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Blackboard Mechanism Based Ant Colony Theory for Dynamic Deployment of Mobile Sensor Networks

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Abstract

A novel bionic swarm intelligence algorithm, called ant colony algorithm based on a blackboard mechanism, is proposed to solve the autonomy and dynamic deployment of mobiles sensor networks effectively. A blackboard mechanism is introduced into the system for making pheromone and completing the algorithm. Every node, which can be looked as an ant, makes one information zone in its memory for communicating with other nodes and leaves pheromone, which is created by ant itself in nature. Then ant colony theory is used to find the optimization scheme for path planning and deployment of mobile Wireless Sensor Network (WSN). We test the algorithm in a dynamic and unconfigurable environment. The results indicate that the algorithm can reduce the power consumption by 13% averagely, enhance the efficiency of path planning and deployment of mobile WSN by 15% averagely.

Keywords: ant colony algorithm, wireless sensor network, blackboard mechanism, bionic swarm intelligence algorithm

1 Introduction

With the dramatic development of WSN, the mobile WSN, which can be deployed movably and conveniently in sensed area, become a new research focus for its mobility. Mobile WSN can be applied into a wide range of applications, such as dynamic observation and monitoring systems, battlefield assessment and management, union attack ammunition *etc*. Compared with mobile WSN, stationary sensor network has several disadvantages. Because of the fixation of stationary WSN, as long as the positions of nodes are deployed once, then the coverage area is fixed and cannot be adjusted automatically. And failure of the sensor node may lead to disconnection of the whole networks which cannot be mended. When the task is changed or the working conditions altered, stationary senor network cannot be reconfigured, so it is difficult to maintain the stationary sensor network. Furthermore, in order to ensure the connections reliability, excrescent nodes are usually needed. Mobile WSN can overcome the above shortcomings of stationary sensor network. Therefore, many researchers focus on the research of mobility WSN[1–5].

However, mobile WSN like traditional WSN has some limitations including power, computation abilities *etc*. These limitations must be considered when designing the hardware and software system of mobile WSN. Low power consumption, low cost and low complication are desired in WSN.

Generally, there are hundreds of mobile nodes in the sensor network, which can be seen as a swarm of mobile ants. So the complicated system looks like one biology-system, and biological-colony optimal theory can be used to optimize the working of system. It is a remarkable significance for the mobile sensor network, because every node equips with only one limited battery. Cutting down the consumption of energy and improving the energy-efficiency are very important for prolonging the life of node and system. As typical biological-colony theory used in WSN, the ant colony algorithms have drawn great attention from researches[6–9]. The characteristic of biological-colony, which individually is limited in capabilities but as a whole is complex and flexible,

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is scalable and robust. The collective behaviour of biological species provides a natural model for distributive problem solving without any extra central control or coordination. The ant colony algorithms have been widely used to solve the routing problem in mobile WSN and planning path in swarm robots[10,11]. However the research using ant colony algorithms to solve the deployment of mobile WSNs is rare.

The planning path and dynamic deployment of mobile WSN is a complex and principal technology for functioning of the system. In order to adjust the position of nodes or change the observation and monitoring sites, all the nodes should have mobile ability. Several approaches have been proposed to solve the problem, but the results are not very suitable. For example, random deployment is used to place the nodes in the network, but it is not the optimal measure because it is not very economical. DT-Score is aimed to maximize the coverage of a sensing area, but only a triangle scheme is adopted and two phases, which may be too complex for battery-supplied WSNs, are needed[12]. OFRD can improve the efficiency of deployment only for regular obstacle sensing area[13]. When applied in practice, this method maybe unsuitable in an unknown environment. In this paper, a novel biology swarm intelligence algorithm, called ant colony algorithm based on a blackboard mechanism, is proposed to solve the autonomous and dynamic deployment of mobiles sensor networks effectively. In this method, the ant colony algorithm is simplified and modified specially for the mobile WSNs. It is the first time using ant colony theory integrated with blackboard mechanism to deploy nodes in an unknown environment.

2 Ant colony optimization algorithms

Ant colony optimization algorithms proposed by Dorigo M[14] is a novel heuristic evolutionary optimization algorithm.

