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An Improved Multidimensional Calibration Algorithm Based on Artificial Bee Colony Algorithm

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Abstract. *In order to reduce the existing error between the shortest path distance and the actual Euclidean distance of nodes under the uniform distribution or the low node density network. The distance between nodes is obtained by reassigning the edges in the sensor network connection graph considering the local density of node. The optimal shortest path between nodes is selected by intelligent algorithm of artificial bee colony to construct the distance matrix between nodes. The simulation results show that the accuracy of the modified algorithm is about 11% higher than that of Classical Multidimensional scaling algorithm.*
Keywords: MDS_MAP, Positioning, Shortest path, Local connectivity, ABC.

1. **Introduction.** The current localization algorithm for wireless sensor network (WSN) includes the beacon (anchor nodes) based type and the none-beacon type [1–4]. According to the distance parameter obtained by the algorithm, the algorithm is divided into Range-based localization and Range-free localization [5]. The algorithm can also be divided into centralized localization algorithm and distributed localization algorithm as the difference in computing mode [6].

The majority of the localization methods require a large number of anchor nodes as well as adequate support from anchor nodes [7]. In recent decades, some approaches have been proposed to handle this problem like the Multidimensional scaling algorithm (MDS_MAP). There is no limit to the number of anchor nodes in MDS_MAP, otherwise, it can be carried out on both distance-based and non-ranging situations. The MDS_MAP algorithm constructs the dissimilarity matrix by using the distance between nodes [8, 9]. The reduced dimension strategy is further concerned to convert the high-dimensional space vectors into any of the lower dimensional vectors. Therefore, the algorithm can conveniently and effectively calculate the node coordinates and it is more suitable for WSN.

However, there are existing error between the shortest path distance of nodes and the actual Euclidean distance of nodes under the uniform distribution or the low node density network. Addressing this issue, this paper proposed a modified artificial bee colony algorithm for multidimensional scaling localization to weaken the negative effect of the uneven distribution of nodes as well as the low density, and the optimal shortest path is selected to improve the localization accuracy.

2. Theory.

2.1. **MDS_MAP Positioning Algorithm.** The Classical MDS_MAP positioning algorithm was first proposed by Shang Yi who is in the United States Missouri University of Columbia in 2003 [10], which makes multidimensional calibration technology more mature in the wireless sensor network node positioning. The three main steps of MDS_MAP are as follows.

(a) Calculate the shortest path distance between all nodes to construct the distance matrix between nodes. First, generate a network topology connected map from the global point of view, which include dividing each edge of the connection graph according to the measured value of the distance between nodes. When the distance value is measurable, the distance value is used as the value between the nodes. When only the connectivity information between adjacent nodes is known, the edge assignment between the nodes given by the connected relation R. Then, the shortest path algorithm is used to deal with the connectivity matrix in order to ensure that there is a distance between all nodes. Finally, the shortest path value is used to replace the Euclidean distance between nodes, and the distance matrix of all the nodes of the network is obtained.

(b) The MDS algorithm is applied to the distance matrix, whose core is the singular value decomposition. According to this step, we can generate a two-dimensional or three-dimensional relative coordinate system of the entire network, then using the metric or non-metric multidimensional scale algorithm to calculate the relative coordinates of the entire network nodes.

(c) The relative coordinate values are converted to absolute coordinate values by linear transformation, which needs at least $m + 1$ beacon nodes for the nodes in the m-dimensional space are positioned.

2.2. **Artificial Bee Colony Algorithm.** As a swarm intelligence optimization algorithm, Artificial Bee Colony (ABC) algorithm is based on the principle of finding the food source for bees honey which was put forward by the Turkish scholars Karaboga in 2005 [11]. The artificial swarm in ABC is divided into three roles: employed bees, onlookers and scouts. The number of employed bees equals to that of onlookers, covering half of population size, and they are responsible for exploitation, while the scout bees are responsible for exploration. Generally, the food sources in ABC are randomly generated at the initialization stage. Let S denote the number of food sources. With the definition above, firstly, the employed bees search the food sources of their neighborhood, generate the new food sources according to Eq. (1), and compute their fitness values. Then, a greedy selection strategy based on fitness value is utilized to choose the better solution between the new food sources and the old ones.

$$v_{ij} = x_{ij} + r_{ij} \left(x_{ij} - x_{kj} \right) \tag{1}$$

Where v_{ij} is the position of a new food source, r_{ij} is random in $[-1, 1]$, K is random and meets $k \neq i$, $k \in \{1, 2, \cdots, S\}$.

