobile nodes will be increased and the path will be redivided.

4) If there is $L_i > L_{max}$, $i = 1, 2, \cdots, k$ and $1 - \gamma < \partial_j < 1 + \gamma$, it is considered that the path division is unreasonable and the adjustment process is started. If the requirements cannot be met after adjustment, the number of mobile nodes will be increased and the path will be redivided.

The path adjustment first adjusts the paths of the two neighboring MNs with the largest deviation rate. The adjustment process is divided into the following two steps:

(1) Get the set of adjustment points. The solution process is as follows, where θ_j is the angle between the x-axis and the boundary of the region H($j+1$) and H(j).

➢ When $\partial_j > 1+\gamma$

1) When $\theta_j < \frac{\pi}{2}$

Let $\theta = \theta_j = \frac{\pi}{k} \times j$, then the boundary line between the regions H($j+1$) and H(j) can be expressed as $y = \tan\theta \bullet x$ or $y = \tan(\frac{\pi}{k} \times j) \bullet x$. According to the formula of distance from the point to the line $d = \left|\frac{Ax_0+By_0+C}{\sqrt{A^2+B^2}}\right|$, then calculate the Euclidean Distance of all the cluster head nodes to the boundary line in the region H($j+1$), and sort in ascending order. Starting from the minimum distance point, take the nodes in turn and divide it into the region H(j);

2) When $\frac{\pi}{2} < \theta_j < \pi$

Let $\theta = \pi - \theta_j = \pi - (\frac{\pi}{k} \times j)$, then the boundary line between the regions H($j+1$) and H(j) can be expressed as $y = \tan\theta \bullet x$ or $y = \tan(\pi - \frac{\pi}{k} \times j) \bullet x$. Calculate the Euclidean distance from all cluster head nodes in the region H($j+1$) to the dividing line, sort in ascending order. Starting from the minimum distance point, take the nodes in turn and divide it into the region H(j);

➢ When $\partial_j < 1-\gamma$

1) When $\theta_j < \frac{\pi}{2}$

Let $\theta = \theta_j = \frac{\pi}{k} \times j$, then the boundary line between the regions H($j+1$) and H(j) can be expressed as $y = \tan\theta \bullet x$ or $y = \tan(\pi - \frac{\pi}{k} \times j) \bullet x$. Then calculate the Euclidean Distance of all the cluster head nodes in the region H(j) to the boundary line , sort in ascending order. Starting from the minimum distance point, take the nodes in turn and divide it into the region H($j+1$);

2) $\frac{\pi}{2} < \theta_j < \pi$

Let $\theta = \pi - \theta_j = \pi - (\frac{\pi}{k} \times j)$, then the boundary line between the regions H($j+1$) and H(j) can be expressed as $y = \tan\theta \bullet x$ or $y = \tan(\pi - \frac{\pi}{k} \times j) \bullet x$, calculate the euclidean distance of all the cluster head nodes in the region H(j) to the boundary line , sort in ascending order. Starting from the minimum distance point, take the nodes in turn and divide it into the region H($j+1$);

(2) Calculate the total path and offset values of the two regions after each adjustment. First take the smallest total path as the optimal result. If the total paths are equal, take the smallest offset value as the best. Then exit the adjustment process and output the adjusted results. If, after traversing all the points in the area, no point can be found that makes the path or offset value better, the adjustment process is skipped and the original value is output.

The adjustment process of the path is shown in Fig. 2 and Fig. 3.The flow chart of path planning is shown in Fig. 4.

IV. SIMULATION ANALYSIS

A. SIMULATION ENVIRONMENT

In order to verify the effectiveness of the scheme, it was simulated and analyzed by MATLAB. Some important parameters are shown in Table 1.

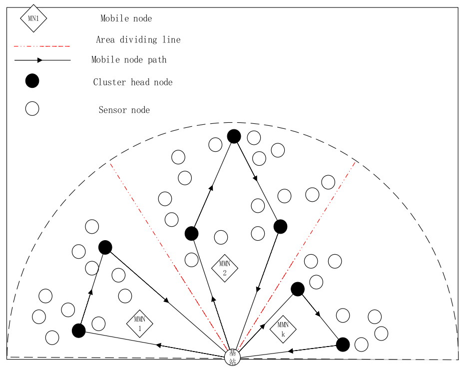


FIGURE 2. Node original path.

