A Self-organizing Wireless Sensor Networks Based on Quantum Ant Colony Evolutionary Algorithm

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Abstract—Aiming at the coverage problem of self-organizing wireless sensor networks, a target coverage method for wireless sensor networks based on Quantum Ant Colony Evolutionary Algorithm (QACEA) is put forward. This method introduces quantum state vector into the coding of ant colony algorithm, and realizes the dynamic adjustment of ant colony through quantum rotation port. The simulation results show that the quantum ant colony evolutionary algorithm proposed in this paper can effectively improve the target coverage of wireless sensor networks, and has obvious advantages compared with the other two methods in detecting the number of targets and the convergence speed. Based on the above findings, it is concluded that the algorithm proposed plays an essential role in the improvement of target coverage and it can be widely used in the similar fields, which has great and significant practical value.

Keywords—self-organizing wireless sensor, quantum ant colony evolutionary algorithm, target coverage

1 Introduction

With the development of embedded computing technology, the wireless sensor network combining sensor technology, computer network technology and distributed formula signal processing technology has become a new research hotspot. In these studies, a class of self-organizing wireless sensor networks with self-organizing ability has received more and more attention.

For the coverage problem of self-organizing wireless sensor networks, Dezun D et al. proposed a graph-based approach [1], which transforms the wireless sensor network coverage problem into the vertex coloring problem. Based on the graph theory, when the scale of the problem is small, the optimal solution can be obtained quickly. But with the increase of sensor nodes and the number of monitored objects, the complexity of the problem grows exponentially, and the algorithm based on graph theory can't get the feasible solution in effective time. Yourim Y et al. gave a coverage method based on the Genetic Algorithm (referred to as GA) [2]. Akbarzadeh et al. [3]

presented a coverage method based on the Simulated Annealing (SA), which can avoid premature convergence and evolution stagnation by adjusting the temperature value adaptively. X. Wang et al. proposed a coverage method based on the Particle Swarm Optimization (PSO), which discretizes the continuous particle position parameters to optimize and obtain the effective solution of the target coverage problem. However, the discretization process leads to the poor accuracy of PSO algorithm and slow convergence in later stage of evolution. Based on the above model, the target coverage method for wireless sensor networks based on QACEA (Quantum Ant Colony Evolutionary Algorithm) is proposed to introduce the quantum state vector into the ACO coding, and the quantum rotation port is used to realize the dynamic adjustment of the ant colony, which verify that a better response can be made for the problem.

2 Review

In the target location, navigation and intelligent monitoring and other applications, each monitored target needs to be perceived by a number of sensor nodes. Due to sensor data processing and perceptual constraints, it is common for each sensor node to be aware of only a limited number of targets within its own monitoring range. Assuming that there are M monitored objects and N sensor nodes in the wireless sensor network, then the overlay relationship between the sensor nodes and the targets in the wireless sensor network can be expressed by the following formula:

$$C = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,N\text{-}1} & c_{1,N} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,N\text{-}1} & c_{2,N} \\ \vdots & & c_{m,n} & & \vdots \\ c_{M-1,1} & c_{M-1,2} & \cdots & c_{M-1,N-1} & c_{M-1,N} \\ c_{M,1} & c_{M,2} & \cdots & c_{M,N-1} & c_{M,N} \end{bmatrix} \left(c_{m,n} \in \{0,1\}\right) \tag{1}$$

In the overlay relationship matrix C shown in Equation 1, *Cm,n* represents an overlay relationship between the n-th sensor node and the m-th monitored object. *Cm,n*=1 indicates that the m-th monitored target is in the coverage area of the n-th sensor node, and Cm,n=0 indicates that the m-th monitored target is outside the coverage area of the n-th sensor node.