Second, by observing the employed bees swing dance the onlooker determines the food source, judges the yield of the food source discovered by each employed bee. According to their fitness values, roulette wheel selection strategy is employed to determine which employed bee to follow. According to the fitness values of all food sources, the probability to select food source can be determined by Eq. (2):

$$p_i = \frac{fit_i}{\sum\limits_{i=1}^{S} fit_i} \tag{2}$$

Where fit_i is the fitness function of food source i, S is the total number food sources.

Finally, if a solution cannot be updated after'limit'cycles, which indicates that this solution may fall into local optimal, this solution will be abandoned, and then the corresponding employed bee becomes a scout bee. Assuming that the abandoned solution is x_i, the scout bee produces a new solution to replace it as defined by Eq. (3):

$$x_i^j = x_{\min}^j + rand(0,1)(x_{\max}^j - x_{\min}^j) \tag{3}$$

2.3. **Improved Multidimensional Calibration (AMDS_MAP) Algorithm for Artificial Bee Colony Algorithm.** Each individual of the colony algorithm selects the global optimal solution of the individual by calculating the fitness value to compare the yield. Hence, the most critical problem of choosing the shortest path by artificial bee colony algorithm is the setting of the fitness function. Assume that the Euclidean distance between AB nodes is $D\left(A,B\right)$, $D\left(A,B\right)$ can be defined as follows:

$$D(A,B) = \sqrt{\left(x_A - x_B\right)^2 + (y_A - y_B)^2} = 2R \tag{4}$$

Where (x_A, y_A), (x_B, y_B) is the coordinates of A and B. There is likely to be a less jump straight path between nodes A and B that the shortest path distance between nodes is approximately equal to the Euclidean distance $2R$ between two points when the nodes in the network are high density and the nodes are evenly distributed, as shown in Fig. 1.