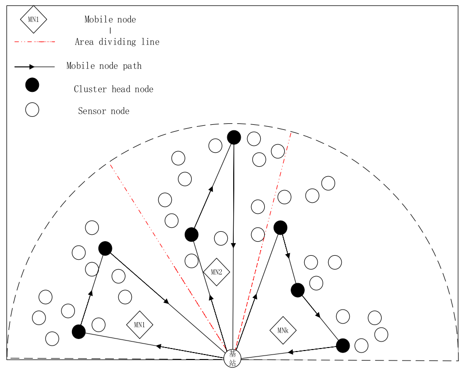


FIGURE 3. Node adjusted path.

TABLE 1. Simulation part of important parameters.

parameter name	Parameter value
Number of sensor nodes	90
Number of cluster head nodes	10
Number of mobile nodes	3
Heuristic factor (α)	1
Expectation heuristic factor (β)	5
Information intensity (Q)	500
Pheromone volatile factor (η)	0.5
Number of ant colonies (m)	18
Deviation rate	0.1
Maximum cruising range	120

B. SIMULATION ANALYSIS

Firstly, several sensor nodes are randomly arranged in the semicircle area with a radius of 50, and the node distribution diagram is shown in Fig.5.

Randomly distributed nodes are clustered, and the clustering results are shown in Fig.6. Then, the cluster head nodes with higher initial energy are manually arranged on the generated virtual center.

According to the number of mobile nodes, the monitoring area is divided into several sectors. Within each sector, the mobile node uses the ant colony algorithm to plan the shortest path. The path and the path length of each mobile node in the sector is shown in Fig.7.

It can be seen from the results that the shortest path lengths of the mobile nodes 1, 2, and 3 in the respective regions are

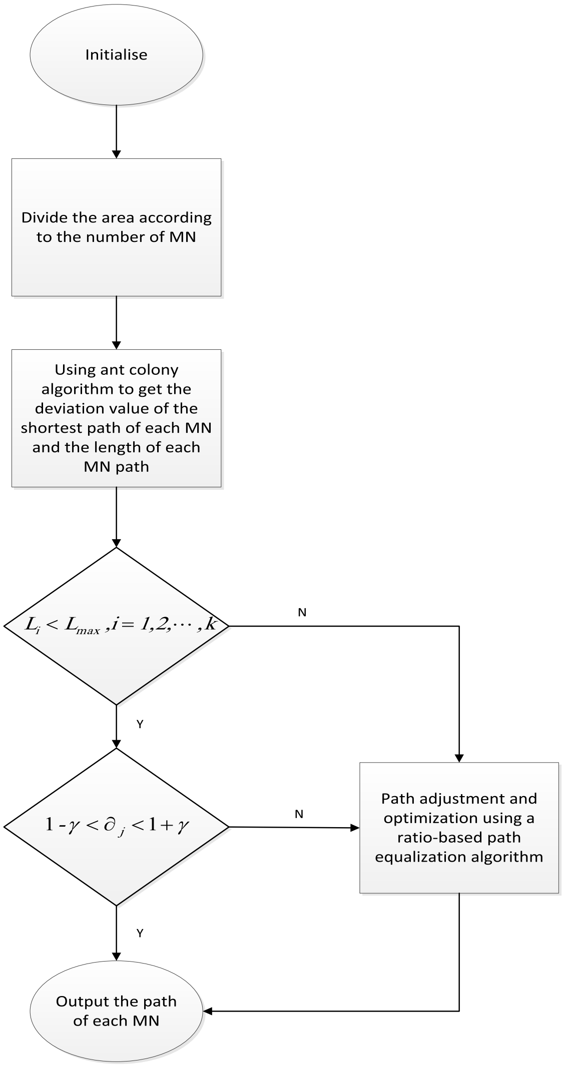


FIGURE 4. Algorithm flow chart.