As a result of monitoring capacity constraints, the sensor node can only choose the limited monitored targets within the coverage scope for monitoring. The monitoring relation between the sensor node and the target in wireless sensor network can be expressed by the monitoring relation matrix S, as shown in formula 2:

$$S = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,N\text{-}1} & s_{1,N} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,N\text{-}1} & s_{2,N} \\ \vdots & & s_{m,n} & & \vdots \\ s_{M-1,1} & s_{M-1,2} & \cdots & s_{M-1,N-1} & s_{M-1,N} \\ s_{M,1} & s_{M,2} & \cdots & s_{M,N-1} & s_{M,N} \end{bmatrix} (s_{m,n} \in \{0,1\}) \tag{2}$$

In the monitoring relation matrix S, $s_{m,n}=1$ indicates that the m-th monitored target is monitored by the n-th sensor node, and $s_{m,n}=0$ indicates that the m-th monitored target is in the coverage area of the n-th sensor node, but not monitored, or the m-th monitored object is outside the coverage of the n-th sensor node. When each sensor node can monitor a maximum of targets in the coverage area, the constraints can be as shown in Equation 3.

$$\sum_{m=1}^{M} S_{m,n} \le F, n = 1 \ldots N \tag{3}$$

Assuming that each monitored target needs to be monitored by at least E sensor nodes and each sensor node can monitor at most F targets at the same time, when the problem optimizes the goal to the maximize number of successfully monitored targets, the mathematical model of the target coverage problem can be expressed as Equation 4:

$$\begin{aligned} &\textit{Objective:} \quad \max f(s_{11}, s_{12}, \cdots s_{MN}) = \sum_{m=1}^{M} w_m \\ &w_m = \begin{cases} 1 & \sum_{n=1}^{N} s_{m,n} \ge E \\ 0 & \sum_{n=1}^{N} s_{m,n} \ge E \end{cases} \\ &\textit{Subjected to}: \sum_{m=1}^{M} s_{m,n} \le F, n = 1 \ldots N \\ &S_{m,n} \le c_{m,n} \end{aligned} \tag{4}$$

In 4, the target function value indicates the number of detected targets when the monitoring relationship matrix is S. $w_n=1$ indicates that the w-th target is successfully detected, otherwise, it is not successfully detected. The first constraint indicates that each sensor node has limited monitoring capability, and the second one indicates that only the monitored nodes in the coverage area are likely to be detected by the sensor.

3 Quantum Ant Colony Evolutionary Algorithm

Quantum ant colony evolutionary algorithm is a new algorithm combining quantum evolutionary algorithm and ant colony algorithm. Based on the concepts of quantum bit and quantum superposition state in quantum computation, quantum ant colony evolution algorithm can greatly enhance the traversal and convergence rate when the scale of the problem is large. Quantum ant colony evolutionary algorithm will use a set of quantum bits' probability amplitude and a set of binary numbers to represent each ant of the ant colony.

In the quantum ant colony evolutionary algorithm, each ant can search several points in the solution space in parallel, which improves the search efficiency and increases the probability of obtaining the global optimal solution. By means of quantum bit coding, each representative quantum in an ant is the probability amplitude of the particle coordinate in the wave function. Each ant in the quantum ant colony evolutionary algorithm can complete the update of the two optimal solutions by the update of the quantum rotation and path optimization in the iterative process, that is, realize the quantum search mechanism in the evolution process. In the process of searching, the quantum ant colony evolutionary algorithm firstly carries out the encoding and quantum bit measurement, and calculates the fitness value of the measurement result. Then each ant in the ant colony completes the movement of the ant and updates the pheromone according to the visibility and the pheromone intensity, and calculates the fitness value of each moving route, and then, finds out the individuals with the greatest fitness in all the binary individuals generated by the qubit measurement and ant movement. With the iterative operation of the algorithm, the pheromone will gradually accumulate to the path of the global optimal solution, so as to achieve the convergence state of the algorithm. The simulation results show that the quantum ant colony evolutionary algorithm has good searching ability and strong robustness, and can effectively avoid the phenomenon of evolutionary stagnation and premature convergence.

