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Adaptive Ant Colony Optimization Algorithm

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***Abstract*—An adaptive ant colony algorithm is proposed to overcome the premature convergence problem in the conventional ant colony algorithm. The adaptive ant colony is composed of three groups of ants: ordinary ants, abnormal ants and random ants. Each ordinary ant searches the path with the high concentration pheromone at the high probability, each abnormal ant searches the path with the high concentration pheromone at the low probability, and each random ant randomly searches the path regardless of the pheromone concentration. Three groups of ants provide a good initial state of pheromone trails together. As the optimization calculation goes on, the number of the abnormal ants and the random ants decreases gradually. In the late optimization stage, all of ants transform to the ordinary ants, which can rapidly concentrate to the optimal paths. Simulation results show that the algorithm has a good optimization performance, and can resolve traveling salesman problem effectively.**

Keywords—optimization; ant colony; adaptive searching; combinatorial optimization

I. INTRODUCTION

Ant colony algorithm is a new evolution algorithm, which can resolve many optimization problems, such as function optimization problems, combinatorial optimization problems, and so on [1-2]. Ant colony optimization algorithm is a kind of meta-heuristic parallel optimization algorithm. Generally, parallel optimization algorithms can find many legal solutions in once search, so ant colony algorithm has better optimization performance than some serial optimization algorithms [3-5], For instance, Hopfield neural network can find only one legal solution in once search. The basic idea of the ant colony algorithm is to use some artificial ants, which are similar to the real ants in nature, to find a minimum cost path, which is a legal solution for a given problem [6-7]. The behaviors of the artificial ants are inspired from real ants. Artificial ants could lay some pheromone on the paths which they passed. As time goes on, the pheromone can also evaporate. Artificial ants choose their path with respect to the probabilities that depend on pheromone trails which have been previously laid by the artificial ants. In this way, artificial ants are easy to choose the paths with high concentration pheromone and lay more pheromone on the paths which they choose. Thus, the paths with high concentration pheromone can attract more ants to choose them. The positive feedback principle of the ant pheromone can guide the ants to find the optimal paths, so it has fast convergence and global optimization performances [8-10]. However, like any other swarm intelligent optimization algorithms, such as genetic algorithm, the artificial fish school algorithm, and so on, the ant colony algorithm has the prematurity problem [11-12]. That is, the premature convergence can make the algorithm lose the global optimization solution.

In order to overcome the above disadvantage, an improved adaptive ant colony is proposed. The artificial ants are divided into three groups. The artificial ants in the first group are ordinary ants, which find the path according to the pheromone positive feedback principle. The artificial ants in the second group are abnormal ants, which search the path with the high concentration pheromone at the low probability, and search the path with the low concentration pheromone at the high probability. And the artificial ants in the third group are the random ants, which search the path regardless of the pheromone concentration. As the iteration goes on, the ant number of the first group and the second group gradually decreases. At the end of the optimization process, all of ants become the ordinary ants, which can ensure the fast convergence of the algorithm.

II. ADAPTIVE ANT COLONY ALGORITHM

Artificial ants, in the conventional ant colony algorithm, search the path according to the concentration of the pheromone. The higher the concentration of the pheromone of the path is, the larger the chosen probability is. Because of the uneven distribution of the initial pheromone concentration, most of ants rapidly move to the path with the high concentration pheromone after some iterative calculation, which leads some global optimal paths with low initial pheromone concentration to be found difficultly. Thus, the ant colony is easy to fall into the local minimum. So we present a new optimal strategy for ant colony algorithm to improve its optimal performance.

The optimization process can be divided into two phases: the coarse search in the early stage and the elaborate search in the late stage.

In the early stage, the ant colony is composed of three groups: ordinary group, abnormal group and random group. Ants in the ordinary group still search the paths with the probabilities which are proportional to the pheromone concentration on the paths. Ants in the abnormal group search

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the paths with the probabilities which are inversely proportional to the pheromone concentration on the paths. And ants in the random group randomly search the paths without any heuristic guidance. So the paths with the low initial pheromone concentration can be easily found by abnormal ants and random ants. Especially, the path without any pheromone can also be easily found by the abnormal ants. Thus, the adaptive ant colony algorithm has better global searching ability.