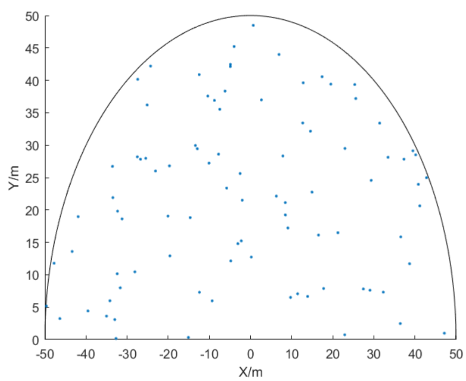


FIGURE 5. Node distribution map.

109.8, 104.5, and 106.7, and the path length deviation ratios between adjacent regions are less than 0.1. And the paths of the respective regions are smaller than the maximum cruising range. It is considered that the area division is reasonable,

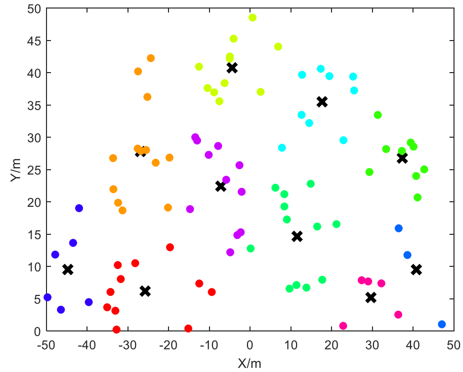


FIGURE 6. Clustering results.

TABLE 2. Comparison of simulation results.

Number of cluster heads	10	10	10	15
MN Quantity	3	3	3	3
MN1path(m)（before）	109	110	73	133
MN2path(m)（before）	104	129	81	101
MN3path(m)（before）	106	73	98	100
MN1path(m)（after）	/	110	76	119
MN2path(m)（after）	/	94	77	114
MN3path(m)（after）	/	108	95	102
Total path length change(m)	/	0	-4	-10
Maximum deviation rate change(%)	/	-0.6	-0.1	-0.17

and the paths of the respective MN are output. Next, a set of examples that do not meet the conditions and need to be adjusted are used to verify the PEABR algorithm.

It can be seen from Fig.8 that the path of each MN after the current division does not satisfy the maximum difference requirement and the path length of the MN1 is no longer within the maximum cruising range. Therefore, the path adjustment is performed, and the adjusted result is shown in Fig. 9 and Fig. 10.

The adjusted path lengths are 119.8, 132.9, and 100.5 respectively, and the requirements of the indicators are still not met. The second adjustment is continued for the area, and adjustment results are shown in Fig.12:

After two adjustments, the shortest paths of the three mobile nodes are 119.8, 114.1, and 102.6 respectively, which meet the requirements of the given indicators. Then we did several experiments, the experimental results are shown in Table 2.

From Table 2, compared with the path length of each mobile node before adjustment, the adjusted path not only makes the path length of each mobile node tend to be balanced, but also shortens the total path length to a certain