4 Methods

Quantum ant colony evolutionary algorithm is an improved ant colony algorithm which combines quantum computing theory with ant colony algorithm. It combines the high efficiency of quantum computation and the robustness of ant colony algorithm. The main steps of the quantum ant colony evolutionary algorithm are: ant colony quantum encoding, initial ant colony generation, qubit state measurement, ant movement and pheromone update, ant colony quantum rotation port update, ant position non-door mutation and so on.

4.1 Ant colony quantum coding

In the wireless sensor network target coverage problem, the number of targets to be monitored is large. Usually, the binary encoding formula will cause the algorithm to converge slowly and become stagnant. In the quantum ant colony evolutionary algorithm, the ants are encoded based on a set of qubits and a set of binary numbers to represent the implementation, the state of each qubit is shown in 5:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{5}$$

In the formula, α and β are the probability amplitude of the corresponding state of the quantum bit. The $|\alpha|^2$ represents the probability that the quantum state is observed as $|0\rangle$ state, the $|\beta|^2$ represents the probability that the quantum state is observed as $|1\rangle$ state. The corresponding normalization conditions can be shown as in 6:

$$|\alpha|^2 + |\beta|^2 = 1 \tag{6}$$

In wireless sensor network target coverage, it is necessary to encode the coverage and monitoring relationship of the sensor and the target node respectively, as shown in Equation 1 and Equation 2. When the m-th monitored target is out of the coverage of the n-th sensor node, the sensor can't monitor the target in the coverage relation matrix C and the monitoring relation matrix S, that is, when *Cm,n*=0, there must be *Sm,n*=0, that is, the bit need not be encoded. The encoding process can be as shown in Equation 7, encoding only the bytes in the matrix S with the underlined position:

$$C = \begin{bmatrix} \underline{1} & 0 & 0 & \underline{1} \\ 0 & \underline{1} & \underline{1} & 0 \\ \underline{1} & \underline{1} & 0 & 0 \\ 0 & 0 & 0 & \underline{1} \end{bmatrix} \quad S = \begin{bmatrix} \underline{0} & 0 & 0 & \underline{1} \\ 0 & \underline{1} & 0 & 0 \\ \underline{1} & \underline{0} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{7}$$

The code length of ants is equal to the number of elements in matrix c. According to the code length, a set of qubit matrix A carried by ants can be expressed as the following:

$$A = \left| \begin{matrix} \alpha_1 \\ \beta_1 \end{matrix} \middle| \begin{matrix} \alpha_2 \\ \beta_2 \end{matrix} \middle| \begin{matrix} \cdots \\ \cdots \end{matrix} \middle| \begin{matrix} \alpha_L \\ \beta_L \end{matrix} \right| \tag{8}$$

The monitoring relation matrix S can be effectively mapped to the qubit matrix A of the ant through the covering relation matrix C. The binary code length of ants is the same as that of qubit coding, and a binary string of length I is generated according to the route of ants.

4.2 Generation of initial quantum bits

In the initial ant colony, the probabilistic amplitude of the corresponding states of all the qubits on each ant in the ant colony is generated by a Logistic mixture map as shown in Equation 9.

$$x_{k+1} = \mu x_k (1 - x_k), k = 0,1,2,\cdots,k \tag{9}$$

When $\mu = 4$, the Logistic map is in a turbid state. Given a random number between (0 ,1), the Logistic map generates K chaotic variables. In the process of initialization, $\alpha = \cos(2\pi x_k)$ and $\beta = \sin(2\pi y_k)$ in the matrix A, the probabilistic amplitude of the qubits carried by the initial ant will be uniformly distributed in the solution space.

4.3 Quantum bit state measurement

In order to obtain the iteration-best ant in the current ant colony, it is necessary to measure the state of each ant's qubit in the iteration process of the quantum ant colony evolutionary algorithm to obtain the corresponding target coverage program and fitness. The measurement of the quantum state at position 1 is shown in Equation 10:

$$\mathrm{z}_t = \begin{cases} 0, random[0,1] > |\alpha_t|^2 \\ 1, random[0,1] \le |\alpha_t|^2 \end{cases} \tag{10}$$

In the formula (10), Z=(*z1*，z，，…，*zl*) is the binary resolving formula corresponding to the ant after the state measurement, and random [0,1] is the random number between [0,1]. After the measurement of the quantum state, the ant will be transformed into the determined binary sequence string, that is, obtaining the corresponding target coverage scheme.