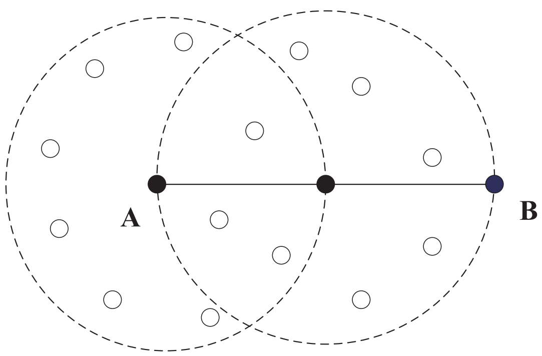


Figure 1. The jump path is close to the straight path of R

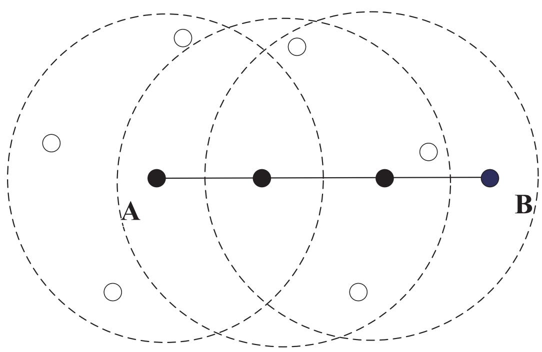


Figure 2. The straight path of the hop path is not near R

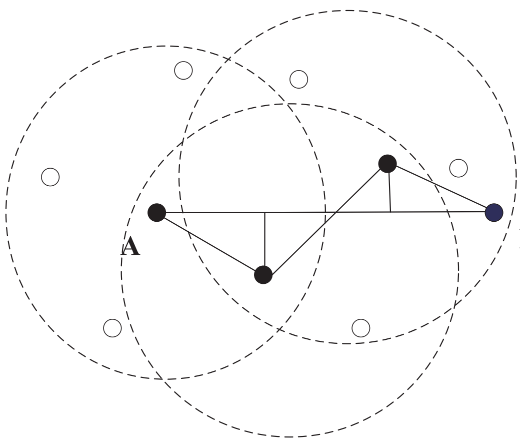


Figure 3. The polyline path is close to the polyline path of R

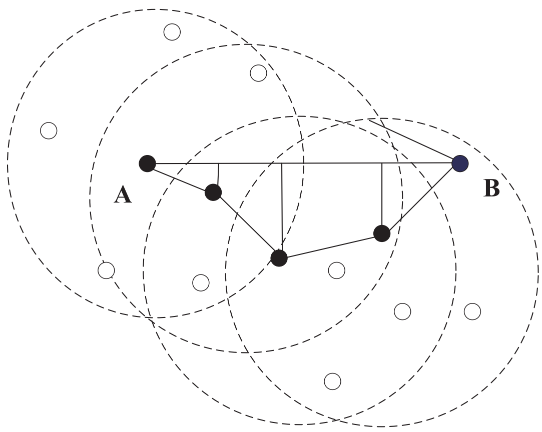


Figure 4. The polyline path is close to the polyline path of R

The shortest path between nodes is likely to occur in the case of Fig. 2 and Fig. 3, when the network node density is low or the nodes are not evenly distributed. As shown in Fig. 2, the shortest path is a straight line, but the path of each hop distance is not close to R. For the Fig. 3, the shortest path although each hop distance is close to R, the path is a broken line between A and B. The shortest path distance between nodes is about 3R, in Fig. 2 and Fig. 3. The shortest path of A and B is about $4R$ in the Fig. 4, it will lead to greater estimation errors.

The straight line distance between A and B can be expressed as Eq. (5) when the distribution of wireless sensor network nodes is not uniform and the density is low.

$$D(A,B) \approx \mu_1 R + \mu_2 R + \cdots + \mu_m R \tag{5}$$

Where m is the minimum number of hops between A and B, and R is the communication radius. The communication radius factor μ can be defined as a function of the node's local density, and the local density can be defined as the number of neighbor nodes in the transmission area per node. So the communication radius factor μ can be expressed as Eq. (6).

$$\mu_i = n_i / \pi R^2 \tag{6}$$

Where n is the node connectivity. The connectivity of a node is the number of neighbor nodes within the hop of the node.

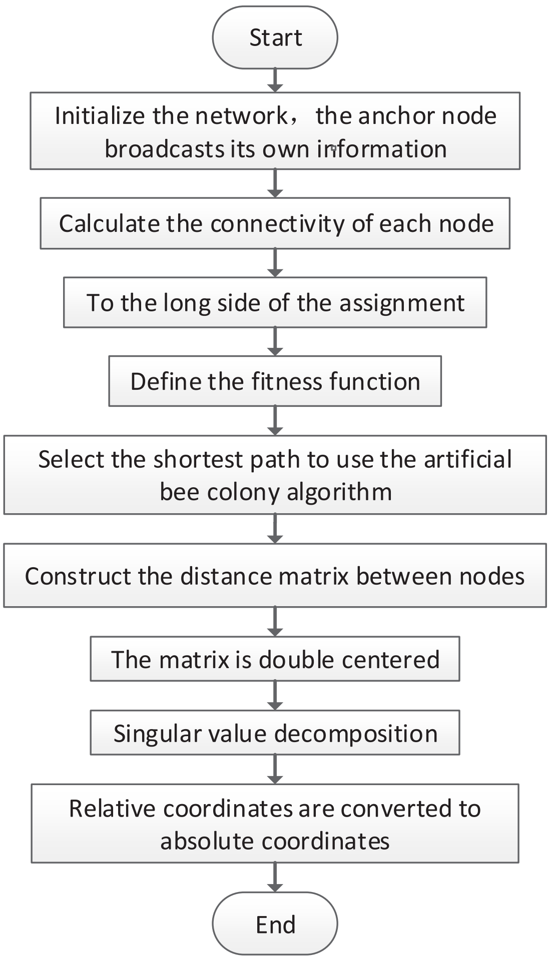


FIGURE 5. A Method of Improved Multidimensional Calibration Algorithm Based on Artificial Bee Colony Algorithm

Through the above analysis, the fitness function can be defined as Eq. (7).

$$fit(x, y) = \sum_{i=1}^{m} \mu_i R \tag{7}$$

Select the shortest path between nodes can be by the Eq. (7) to reduce the error between the shortest path and the actual Euclidean distance.