As shown in Fig. 1, A is defined as nest, D is defined as food, line BC is defined as obstacle; the D_{ABD} and D_{ACD} denote the distances between A and D along different routes R_{ABD} and R_{ACD} respectively. We assume $D_{ABD}>D_{ACD}$. IF an ant is at a choice point when there is no pheromone, it will make a random choice to select either R_{ABD} or R_{ACD} with a probability of 0.5 (Fig. 1a).

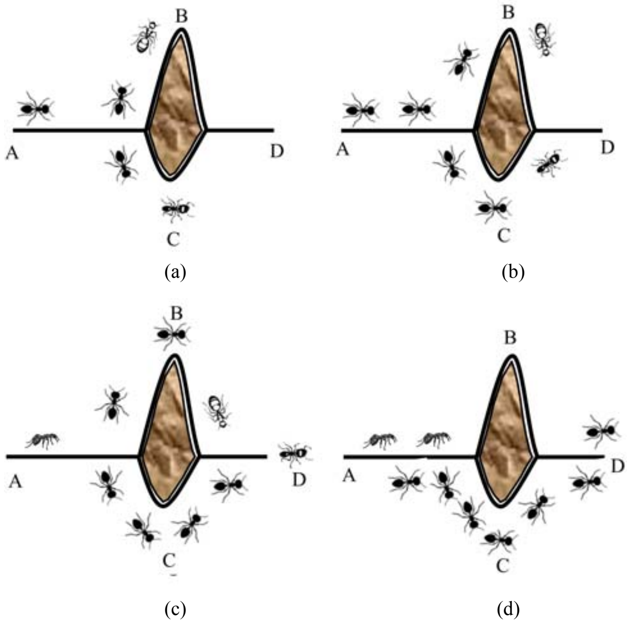

Fig. 1 Simulation of ant finding food behaviour in nature world.

At the same time, the ant will leave pheromone according to the distance of its journey. The longer the journey, the less the pheromone left by the ant. How to dispose pheromone is a positive feedback mechanism to recruit more ants so that more pheromones are disposed on the shorter path. However, the evaporation of pheromone is a negative feedback to reduce the pheromone strength. When other ants meet the choice point again, they will choose the route with much more pheromone, that is to say, they will choose the upper probability way. On the other hand, the pheromone on the other way will evaporate gradually with time. Fig. 1b and Fig. 1c denote that, after a short time, because of $D_{ABD}>D_{ACD}$, more and more ants choose R_{ACD} with more pheromone than R_{ABD}. With the time consumption, ants will choose R_{ACD} with higher and higher probability. Finally, as shown in Fig. 1d the whole ant colony will find the optimal way R_{ACD} to get the food. The ant colony theory model can be narrated as follows.

The probability $p_{ij}^k(t)$ representing the probability ant k move from point i to point j, can be calculated as follows

$$p_{ij}^k(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^\alpha[\eta_{ik}(t)]^\beta}{\sum_{s\subset \text{allowed}_k}[\tau_{is}(t)]^\alpha\cdot[\eta_{is}(t)]^\beta}, & \text{if } j\in \text{allowed}_k \\ 0, & \text{else}\end{cases} \tag{1}$$

where $\tau_{ij}(t)$ is the intensity of pheromone leaving by passing ants at time t; $\eta_{ik}(t)$ is the expectation which ants move from point i to point j; allowed$_k$ is point set which ant k can choose next step; α is the information heuristic factor and β is the desired heuristic factor.

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \ , \tag{2}$$

where d_{ij} is the distance from point i to point j; for ant k, d_{ij} is shorter, the value of $\eta_{ij}(t)$ and $p_{ij}^{k}(t)$ is higher.

The pheromone on the way can be updated as follows

$$\tau_{ij}(t+n) = (1-\rho)\cdot\tau_{ij}(t) + \Delta\tau_{ij}(t) \ , \tag{3}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \ , \tag{4}$$

where ρ is an evaporating coefficient of pheromone, $\rho \subset [0,1]$; $\Delta\tau_{ij}(t)$ represents the increment of route(i, j) in one cycle; $\Delta\tau_{ij}^{k}(t)$ is the increment of ant k leaving on the way. $\Delta\tau_{ij}^{k}(t)$ can be updated as follows

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{L_k}, \text{ if ant } k \text{ pass route}(i,j) \\ 0, \quad \text{else} \end{cases} . \tag{5}$$

In this model, the global updating strategy is adopted. Q is the intensity of pheromone; L_k is the total distance ant k has walked in one cycle.