4.4 Evaluation of ants' fitness

After determining the state of all the qubits of each mute, the formula of the solution Z measured by the ants is mapped back to the matrix S, and brought into the objective function as shown in Eq. 4 to find the objective function value corresponding to each scheme. The fitness value generated by each mute is compared with the current optimal solution Zbest generated by the previous iteration. If it is larger than the current optimal solution, the current optimal value is replaced by Zbest with the current fitness value.

4.5 The movement of ants and the updating of pheromones

In the quantum ant colony evolutionary algorithm, we can generate the ant binary route by the pheromone strength and visibility to update the current optimal solution. The movement rule and transition probability of ants can be shown in Equation 11:

$$p_{ij}(t) = \frac{\tau_{ij}^{\lambda}(t)\eta_{ij}^{\mu}(t)}{\tau_{i0}^{\lambda}(t)\eta_{i0}^{\mu}(t) + \tau_{ij}^{\lambda}(t)\eta_{ij}^{\mu}(t)} \tag{11}$$

In equation 11, t represents the number of iterations of the algorithm, and the number of steps that the ant has traveled. $j \in \{0,1\}$ respectively indicate the two possible positions of the ants at step i. Assuming that the current position of the ant corresponds to the m-th row and n-th column of the monitoring relation matrix S, then the visibility parameter setting of the position 1 selected in the next step in the t-th cyclic process is as follows:

$$\eta_{m,n}^{l}(t) \begin{cases} \left(1 + \sum_{i=1}^{n} s_{m,i}\right) & \sum_{i=1}^{n} s_{m,i} < E \\ 0 & \sum_{i=1}^{n} s_{m,i} \geq E \end{cases} \tag{12}$$

Equation 12 shows that when the number of the sensors monitoring the target is close to the required number E, the visibility will be higher, and the additional sensors are not required to monitor the target, then the visibility is set to zero.

At the initial stage, the pheromone intensity of all paths is set as the upper limit $[\tau_{\min}, \tau_{\max}]$ of the pheromone on the path. After every ant in each ant colony completes the circulation, only the pheromone on the best path of the current ant is updated, the update rule of the trajectory is shown in Equation 13:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau^{best} \tag{13}$$

4.6 Quantum rotation port update of ant position

When all the ants in the ant colony are moving, the quantum rotation of each ant bit must be updated according to the optimal solution in the previous iteration. The updating process is shown in Equation 14:

$$\begin{bmatrix} \alpha_l^{new} \\ \beta_l^{new} \end{bmatrix} = \begin{bmatrix} \cos\theta - \sin\theta \\ \sin\theta - \cos\theta \end{bmatrix} \begin{bmatrix} \alpha_l \\ \beta_l \end{bmatrix} \tag{14}$$