As the optimization calculation goes on, the number of the abnormal ants and the random ants decreases gradually. In the late stage, all of ants transform to the ordinary ants, which search the different concentration path with different probability. That is, the higher the concentration of the path, the greater the searching probability. Thus, the algorithm can rapidly converge to the global optimal solution.

Traveling Salesman Problem (TSP) is a classical NP-Hard combinatorial optimization problem, which can be described as: if a salesman has to visit a bunch of cities, how do you get him to all of them once via the shortest possible route. Because too many engineering practical problems can be translated into this problem, TSP becomes a typical test problem.

The above adaptive ant colony algorithm can be used to resolve the traveling salesman problem (TSP), and the calculation process can be described as follows:

Step1. Initialize the time t=0. We randomly put m ants on the n cities. The categorization judgment probability $p_{\text{num}}(0)$=0.3. The trail, the concentration of the pheromone at each path, is set $\tau_{ij}(0)=c$ (c is constant).

Step2. Every ant has a tabu list which contains all cities which are infeasible to reach. The tabu$_k$ is the tabu list of the k-th ant. The probability, p_{ij}^{k}, presents the transition probability of the k-th ant from the i-th city to the j-th city. If the j-th city is in the tabu list of the k-th ant, the transition probability p_{ij}^{k} is set to 0. Otherwise they are computed according to different ant groups.

Generate a random number r_k in the interval (0,1) for the k-th ant, that is, r_k=random(0, 1).

If $r_k< p_{\text{num}}(t)$, the transition probability p_{ij}^{k} is calculated according to the behaviours of the abnormal ants as follows:

$$p_{ij}^{k}(t)=\left[1-\frac{(\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta})}{\sum_{r\notin \text{tabu}_k}(\tau_{ir}^{\alpha}(t)\eta_{ir}^{\beta})}\right]\Big/(n_k-1) \tag{1}$$

Where, n_k is the amount of the cities which are out of the tabu list of the k-th ant at the i-th city.

If $r_k>(1-\ p_{\text{num}}(\text{t}))$, the transition probability p_{ij}^{k} is calculated according to the behaviours of the random ants as follows:

$$p_{ij}^{k}(t)=\frac{1}{n_k} \tag{2}$$

Otherwise, $p_{\text{num}}(\text{t})<r_k<(1-p_{\text{num}}(\text{t}))$, the transition probability p_{ij}^{k} is calculated according to the behaviours of the ordinary ants as follows:

$$p_{ij}^{k}(t)=\frac{(\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta})}{\sum_{r\notin \text{tabu}_k}(\tau_{ir}^{\alpha}(t)\eta_{ir}^{\beta})} \tag{3}$$

Where, the two parameters, α and β (0≤α, β≤1), are the parameters which specify the impact of trail and heuristic information, respectively.

The parameter η_{ij} represents the heuristic information of the optimization problem. For the traveling salesman problem, we use d_{ij} to represent the distance between the i-th city and the j-th city, and the parameter η_{ij} can be defined as follows:

$$\eta_{ij}=1/d_{ij} \tag{4}$$

Step3. After all ants have completed the path search, all of trails will be updated according to Eq.(5).

$$\tau_{ij}(t+1)=\max\{\tau_h(t),\rho\tau_{ij}(t)+\Delta\tau_{ij}\} \tag{5}$$

Where, the parameter $\Delta\tau_{ij}$ is the increment of the pheromone, which can be calculated by Eq.(6).

$$\Delta\tau_{ij}=\sum_{k=1}^{K}\Delta\tau_{ij}^{k} \tag{6}$$

Where, K is the number of ants which pass the path between the i-th city and the j-th city at the t-th iteration. And $\Delta\tau_{ij}^{k}$ is the amount of trail laid on the path between the i-th city and the j-th city by the k-th ant. It can be calculated by Eq.(7).

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q}{L_k}, \text{if ant } k \text{ uses arc}(ij) \text{ in its tour}\\ 0, \quad \text{otherwise}\end{cases} \tag{7}$$

Where, Q is a constant parameter. L_k is the total path length which the k-th ant finds at the t-th iteration, that is, it is the index value of the solution.