In this paper, an improved multidimensional calibration algorithm based on artificial bee colony algorithm is proposed. The algorithm flow is shown in the Fig. 5.

3. Results and discussion.

We conducted computer simulation to evaluate the propose approach, and compared with the experimental results of MDS_MAP and MDS_MAP (C).

3.1. Simulation setups and parameters.

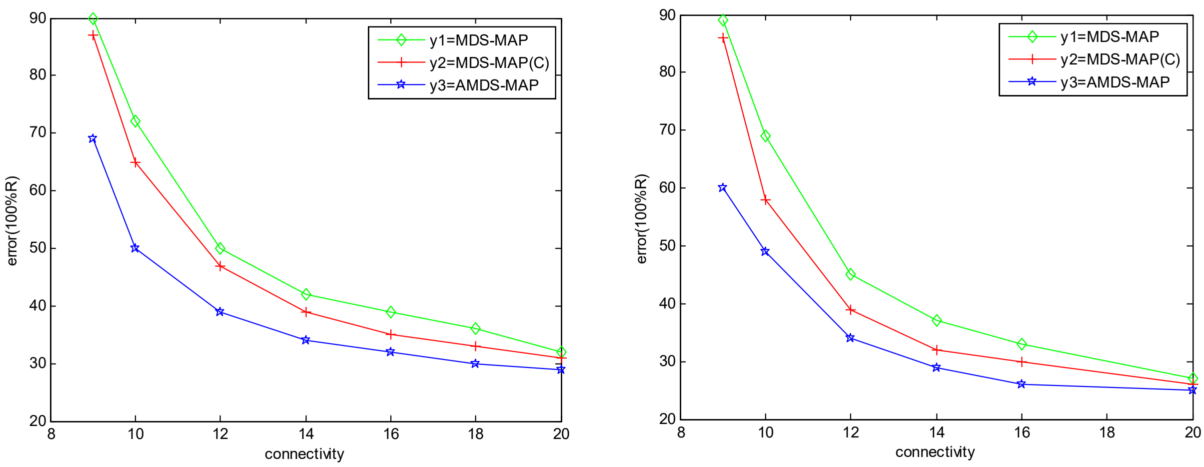
In our experiment, we assume that the communication radius of the node is the same and all the nodes are deployed in a 200 m × 200 m region, the region distribution of 200 nodes, the anchor node is randomly selected and the location is known. Set the number of bees $S = 200$, which include 100 employed bees and 100 onlookers $N_c = N_g = 100$. The number of cycles $K = 500$. The searching range is $0 \le x \le 200$, $0 \le y \le 200$. The convergence condition of the experiment is set to $|fit(x, y)| \le 10^{-4}$. The value of 'limit' is 100, and the dimension is set to $M = 2$. The evaluation index of the experiment is the average error, the average error formula is as follows.

$$error = \frac{\sum_{i=1}^{m} \sqrt{(x_i - x_i')^2 + (y_i - y_i')^2}}{km \times R} \times 100\% \tag{8}$$

Where (x_i, y_i) is the actual coordinates of the unknown node, $\left(x_i', y_i'\right)$ is the estimated coordinates of unknown nodes, m is the number of the unknown node.

3.2. Uniform random network layout.

We assume that the communication range is set to be 15m and 200 nodes are randomly distributed in a 200 m × 200 m area. The average connectivity of the sensor network is 12.3. The three algorithms of AMDS_MAP, MDS_MAP and MDS_MAP (C) are simulated in the case of selecting three anchor nodes and six anchor nodes randomly. The results are shown in Fig. 6.



(a) 3 anchor nodes (b) 6 anchor nodes

FIGURE 6. The relationship between the average positioning error of nodes and the degree of connectivity

Fig. 6 respectively show the relationship between the average positioning error of nodes and the degree of connectivity in the three different algorithms of MDS_MAP, MDS_MAP(C), AMDS_MAP. From Fig. 6, we can see that the average positioning error of the AMDS_MAP algorithm is significantly lower than that of MDS_MAP and MDS_MAP(C). With the increase of the connectivity value, the decreasing trend of the average positioning error of the three algorithms becomes smaller, and the average positioning error value is basically the same. This is because the three algorithms calculate the shortest path closer to the actual Euclidean distance, the higher the positioning accuracy while the network connectivity is increased to a certain extent.