4.7 Basic steps of quantum ant colony evolutionary algorithm

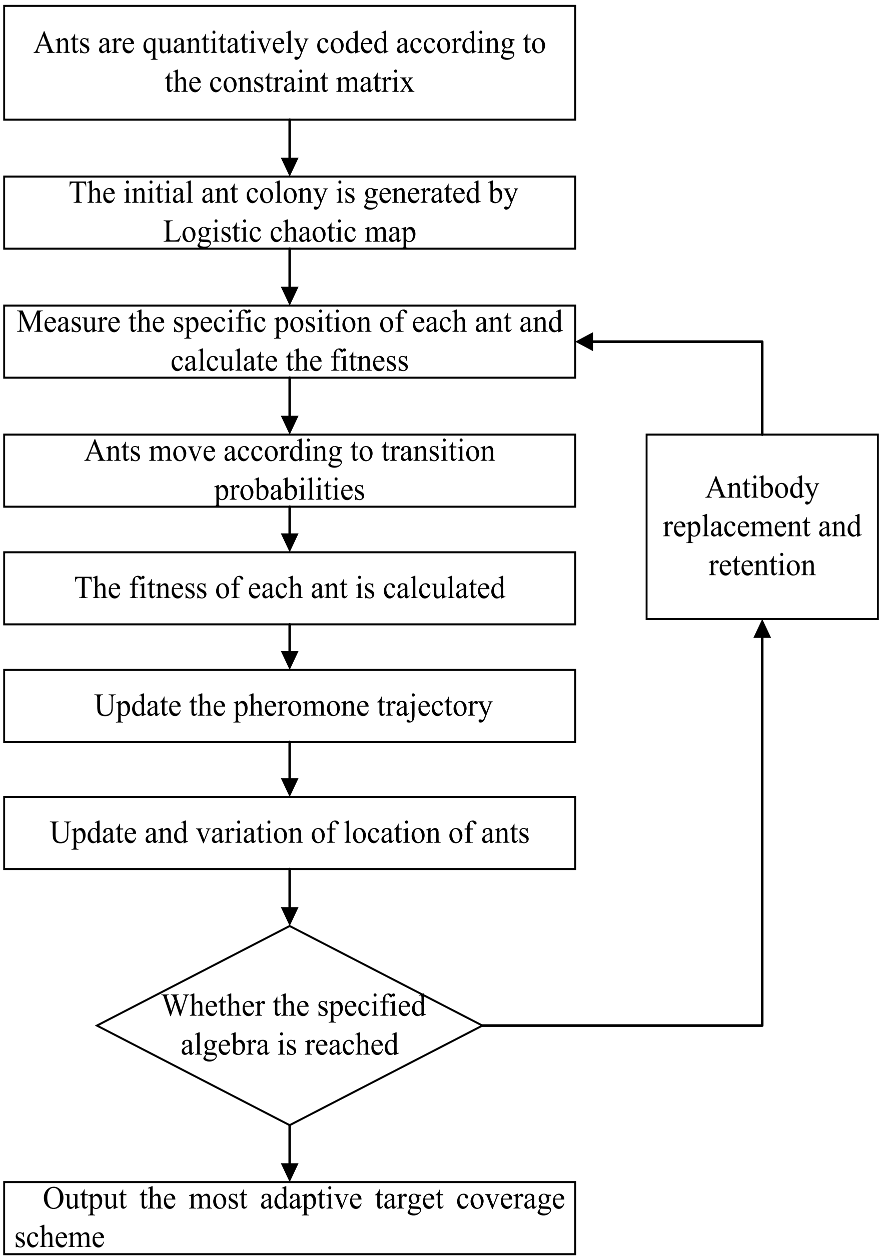


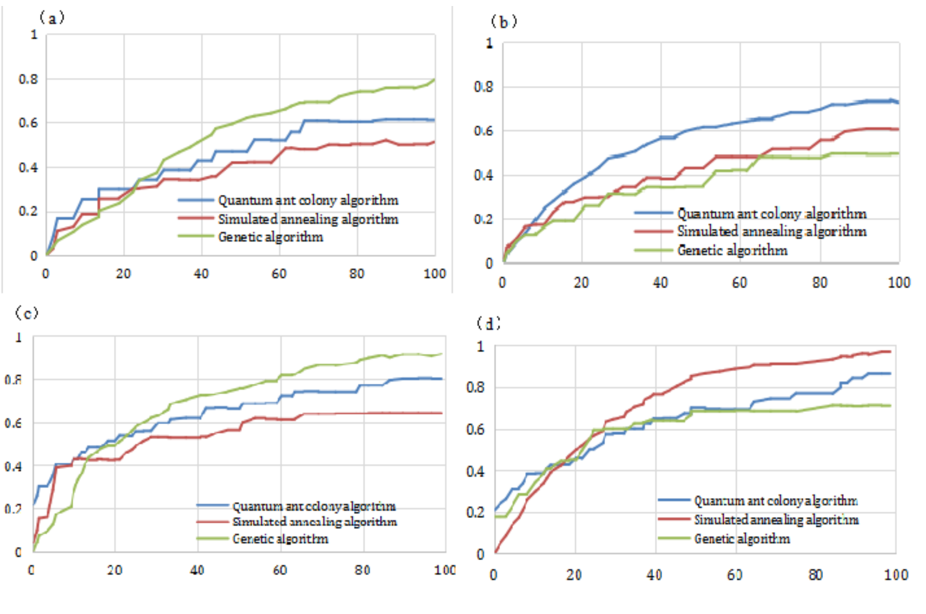
Fig. 1. Basic step of the wireless sensor network target coverage based on the quantum ant colony evolutionary algorithm