3 Optimal path-planning using modified ant colony algorithm

3.1 Model of modified ant colony algorithm

In order to test our modified ant colony algorithm, a map with obstacles is built as the scene for the working system. As shown in Fig. 2, a square field (600 m × 600 m) is built. The departure point locates at the bottom left corner of the map, the destination point locates at the top right corner, and the black blocks are obstacles on the path. The grid method which is used in the map to show the position and value is expressed by Eq. (6). In Eq. (6), m is the number of grid rows and n is the number of gird columns in the map. If there is an obstacle in the field, '1' will be set in the mapping matrix. On the other hand, '0' will be used to represent free environment.

$$\text{map}(m,n) = \begin{bmatrix} 0&0&0&0&0&\cdots&0 \\ 0&0&0&0&0&\cdots&0 \\ 0&0&1&1&0&\cdots&0 \\ 0&0&1&1&0&\cdots&0 \\ 0&1&1&1&0&\cdots&0 \\ 0&1&1&1&0&\cdots&0 \\ 0&0&0&0&0&\cdots&0 \\ \vdots&\vdots&\vdots&\vdots&\vdots&\vdots&0 \\ 0&0&0&0&0&0&0 \end{bmatrix} , \tag{6}$$

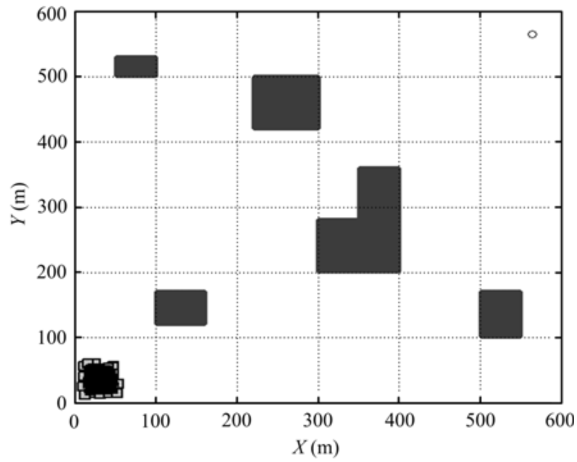

Fig. 2 The initial environment for simulation.

All the artificial ants will move from the departure point to the destination point. Every artificial ant can detected the obstacles in the range of 10 m according to the detection capability of node in mobile WSNs. When detecting an obstacle on the way, the artificial ant will choose the route according to the pheromone. If there is no any pheromone available, the artificial ant will choose a way randomly. In this model, the updating of pheromone is decided by the total distance of every route. The distances of different routes maybe different, so the pheromone left by artificial ant is different. The obvious possible routes are shown in Fig. 3. At the initial time, several artificial ants are assigned to the obvious possible route and initial pheromone is distributed on every route. Then other artificial ants are sent to the destination again. After several cycles, more and more pheromone will be left on the shortest route, although the evaporation of pheromone is processing. The optimal path can be found soon and remainder artificial ants taking the large percent in the ant colony will move towards the destination along this optimal path. In order to apply the method into practice, the efficiency, brevity and economy of the algorithms must be considered. So some details in the basic ant colony algorithms are neglected in this modified model.

The classical ant colony algorithm needs pheromone to choose the optimal path, but the practical situation is often that there is no available pheromone. So a blackboard mechanism is introduced into the system for making pheromone and completing the algorithm. All the mobile nodes can communicate and exchange information each other on the virtual blackboard through wireless media.

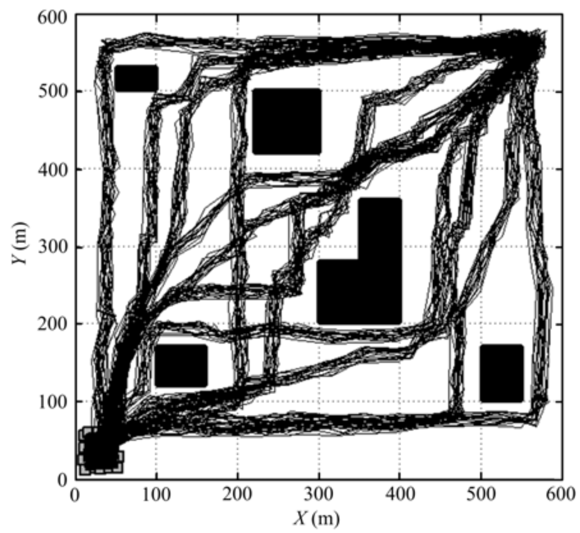

Fig. 3 All the obvious possible routes in an obstacle environment.