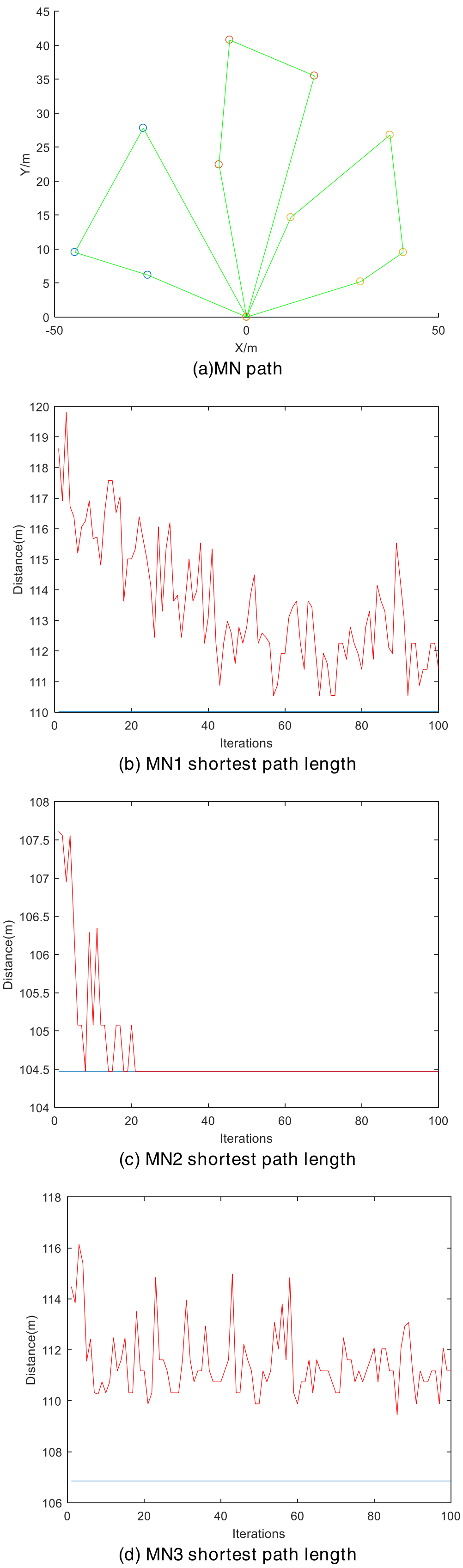


FIGURE 7. **Mobile node shortest path length.**

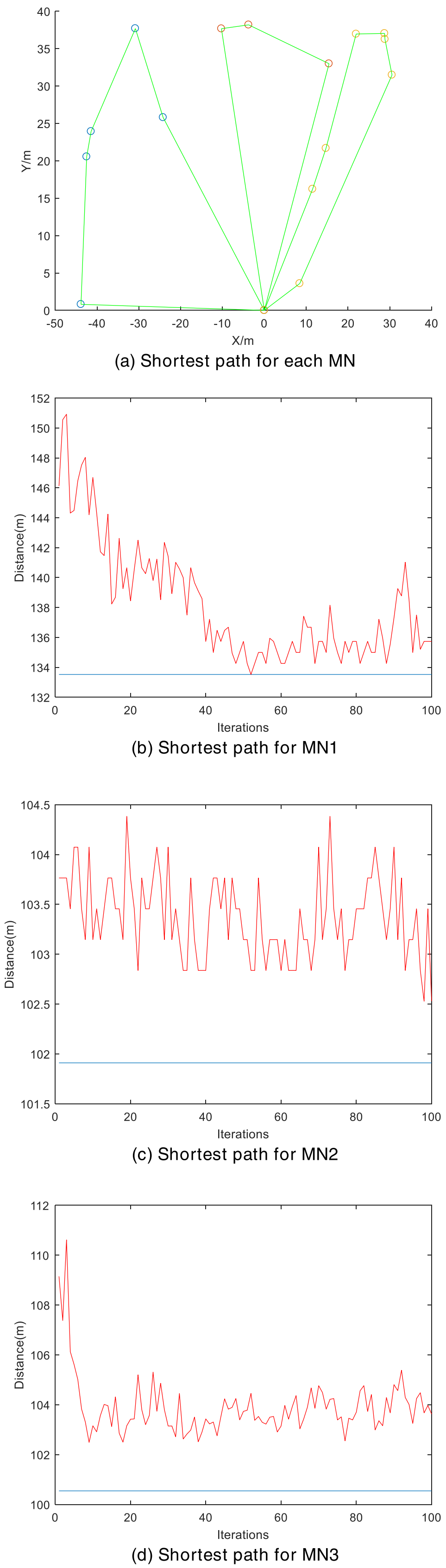
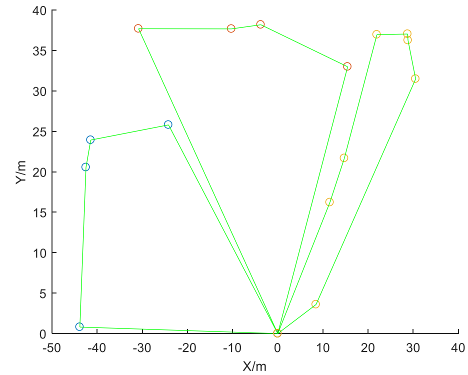
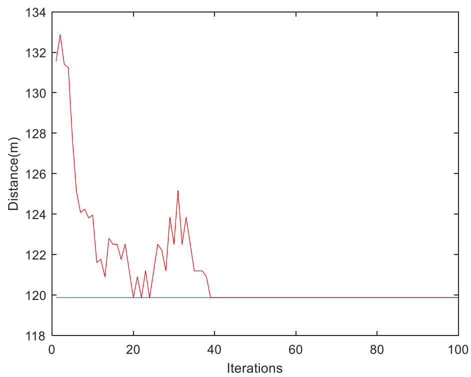