5 Results

In the algorithm simulation, the monitoring range is 600x600m, the number of monitored targets is 200, and the monitored targets and the sensor nodes are all randomly distributed. Each monitored target needs at least three sensor nodes to monitor, and each sensor node can simultaneously perceive five targets within the coverage. In the quantum ant colony evolutionary algorithm, the number of ants in the ant colony is fixed at 40, the pheromone trajectory intensity takes the parameter $\lambda = 2$, the visibility parameter takes $\mu = 2$, and the pheromone volatilization coefficient takes $\beta = 0.9$. In the genetic algorithm, the number of chromosomes in the population is 40, the computation time is 9, the crossover probability is 7, and the mutation probability is 0.5. In the simulated annealing algorithm, the initial temperature is set at 300 degrees, and the annealing temperature coefficient is set at 85. The iteration times of all three algorithms are 100 times.

When the sensor nodes are 150, Figure 2 shows the target coverage of the target coverage method based on the quantum ant colony evolutionary algorithm, genetic algorithm and simulated annealing algorithm respectively during the target coverage of the wireless sensor network.

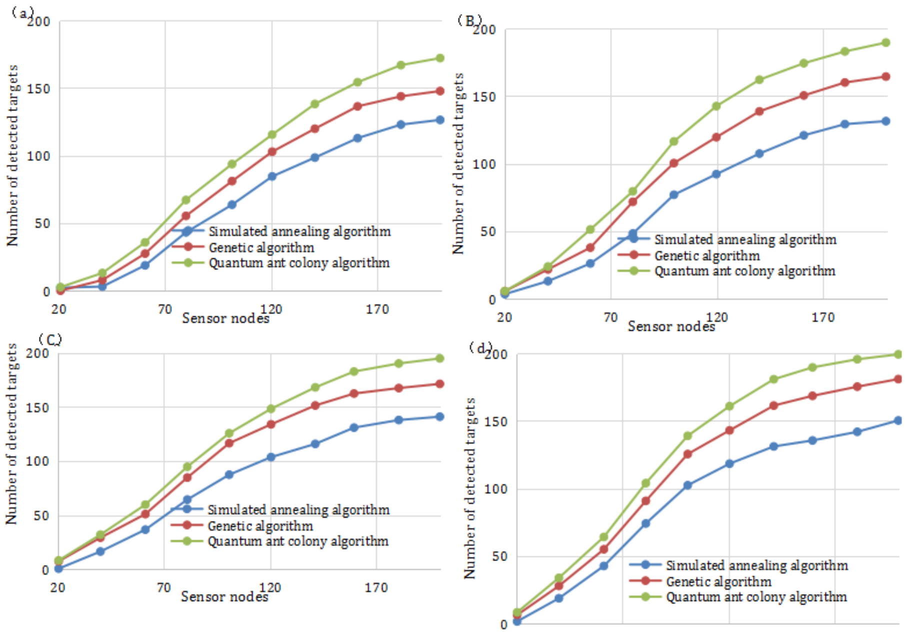
Target coverage is defined as the percentage of the total number of successfully detected targets in the monitoring range. In order to determine the performance of the algorithm under different sensor conditions, the sensed radii of the sensors are set at 50 m, 60 m, 70 m and 80 m respectively in the four subgraphs.