3.2 Modified ant colony algorithm

In the modification of ant colony algorithm, a taboo, which used in the basic ant colony algorithm, is abandoned. In order to cut down the calculating time and avoid getting local optimal result, the global strategy of updating pheromone is adopted. The transferring probability of each step of artificial ant is not calculated in the algorithm; only the selected probability of one complete path is taken into account.

The length of every path can be gotten as follows

$$d_l(NC) = \sum_{l=1}^{m} \sqrt{(x_{i+1}^l - x_i^l)(x_{i+1}^l - x_i^l) + (y_{i+1}^l - y_i^l)(y_{i+1}^l - y_i^l)} \,, \tag{7}$$

where $d_l(NC)$ is the length of path l at cycle time NC; (x_i^l, y_i^l) is the coordinate of point (i, j) on the path l.

The heuristic function, which shows the degree of heuristic information, is taken into consideration by the artificial ant in choosing the path. The function is

$$\eta_l(NC) = \frac{1}{d_l(NC)} \,, \tag{8}$$

where the $\eta_l(t)$ and $d_l(NC)$ are inversely proportional. That is to say, the longer the path, the lower the probability to get chosen. The updating of pheromone left on the path by artificial ant is carried out after it has reached the destination point. The pheromone on the path is derived as follows

$$\tau_l(NC+1) = (1-\rho)\cdot\tau_l(NC) + \Delta\tau_l(NC) \,, \tag{9}$$

where ρ is the evaporating factor of pheromone and $1-\rho$ is the residual factor. $\Delta\tau_l(NC)$ is the increment of pheromone at cycle time NC on the path l and is decided as follows

$$\Delta\tau_l(NC) = \begin{cases} \dfrac{Q}{L_l}, & \text{if path } l \text{ is chosen} \\ 0, & \text{else} \end{cases} \tag{10}$$

With the above factors, the probability for path l to be chosen by an artificial ant can be calculated as

$$p_l(NC) = \frac{[\tau_l(NC)]^{\alpha}\cdot[\eta_l(tNC)]^{\beta}}{\sum_{s\subset \text{route set}}[\tau_{ls}(NC)]^{\alpha}\cdot[\eta_{ls}(NC)]^{\beta}} \,, \tag{11}$$

where $p_l(NC)$ is the probability; α and β is the heuristic factor of information and heuristic factor of expectation that artificial ant chooses the path l. In this model, every path can be selected at any cycle time, so $p_l(NC)$ is not always equal to zero only when the pheromone is empty.

3.3 Modified ant colony algorithm used in the dynamic deployment

How to find the optimal path is a key problem in the dynamic deployment of mobile WSNs. It is an important significance that for the prolonging life time of the whole system. We propose the modified ant colony algorithm aimed at mobile WSNs and consider the practicability into the algorithm. The main steps of this modified ant colony algorithm are explained below.

Step 1: To initialize the scene of background for artificial ant.

A map with obstacles is built as Fig. 2, in which some obvious routes are given out at initial time. The initial pheromone, $\Delta\tau_l(NC) = 0$ and other parameters are initialized.

Step 2: To choose the route according to the pheromone.

According Eq. (11), every artificial ant chooses one route. If an obstacle is detected on the way, the ant will move randomly towards a free adjacent point. A route table is generated to memorize the path information.

Step 3: To update the pheromone on every path.

The pheromone on a path is changed according to Eq. (9). If the path is not been chosen, according to Eq. (10), the quantity of pheromone on the path will evaporate with time.

Step 4: To generate the moving path for artificial ant.

Eq. (11) shows how to use the heuristic distance information and pheromone to generate the feasible path. Then, go to **Step 2**.

Step 5: Output the optimal path.

When the termination condition of algorithm is fulfill, the modified ant colony algorithm will stop running and export the optimal path for the mobile node in sensor network. The information will be written on the virtual blackboard in the special memory space of mobile node and broadcasted by wireless media to other nodes in the WSNs. The blackboard is used to notify other residual nodes to get to the optimal path.

Step 6: Deploy the node of mobile WSNs.

According to **Step 5**, all the other nodes choose the optimal planning path to complete the deployment of mobile WSNs.

