Network coverage optimization strategy of ant colony optimization algorithm

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Abstract

As a new-type intelligent optimization algorithm, artificial ant colony algorithm has been applied widely. However, there still exist certain limits in the algorithm itself. The present thesis will make a deep analysis of the optimization principles of ant colony algorithm, figure out existing problems, systematically perceive available improvement approaches and eventually propose a modified artificial ant colony algorithm. During the experiment simulation phase, the modified artificial ant colony algorithm and genetic algorithm will be adopted to optimize the wireless sensor network coverage in an examination area. By virtue of the coverage optimization strategy of the algorithm proposed by the present research, it can be achieved to acquire satisfactory coverage optimization scheme within short periods. Besides, the algorithm proposed by the research possesses better instantaneity and can reduce the vibration of network.

Keywords: ant colony optimization algorithm, wireless sensor, network coverage optimization

1 Introduction

With the increasingly high requirements by people and the constant progress of scientific technologies, people are facing more and more complex optimization problems in daily life and work. It is difficult to resolve such problems through traditional optimization methods. Meanwhile, people are always trying every possible way to utilize the nature to benefit human beings. During the interacting process between the nature and human being, it has been found that some highly complex optimization problems can be perfectly resolved by creatures and natural ecosystem through autologous evolution. Hence, various evolution optimization algorithms are proposed one after another, become effective ways to resolve complex optimization problems and play a very important role. Artificial ant colony algorithm is a kind of newly emerging optimization algorithm, which has a history of less than one decade, but has been widely applied into various fields. It is clear that it is of great significance to conduct a further research on this algorithm.

Since its presence, artificial ant colony algorithm has been drawing significant attention from foreign scholars and the ant colony algorithm has been also widely applied into various fields. The problems which can be resolved through the ant colony algorithm have been also developed from one-dimensional static optimization problems to multi-dimensional dynamic portfolio optimization problems. Through researches, it is found that artificial ant colony algorithm has some limits although it has many advantages. For instance, when the optimizing area is relatively flat, the speed of searching a more optimal solution will become slow and the searching efficiency will decrease; the convergence rate during the latter period of this algorithm is rather slow [1].

In essence, artificial ant colony algorithm is a type of concurrent overall random search algorithm. Although ant algorithm has its own advantages, it has also some disadvantages like slow convergence rate.

In allusion to the disadvantages of basic artificial ant colony algorithm, the present research proposed an algorithm based on improved artificial colony. In this paper, during the experiment simulation phase, the improved artificial ant colony algorithm and genetic algorithm will be adopted to optimize the wireless sensor network coverage in an examination area. The improved ant colony algorithm always maintains faster convergence rate and better coverage optimization effects. Besides, the improved ant colony algorithm is effective to acquire satisfactory coverage optimization scheme within short periods, is featured with better instantaneity and can reduce the vibration of network [2].

2 The basic ant colony algorithm

2.1 THE BASIC PRINCIPLES OF ANT COLONY ALGORITHM

There exits an interesting phenomenon while the ant is foraging: the ant can always successfully find the shortest path to forage for food in the event of lacking walking experience and not knowing the information about the topology of the path and the distance, even if the path is changed in the middle, such as it is added obstacles

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artificially. In other words, the ant has the self-adaptability in finding the shortest path [3].

As shown in Figures 1, 2 and 3, the cross-star indicates the ant. In Figure 1 the upper and the lower paths are equal. So the ants select a path randomly and the numbers of ants at both path are almost equal. In Figure 2, although the obstacle is added, the numbers of ants at both path are also almost equal since the lengths of the upper and the lower paths are the same. In Figures 3, the obstacle is added, but obviously the length of the upper path is shorter, so the ants finally select the upper path.

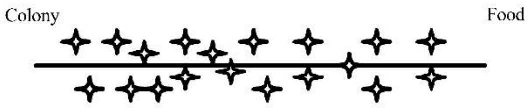

FIGURE 1 Schematic diagram of the ant colony algorithm (No obstacle)

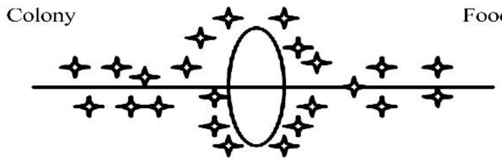

FIGURE 2 Schematic diagram of the ant colony algorithm (Set obstacle, but not changing the distance)