(a) Perceptual radius is 50 m (b) Sensing radius is 60 m (C) Sensing radius is 70 m (d) Sensing radius is 80 m

Fig. 2. Changes of the target detection rate with the number of the iteration in the algorithm

It can be seen from the simulation results that the target coverage rate of the target coverage method based on the simulated annealing algorithm increases slowly with the increase of the number of the iteration algorithm, and tends to stagnate in the later period of the algorithm. The coverage rate of target coverage method based on genetic algorithm is relatively stable, but it is difficult to introduce new genes when the mutation probability is low because of using a fixed encoding formula, and it is easy to fall into premature convergence. When the mutation probability is high, there will be a large degree of volatility, and the target coverage is difficult to be improved. Quantum ant colony evolutionary algorithm uses the encode formula based on quantum bit, the state vector of quantum is introduced into the coding of ant colony algorithm, which avoid premature convergence and evolution stagnation caused by deterministic state. It can be seen from the figure that the target coverage of the quantum ant colony evolutionary algorithm is increased by 10 percentage points and 20 percentage points respectively compared with the genetic algorithm and the simulated annealing algorithm under different radius conditions.



(a) Perceptual radius is 50 m (b) Sensing radius is 60 m (C) Sensing radius is 70 m (d) Sensing radius is 80 m

Fig. 3. Successful detection of the number of targets with its changes of iteration number

Figure 3 shows the curve of the successful detection target number with increase of the sensor node number. As can be seen from the figure, because of only the implementation of single-point search, the simulated annealing algorithm is easy to fall into premature convergence. Under different conditions of semi-transport, the number of targets successfully detected by simulated annealing algorithm is small. Genetic algorithm contains multiple individuals within the population, the number of successful detection targets is more than simulated annealing algorithm.

Quantum ant colony evolutionary algorithm (quantum ant colony algorithm) is optimized by quantum evolution and pheromone-based ant routing search. Compared with the former two algorithms, the search range is enlarged. At the same time, the quantum ant colony evolution algorithm will undergo the process of updating the optimal solution twice in each iteration, and can detect more targets more efficiently. It can be seen from the figure that, as the number of sensor nodes increases, the increment of the number of targets successfully detected of the quantum ant colony evolutionary algorithm increases compared with the other two algorithms, mainly because the complexity of the problem increases exponentially with the increase of the number of sensors. The traditional genetic algorithm and simulated annealing algorithm are easy to fall into premature convergence. The quantum ant colony evolutionary algorithm has the coding formula of the quantum bit probability amplitude. Each quantum bit can be expressed as a superposition of several quantum states, and has the parallelism compared with the genetic algorithm and simulated annealing algorithm. At the same time, the search driven by the quantum rotation port can transform the global search into the local search so that the equalization of rough search and fine search can be improved to avoid the stagnation of evolution and improve the convergence rate of the algorithm, that is, with the increase of the number of the sensor nodes, the performance advantage of the quantum ant colony evolutionary algorithm is more obvious compared with the other two algorithms.

6 Conclusion

How to improve the target coverage ratio of the monitored area has become a key issue in the research of self-organizing wireless sensor networks with limited number of sensors and monitoring radius. A new method of target coverage for self-organizing wireless sensor networks based on quantum ant colony algorithm is proposed. The simulation results show that the proposed method can optimize the parameters in the optimization process. Compared with the other two methods, the proposed method has obvious advantages in target coverage and the number of targets detected successfully. The quantum ant colony evolutionary algorithm has the coding formula of the quantum bit probability amplitude. At the same time, the search driven by the quantum rotation port can transform the global search into the local search so that the equalization of rough search and fine search can be improved to avoid the stagnation of evolution and improve the convergence rate of the algorithm. That is to say, with the increase of the number of the sensor nodes, the performance advantage of the quantum ant colony evolutionary algorithm is more obvious compared with the other two algorithms and it can be widely applied. While there are still some uncertainties in the properties of the algorithm, which remained to be further studied.

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