3.3. **Uneven network layout.** 200 nodes are distributed in the heterogeneous network as shown in Fig. 7. The whole network of 200 m × 200 m is divided into four equal parts of the area, the number of each part of the nodes were: 40, 60, 60, 40. The three algorithms are simulated and analyzed in this uneven network. The results are shown in Fig. 8.

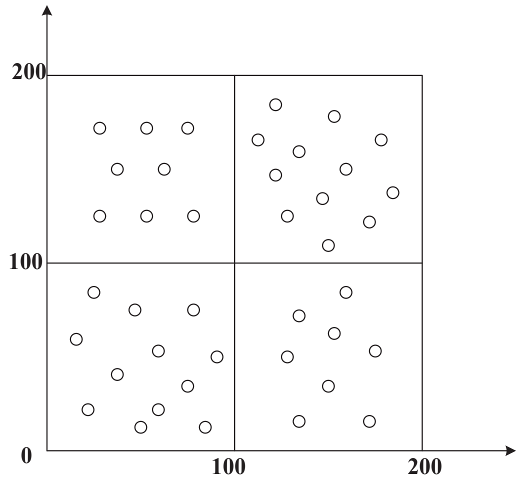


FIGURE 7. Uneven network distribution

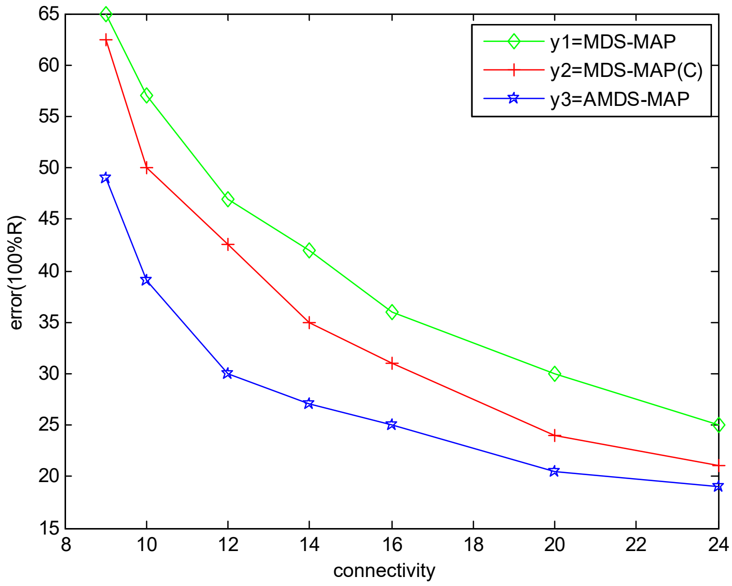


FIGURE 8. The change of mean positioning error of node in uneven network with the degree of connectivity

From Fig. 8, we can see that the accuracy of AMDS_MAP that we have proposed in this paper is significantly higher than that of MDS_MAP and MDS_MAP (C) in this uneven network while the network connectivity is low. With the increasing of the network connectivity, the area with little node distribution affected by the node density, which local connectivity of the node is still very low, and the connectivity of the whole network is still different. As shown in Fig. 8, our proposed algorithm performs better than other algorithms when the degree of connectivity becomes larger. Thus, the AMDS_MAP algorithm can be better applied to the uneven network.

4. **Conclusion.** In the practical application, there is a large error between the shortest path distance and the actual Euclidean distance of nodes under the uniform distribution or the low node density network. Therefore, an Improved Multidimensional Calibration Algorithm Based on Artificial Bee Colony Algorithm is proposed in this paper. The different coefficient values are defined, and then the side of sensor network connection graph will be reassignment depending on the local connectivity. The path closest to the actual Euclidean distance is found by searching the shortest path through the Artificial Bee Colony intelligence algorithm. Simulation results show that the proposed AMDS_MAP has better performance on accurate localization. We will focus on studying the matrix iterative algorithm and the way for reducing the error when the relative coordinates are converted to absolute coordinates.

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