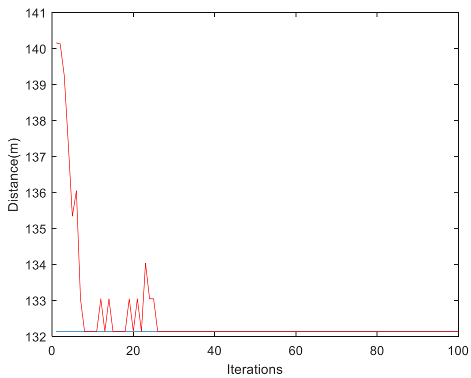
FIGURE 8. **Shortest path of each MN.**



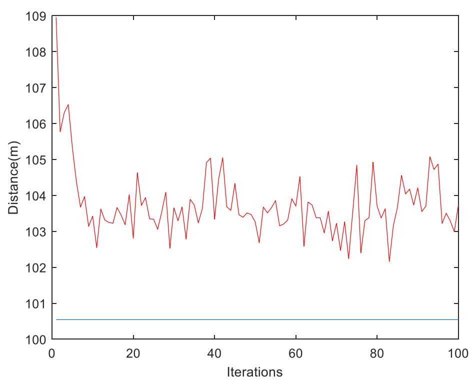
(a)MN path after the first adjustment



(b)Shortest path of MN1 after the first adjustment

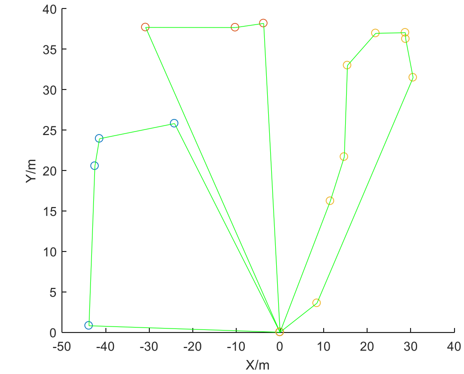


(c)Shortest path of MN2 after the first adjustment

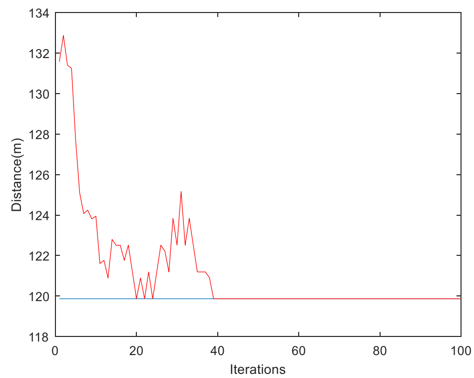


(d)Shortest path of MN3 after the first adjustment

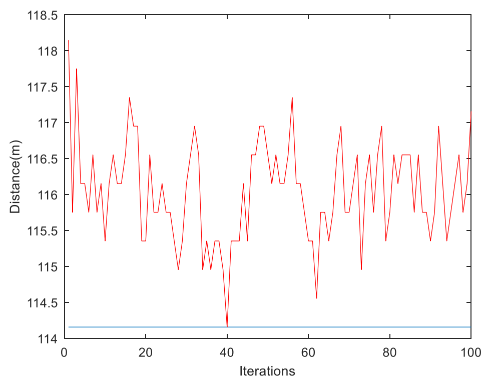
FIGURE 9. Shortest path of each MN after the first adjustment.