4 Results and discussion

After the scene was built, a simulation with 600 m × 600 m field was carried out to test the performance of the modified ant colony algorithm. The number of artificial ants in the colony is 20; $\rho = 0.7$; $\alpha = 1$ and $\beta = 5$.

Fig. 4 shows the moving path with the cycle time is 1. All the artificial ants depart from the original point and move towards the destination point. With the cycle time growth, more and more artificial ants choose the shorter path, as show in Fig. 5 and Fig. 6.

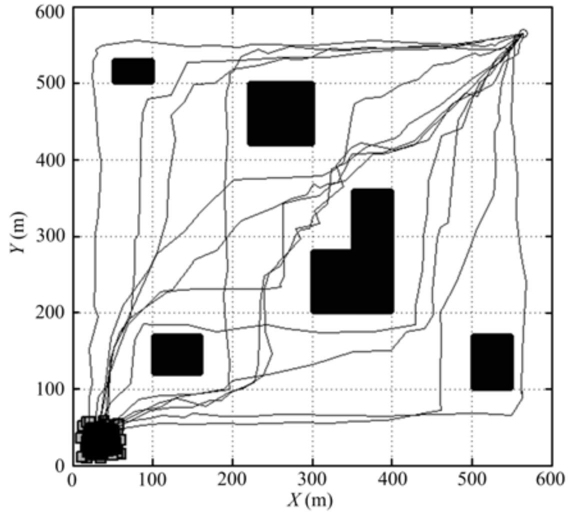

Fig. 4 The moving path at cycle time 1.

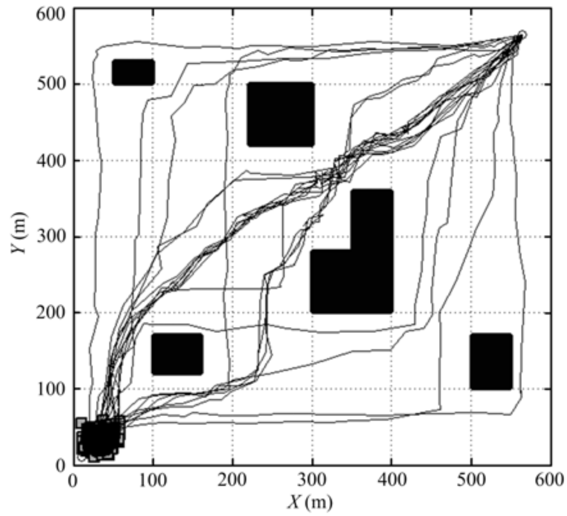

Fig. 5 The accumulative trace of artificial ant at cycle time 10.

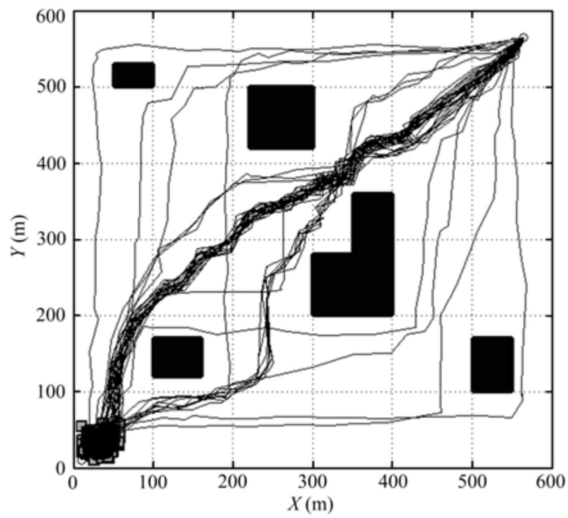

Fig. 6 The accumulative trace of artificial ant at cycle time 30.

As shown in Fig. 7, an optimal path between the original point and the destination point has been found with the cycle time of 50.

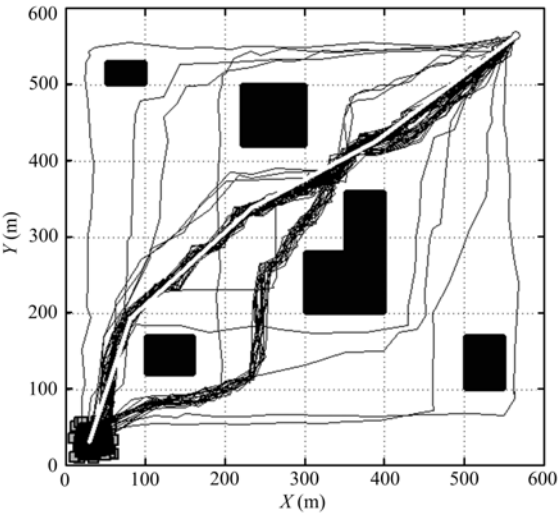

Fig. 7 The output of optimal path at cycle time 50.