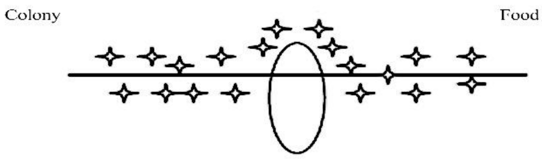

FIGURE 3 Schematic diagram of the ant colony algorithm (set obstacle and change the distance)

Biologically speaking, although ants have no language, they can complete the information exchange via pheromone. The process of exchange is as follows: ants will volatilize pheromone while moving from the nest to the food, so the intensity of the pheromone will be growing and more ants will be attracted if the number of ants on a path becomes larger.

Provided that the pheromones volatilized by each ant in a unit time are the same, at the same time the rates of pheromone volatilization are also the same. For example, as shown in Figure 3, the ants select the paths around the obstacle randomly, i.e., the numbers of ants at both sides are the same, so the total volatilized pheromones are also equal. Since the rates of pheromone volatilization are also the same, the pheromone intensity on the shorter path shall be greater than that on the longer path. Therefore more ants shall select the shortest path until all ants select this path. It can be easily seen from this process that the addition of the obstacle may change the length of the path, but the pheromone intensity shall also change after the length is changed, so as to ensure the ants to find the shortest path [4].

2.2 THE BASIC MODEL OF ANT COLONY ALGORITHM

Traveling salesman problem (TSP) is a typical combinational optimization problem and the first applied and the most successful example of ant colony algorithm, and the initial proposal of the algorithm is the description on the TSP problem. Therefore, we will describe it by taking the TSD problem as the application background.

The so-called travelling salesman problem means the minimum path cost used by a single traveling salesman starts from the starting point, passes all the connecting points in the connected graph and gets back to the starting point [5]. Dantzig and other people first proposed the mathematical model of the TSP problem in 1959.

Generally, TSP uses the directed graph $G=(N,A)$ to describe. Wherein each vertex $N=\{1,2,...,n\}$ stands for each city; the distance between cities: $(d_{ij})_{n\times n}$; the objective function: $f(w)=\sum_{l=1}^{n} d_{i_{l-1}i_l}$.

Wherein $w=(i_1,i_2,\ldots i_n)$ is a permutation of the city $1,2,3,...,n$.

According to the above description, the ant colony algorithm follows the following steps:

First, set the maximum number of iterations NC and initialize the pheromones of the ants and the paths $\tau_{ij}=c$, which will impact the path selection of the ants.

At a certain time t, the probability P_{ij}^k for the ant k moving from i to j shall be calculated by Equation (1):

$$P_{ij}^k(t)=\begin{cases}\dfrac{[\tau_{ij}(t)^{\alpha}][\eta_{ij}(t)]^{\beta}}{\sum\limits_{s\in allowed_k}[\tau_{is}(t)^{\alpha}][\eta_{is}(t)]^{\beta}}, if \;\; j\in allowed_k \\ 0, \quad otherwise\end{cases}. \tag{1}$$

Wherein the meaning of $allowed_k$ in the Equation (1) is the list of connecting points that ant k can visit. The number of collections shall minus one each time the ant visits a city. When $allowed_k$ is empty, it shows that ant k has completed the traversal of every city, so that the ant find the solution to the problem. η_{ij} is the inspiration factor and its value is generally related to the distance between two cities. The larger the distance is, the smaller the value is. On the contrary, the larger the value is, so that the ants shall select the shortest part with a greater probability. α is the mark of the importance degree of the pheromone, and β is the mark of the importance degree of the inspiration factor. The update of the pheromone is in accordance with the following rules:

$$\tau_{ij}(t+n)=(1-\rho)*\tau_{ij}(t)+\Delta\tau_{ij}\ , \tag{2}$$

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^k\ . \tag{3}$$

The meaning of $\rho(0<\rho<1)$ in the Equation (2) is the pheromone volatilization coefficient on the path between the cities. The larger of its value means the faster of the pheromone volatilization. On the contrary, it means the slower of the pheromone volatilization. $\Delta\tau_{ij}$ means the variation of the pheromone on path *(i,j)* in an iteration. Correspondingly, $\Delta\tau_{ij}^k$ means the volume of the pheromone left at the side *(i,j)* in an iteration. The calculation Equation of $\Delta\tau_{ij}^k$:

$$\Delta\tau_{ij}^k=\begin{cases}\dfrac{Q}{L_k}, \ If\ ant\ k\ passes\ the\ side\ i,j\ in\ the\ traversal\\ 0,\ \ Otherwise\end{cases}, \quad (4)$$

where Q is a fixed number, L_k is the length of k ants' total paths.