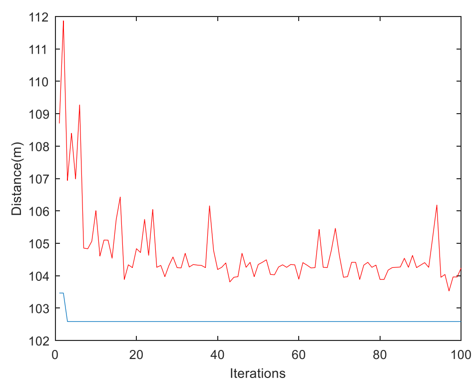
(a) MN path after the second adjustment



(b) Shortest path of MN1 after the second adjustment



(c) Shortest path of MN2 after the second adjustment



(d) Shortest path of MN3 after the second adjustment

FIGURE 10. Shortest path of each MN after the second adjustment.

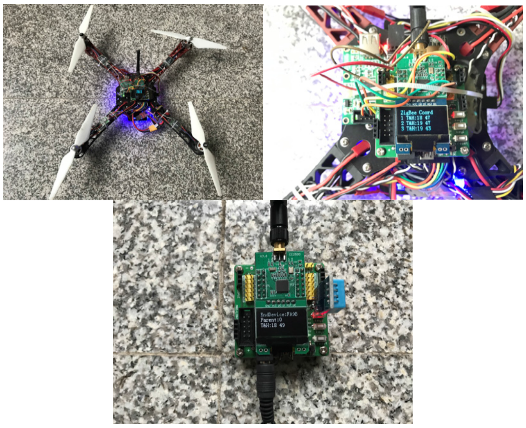


FIGURE 11. Physical picture.

TABLE 3. Test results of communication quality.

distance （m）	Number of packets sent	Number of packets lost	packet loss rate
10	1000	0	0
15	1000	0	0
20	1000	1	0.001
25	1000	23	0.022
30	1000	101	0.121
35	1000	382	0.394
40	1000	1000	1

extent, and achieves the expected effect and verifies the effectiveness of the algorithm.

C. DATA COLLECTION RELIABILITY VERIFICATION

According to the simulation analysis above, the simulation experiment is carried out in the laboratory environment to further verify the reliability of data transmission. The experiment used ten sensor nodes as cluster head nodes and three mobile nodes. We selected the temperature and humidity as the data to be collected, using the DHT11 temperature and humidity sensor, and carrying the mobile node as the mobile data collector in the unmanned aerial vehicle(UAV), the physical picture is as shown in Fig.11.

We tested the communication quality of the hardware, and test results are shown in Table 3.

Then, three rounds of experiments were carried out, and the temperature and humidity data in the laboratory environment were as shown in Table 4. The results show that the experimental system can effectively collect temperature and humidity data, and the data transmission is reliable.

TABLE 4. The experimental values of the system.

Number of experimental rounds	MN1Collected temperature and humidity data （13:30）	MN2Collected temperature and humidity data （15:30）	MN3Collected temperature and humidity data（17:30）
1	18/47	16/55	15/57
	19/47	15/56	14/60
	19/43	16/53	15/60
2	19/45	15/55	16/55
	18/45	14/56	15/55
	19/47	14/59	15/57
3	18/45	16/54	15/57
	18/47	16/56	16/59
	18/47	16/59	16/59
	18/47	15/56	16/60

V. CONCLUSION

This paper proposes a path planning scheme for collaborative data collection by multiple mobile nodes. This paper clusters and randomly arranges sensor nodes, and then manually arranges cluster head nodes on the generated virtual cluster center, and then divides the monitoring network into fan-shaped regions. Aiming at minimizing the path length of mobile nodes as an optimization goal, a path optimization algorithm PEABR for multiple MNs is proposed. The algorithm can adjust the divided area according to the path length and deviation value under the premise of meeting a series of constraints such as time and energy, and to some extent, it can equalize the movement paths of each MN and reduce the total path length. The simulation results show that the algorithm can balance the path length of each MN to meet the constraints such as the maximum cruising range without increasing the additional path cost, and it is possible to further reduce the total path cost. Finally, experiments are carried out to further verify the reliability of the proposed path planning scheme for collecting data.

Data Availability statement

The data used to support the findings of this study are included within the article. If other data or programs used to support the findings of this study are needed, you can obtain them from the corresponding author.

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