In this dynamic deployment model of mobile WSNs, every mobile node can be seen as an artificial ant, so the modified ant colony algorithm used to plan the optimal path is practicable. Compare with the basic ant colony algorithm and some other Ant Colony Optimizations, the convergence of the proposed algorithm is better[15]. In this algorithm, only about 30 steps are needed to get the optimal result, while for most other algorithms, more 100 steps are required to find the optimal result. Furthermore, the computational complexity is usually high in some deployment algorithms[16], yet this modified algorithm is still low. These modified measures improve the performance of algorithm greatly.

Figs. 8 and 9 show the comparisons between the performance of the modified ant colony algorithms and random deployment method under the same conditions. In Fig. 8, the solid lines are the deployment time when adopting random deployment method in 30 cycles with random path. The line with stars represents the deployment time of the modified ant colony algorithm for optimal path. We can see that there is about 6 % to 25 % time saving with average of 15 % when the modified ant colony deployment is adopted. Furthermore, Fig. 9 shows that there is an average of 13 % power saving with maximal 25 % and minimal 4% saving under the same conditions. In Fig. 9, the solid lines are the power-consumption when adopting random deployment method in 30 cycles with random path, and the line with stars is the power-consumption of the modified ant colony algorithms for optimal path.

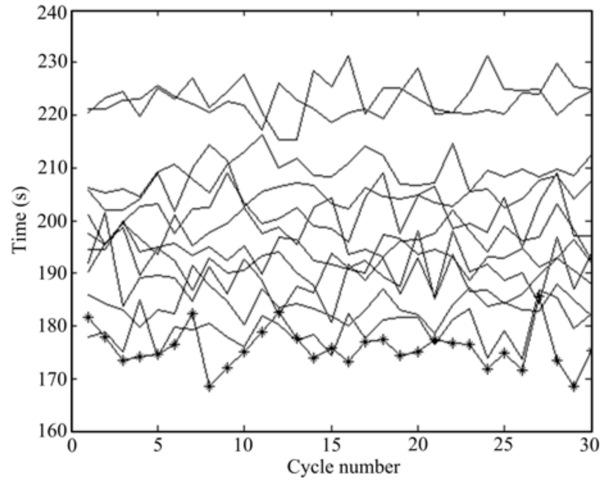

Fig. 8 Comparison of performance efficiency between the modified ant colony algorithms and random deployment.

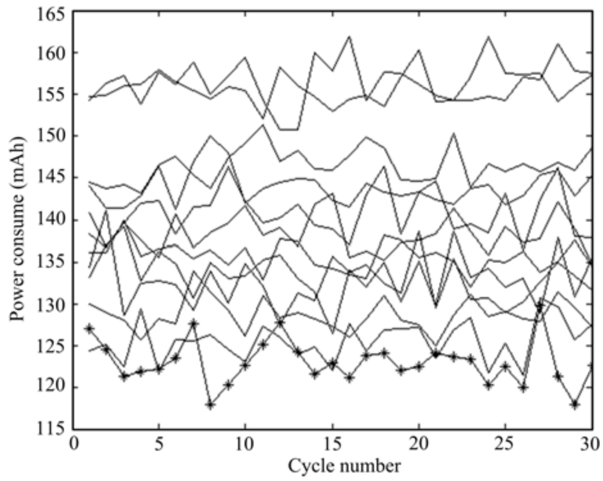

Fig. 9 Comparison of power-consumption between the modified ant colony algorithms and random deployment.

5 Conclusions

Mobile WSN, which generally includes many nodes, is similar to a complex biology-system. Researches on the deployment of mobile WSNs have been conducted, but the practicability aimed at WSNs was considered insufficiently[17]. In this paper, a novel bionic swarm intelligence algorithm, called ant colony algorithm based on a blackboard mechanism, is proposed to solve the autonomous and dynamic deployment of mobiles sensor networks effectively. Every mobile node in the sensor networks, which can be looked as an artificial ant, makes one information zone in its blackboard memory for communicating with other nodes and leaves its pheromone. The ant colony algorithm is used to find the optimal scheme for path planning and deployment of mobile WSN. We test the algorithm in one dynamic and unconfigurable environment. The results indicate that the algorithm can reduce the consumption of power by about 13%, enhance the efficiency of path planning by about 15% and deployment of mobile WSN and make the working system quicker.