When the number of iteration is NC, the algorithm is ended [6].

2.3 THE BASIC ANT COLONY ALGORITHM IMPLEMENTATION

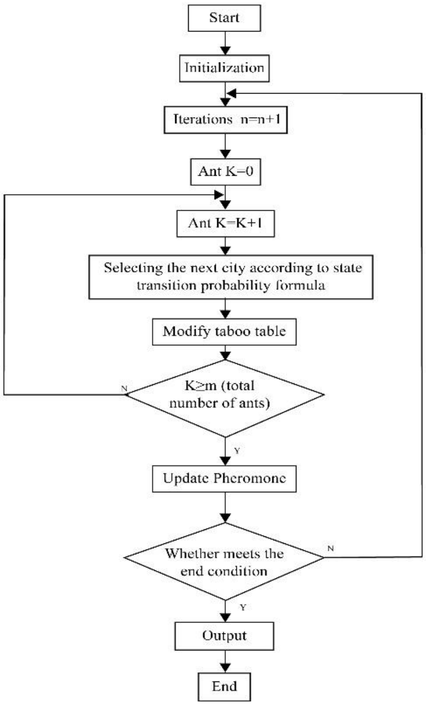

FIGURE 4 Flow chart of the basic ant colony algorithm

3 Improvement of basic ant colony algorithm

Ant Colony Algorithm, this meta-heuristic algorithm has strong capacities to find better solutions, but it has some defects of slow convergence and stagnation behavior. In 10 years, people continue to study the Ant Colony Algorithm, and its role in solving the optimization problem continues to improve. However, there are still shortcomings of the Ant Colony Algorithm. The following proposals modify Ant Colony Algorithm based on the shortcomings of old ones. The new algorithm uses a new method which based on updated features of Ant Algorithm Pheromone, and utilizes it to solve the TSP problem. Simulation results show that the method has a good performance [7].

3.1 DESIGN OF THE ALGORITHM

Ant k, which stood in the city i, chose the urban J as its next sightseeing place according to the pseudo-random proportional rules. The rule is given by the following Equation:

$$j=\begin{cases}\arg\max\limits_{l\in allowed_k}\left\{\tau_{il}[\eta_{il}]^{\beta}\right\}, if \quad q\le q_0\\ \quad J, otherwise\end{cases}. \quad (5)$$

In Equation (5), q is a random variable uniformly distributed in the interval (0, 1]. $q_0(0\le q_0\le 1)$ is a parameter, and J is a random variable in the Equation (6) given by the probability distribution. This strategy increases search-path diversity of ants. It can effectively prevent premature sectional optimum, or into the stagnant status.

$$P_{ij}^k(t)=\begin{cases}\dfrac{[\tau_{ij}(t)^{\alpha}][\eta_{ij}(t)]^{\beta}}{\sum\limits_{s\subset allowed_k}[\tau_{is}(t)^{\alpha}][\eta_{is}(t)]^{\beta}} & if \quad j\in allowed_k\\ 0 \quad else\end{cases}, \quad (6)$$

$P_{ij}^k(t)$ is a probability, at the time t, the ant k transfer from i to j. $allowed_k=\{1,2\cdots\cdots n\}-tabu_k$ represents all cities that allow ant's selection of the next step, and $tabu_k$ in the list records all cities that the ant walked through.

Sectional pheromone update makes pheromone of ant's tracking path being reduced, and it also makes the path less effective for the following ants. Thus, the ants will have stronger exploratory abilities towards the unselected edges. Therefore, update strategy can be added to sectional algorithm. The algorithm which repeatedly applied to the TSP problem showed, in one trip during the first half of ants traveling, the trip quality is higher than the second half. Results of the latter path selection were significantly worse than the former.

In comparison with the optimal solution of known path, the last half travelled path of ants is impossibly an integral part of best solution, so we can implement the new update strategy of sectional pheromone. As the performance of ant-cycle model is better, so we use the ant-cycle model, and combine the sectional update pheromone with overall update pheromone.