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References

[1] Kumar S, Lai T H, Arora A. Barrier coverage with wireless sensors. *Proceedings of the 7th Annual International Conference on Mobile Computing and Networking (MobiCom)*, Cologne, Germany, 2005, 284–298.

[2] Mysorewala M F, Popa D O, Giordano V, Lewis F L. Deployment algorithms and in-door experimental vehicles for studying mobile wireless sensor networks. *The Seventh ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing*, Washington DC, USA, 2006, 290–298.

[3] Seovv C K, Seah W K G, Liu Z. Hybrid mobile wireless sensor network cooperative localization. The *22nd IEEE International Symposium on Intelligent Control*, Singapore, 2007, 29–34.

[4] Chang R S, Wang S H. Deploying sensors for maximum coverage in sensor networks. *Proceedings of the 2007 International Conference on Wireless Communications and Mobile Computing*, Honolulu, Hawaii, USA, 2007, 220–224.

[5] Brass P. Bounds on coverage and target detection capabilities for models of networks of mobile sensors. *ACM Transactions on Sensor Networks*, 2007, **3**, 1–19.

[6] Ding N N, Liu P X. A centralized approach to energy-efficient protocols for wireless sensor networks. *IEEE International Conference on Mechatronics and Automation*, Niagara Falls, Canada, 2005, 1636–1641.

[7] Okdem S, Karaboga D. Routing in wireless sensor networks using ant colony optimization. *The First NASA/ESA Conference on Adaptive Hardware and Systems*, Istanbul, Turkey, 2006, 401–404.

[8] Kulatunga A K, Liu D K, Dissanayake G, Siyambalapitiya S B. Ant colony optimization based simultaneous task allocation and path planning of autonomous vehicles. *IEEE Conference on Cybernetics and Intelligent System*, Bangkok, Thailand, 2006, 1–6.

[9] Iyengar S S, Wu H C, Balakrishnan N, Chang S Y. Biologically inspired cooperative routing for wireless mobile sensor networks. *IEEE System Journal*, 2007, **1**, 29–37.

[10] Wang L, Zhang Q, Wan N. Simulation study on searching for food by cooperation of multi-robots with swarm intelligence. *Proceedings of the IEEE International Conference on Automation and Logistics*, Jinan, China, 2007, 2296–3000.

[11] Lv N, Feng Z R. Numerical potential field and ant colony optimization based path planning in dynamic environment. *Proceedings of the 6th World Congress on Intelligent Control and Automation*, Dalian, China, 2006, 8966–8970.

[12] Wu C H, Lee K C, Chung Y C. A delaunay triangulation based method for wireless sensor network deployment. *Proceedings of the 12th International Conference on Parallel and Distributed Systems*, Minneapolis, USA, 2006, 253–260.

[13] Chang C Y, Chang H R, Hsieh C C, Chang C T. OFRD: Obstacle-free robot deployment algorithm for wireless sensor networks. *Proceedings of the IEEE Wireless Communications and Networking Conference*, Hongkong, 2007, 4374–4379.

[14] Colorni A, Dorigo M, Maniezzo V. Distributed optimization by ant colonies. *Proceedings of the 1st European Conference on Artificial Life*, Paris, France, 1991, 134–142.

[15] Fan X, Luo X, Yi S, Yang S Y, Zhang H. Optimal path planning for mobile robots based on intensified ant colony optimization algorithm. *Proceedings of the 2003 IEEE International Conference on Robotics, Intelligent Systems and Signal Processing*, Changsha, China, 2003, 131–136.

[16] Yang S H, Li M L, Wu J. Scan-based movement-assisted sensor deployment methods in wireless sensor networks. *IEEE Transaction on Parallel and Distributed Systems*, 2007, **18**, 1108–1121.

[17] Machado R, Tekinay S. Bounds on the error in estimating redundancy in randomly deployed wireless sensor networks. *Proceedings of the International Conference on Sensor Technologies and Applications*, Valencia, Spain, 2007, 319–324.