Sectional pheromone update: When ant k has completed a side, follow the below equation for sectional pheromone updating:

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\Delta\tau_{ij}\,, \tag{7}$$

where,

$$\Delta\tau_{ij} = \frac{Q_1}{L_z}\,. \tag{8}$$

In Equation (8), Q_1 will be calculated as below:

$$Q_1 = s\cdot e^{(1-s)}\cdot Q \quad \forall i, j = 1, 2, ..., n\,. \tag{9}$$

n is the size of the TSP, s stands for the number of $tabu_k$ elements. L_z is the k-th ant's length of the current travelled path.

In order to expand searching space of solution, and to avoid falling into sectional optimal algorithm, ACS is no longer used in this article to update the optimal concentration of pheromone path. Instead, it uses a new update strategy and a new pheromone update equation. When all the ants complete a whole parade, randomly select from an ant's path length L_k as a standard, and comparing with the path length $L_i (i \neq k)$ of other ant parade route. Updating the pheromone L_k of the path and another path which is shorter than the former path's concentration, the method will not only has the ability of expanding solutions on searching space, but also makes the updated path much easier to search out the sectional optimal solution.

1) When the randomly chosen path L_k is not the optimal path for this ant's parade, we use the following equation for the overall pheromone updating:

$$\tau_{ij}(t+n) = (1-\rho)*\tau_{ij}(t) + \Delta\tau_{ij} \qquad \rho\in(0,1) \tag{10}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m}\Delta\tau_{ij}^k\,. \tag{11}$$

The definition of $\Delta\tau_{ij}^k$ as following:

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{Q_2}{L_k - nBestTourLen + 1} & if \quad j \in allowed_k \\ 0 & otherwise \end{cases} \tag{12}$$

2) When the path L_k is just a random selection of the best solution found in this parade, in order to avoid falling into sectional optimum (10), (11) to update the overall pheromone, in it, $\Delta\tau_{ij}^k$ which is defined as following:

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{Q_2}{nBestTourLen} & if \quad j \in allowed_k \\ 0 & otherwise \end{cases} \tag{13}$$

Q_2 is a constant and $Q_2 \in (0,1)$. L_k is the k-th ant's path length which completed through this cycle, *nBestTourLen* represents the optimal solution in the cycle. This Equation enables increasing amounts more obvious of pheromones in approaching solutions; meanwhile, this equation helps to accelerate searching speed, and improving searching capacity of optimal solutions [8].

3.2 THE IMPLEMENTATION PROCESS OF ALGORITHM

Step 1: Initialization. Commanding cycle index *t=0*, maximum number of cycles $N_{\max}$, randomly place *m* ants on *n* cities. The quantity of initial pheromones at each side *(i,j)* is $\tau_{ij} = const$.
Step 2: amount of ants, $k = 0$
Step 3: number of cycles, $t = t+1$
Step 4: amount of ants, $k = k+1$
Step 5: While $(Allowed_k \neq \varnothing)$

According to pseudorandom proportion mechanism, Equation (5) selects the following cities; $tabu_k{+}{+}$;

End while

If $(Allowed_k \neq \varnothing)$ ants *k* return to the initial city;

Step 6: Calculate the length of the current path; partially update the pheromone of the current path according to Equations (7), (8) and (9);
Step 7: if the amount of ants $k < m$, turn to Step 4; Otherwise, turns to the next step.
Step 8: determine current optimal path and randomly select a path passed by ants to compare with other paths;
Step 9: judge the relationship between the path length L_i and L_k,

If ($L_i < L_k$, L_k is not the optimal solution)

{Partially update the pheromone L_k and L_i according to Equations (10), (11) and (12)}

If (L_k is the optimal solution)

{Totally update the pheromone of current optimal path according to Equation (13)}

Step 10: if the iteration *t* is less than $N_{\max}$ and no stagnation behavior occurs, turn to Step 2; Otherwise, end the algorithm and output results.

3.3 SIMULATION EXPERIMENT

Assuming that the examination area of wireless sensor network is 150m x 150m and the sensing radius of each wireless sensor node R_s =12m, a computer whose dominant frequency is 2.6GHZ will be used to simulate the network coverage optimization of wireless sensor on VC platform.

Firstly, according to the area of testing region and parameters of sensor, 62 sensor nodes are determinedly placed in the testing region and should be distributed approximately to be optimal. Then, randomly disseminate another 38 sensor nodes. The modified ant colony algorithm will be utilized to optimize the wireless sensor network coverage of the testing region.

Set the amount of ant colony to be 200, the maximum iterations of ant colony algorithm to be 600. Conduct experiments for 30 times. Average 80 nodes are utilized during optimizing the coverage of testing area. The utilization rate of nodes reaches to 83.95% and the average coverage rate is 91.05%, which achieves the aim of coverage optimization.

The optimization coverage mechanism based on genetic algorithm is adopted to compare with the algorithm proposed by the present research. Because both of these two algorithms are featured with random characteristics, average value of 30 groups of check experiments is regarded as the final result. From Figure 5, it can be seen that when the amount of ants is small, the performance of genetic algorithm is better; however, when the amount of ants is large, the modified ant colony algorithm shows better performance in gregariousness optimizing effect.

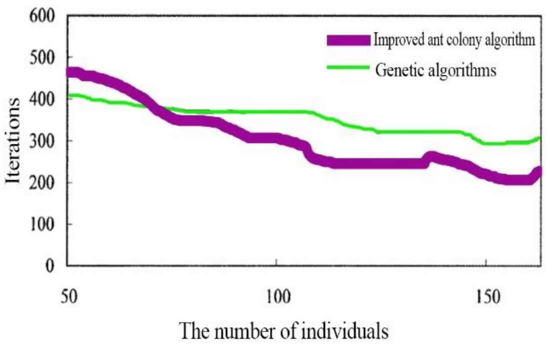

FIGURE 5 Convergence comparisons between ant colony algorithm and genetic algorithm

Basic ant colony algorithm is utilized to serve for coverage optimization and the results are used to make a comparison analysis. For the case, a comparison between the coverage optimization of ant colony algorithm and the modified ant colony algorithm is made. The modification effect of the algorithm is as shown in Figure 6, from which it can be seen that the modified ant colony algorithm has certain improvement in performance.

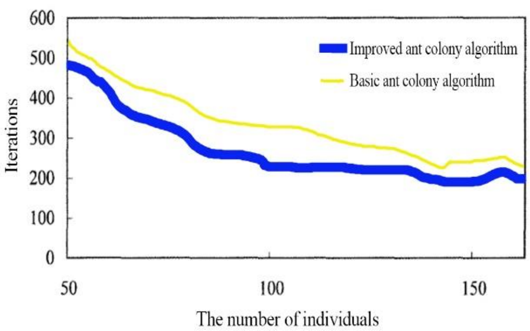

FIGURE 6 Convergence comparisons between improved ant colony algorithm and basic ant colony algorithm

Finally, the present research compares the real-time convergences of the modified ant colony algorithm with that of genetic algorithm. Refer to Table 1 for relevant comparison detailed dates. As operation time increases, ant colony coverage rate increases and working nodes tends a convergence trend toward the direction of slow decelerating speed. When the algorithm operates for 300 times the coverage optimization effect obtained by ant colony has approaches to the final optimal coverage effect of genetic algorithm. During the early operation stage, ant colony algorithm always keeps faster convergence speed and better coverage optimization effect. Therefore, for some wireless sensors which can extremely slightly lower the requirements for coverage rate, the coverage optimization strategy based on ant colony algorithm can meet the network coverage requirements with shorter period and less working nodes. To sum up, the coverage optimization strategy based on ant colony algorithm can be effective in achieving satisfactory coverage optimization scheme; it has better instantaneity and can reduce the vibration of network.

TABLE 1 Node scheduling of ant colony algorithm and genetic algorithm

Iteration	ACA coverage rate	GA coverage rate	ACA node amount	GA node amount
100	83.85	84.47	73	76
200	86.91	87.36	71	73
300	90.47	90.49	68	72
400	93.18	91.46	66	69
500	95.57	92.35	64	65
600	96.36	94.27	64	64

4 Conclusion

On the basis of deeply analyzing the basic principles of algorithm, reasons causing the problems of the algorithm and currently existing improvement methods, the present research proposes a new-type modified artificial ant colony algorithm and applies the modified artificial ant colony algorithm in wireless sensor network coverage optimization. Artificial ant colony algorithm has many problems to further explore, unlike mature intelligent algorithms which have formed systematic analyzing methods and certain mathematic basis. Due to the deficiency of theoretic researches, some features of artificial ant colony algorithm have not shown yet, which limits the application of this algorithm to some degrees.

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