The ants' pheromone contributions are proportional to the quality of the solutions achieved, That is, the better the solution is, and the higher the trail contributions will be. Thus, the chosen path could get more increment of the pheromone.

The user-defined parameter ρ, $0\le\rho\le1$, is the evaporation coefficient, which describe the percentage of the pheromone decrement.

The variable $\tau_h(t)$ is the minimum amount of the pheromone laid on every path at the t-th iteration. It can prevent the pheromone to evaporate away completely. Thus, each path can keep some opportunities found by ordinary ants. It helps to enhance the global optimization ability of the algorithm.

Step4. Annealing treatment to the parameters $p_{\text{num}}(t)$ and $\tau_h(t)$ by Eq.(6) and Eq.(7).

$$p_{num}(t+1)=(1-\delta)p_{num}(t) \tag{8}$$

$$\tau_n(t+1) = (1-\delta)\tau_n(t) \tag{9}$$

Where, the parameter δ, 0<δ<1, is a small constant parameter. In the late optimization stage, the parameters $p_{num}(t)$ and $\tau_h(t)$ will decayed to zero. At the time, the optimization algorithm has become the conventional ant colony algorithm. That is, the heuristic information and pheromone trails play the crucial role guide the ants to find a good path, which can make the algorithm rapidly convergence to the global optimization solutions.

Step5. When the best solution is got or the max iteration number is arrived, the algorithm will be ended, and the optimal solutions obtained by the algorithm can be output. Otherwise, return to Step2 to do the next iteration searching.

Each ant finds the next city to move, and get a new state to construct a new solution according to the state transition rule.

Though all of the ants in the conventional ant colony algorithm can quickly congregate the current better paths, some good paths or states with the low pheromone concentration are hard to be explored.

In the adaptive ant colony algorithm, some new state transition rules are given to guide ants to find good paths.

In the early stage, three groups of ants have different state transition rules. The ordinary ants search paths according to the heuristic information of the pheromone trails, which can ensure the convergence of the algorithm. The abnormal ants are responsible for finding the new paths which have the low pheromone concentration, which can avoid losing the possible optimal paths. The random ants search the paths randomly, and the heuristic information and pheromone trails almost had no effect on their state transition rules. The random ants can search any path randomly with the same probability. Therefore, any new path or state is easier to find because of the random search. The random ants can balance the interaction between the ordinary ants and the abnormal ants. Three groups of ants can collectively provide a good initial state of pheromone trails, which helps to find the global optimal solution.

In the late optimization stage, the number of the abnormal ants and random ants decreases gradually to zero, and the state transition rules transform to the conventional ones. The algorithm gradually turns to become the conventional ant colony optimization algorithm, which can ensure the algorithm to converge to the global optimal solution quickly. In this way, the adaptive ant colony algorithm can get better optimization performance.

III. SIMULATION RESULTS

Many practical engineering problems can be converted into traveling salesman problems (TSP). Therefore, it is very important to resolve the TSP effectively for many practical engineering problems. However, as the number of cities grows, the problem gets more complicated because of the combinatorial explosion. It is difficult to find an optimal solution for a massive TSP. Generally, we can only get a better solution in the finite time. For comparing the optimization performances of different algorithms, we define the volatility index J as follows:

$$J = \frac{\text{the average solution - the global minimum}}{\text{the global minimum}} \times 100\% \tag{10}$$

The data used in the simulation experiments are from the website as follows:

"http://wwww.iwr.uniheidelberg.de/groups/comopt/software/TSPLIB95".

Many instances of TSP are resolved separately by conventional ant colony algorithm and adaptive ant colony algorithm. Each instance is resolved 100 times.

Simulation results show that when the city number is less than 50, our algorithm can almost find the best solution every simulation experiment. When the city number is greater than 50, the difference of the optimization performance between the two algorithms becomes obvious. Simulation results are summarized in Table 1.

TABLE I. SIMULATION RESULTS OBTAINED BY DIFFERENT ALGORITHMS

TSP	Ant colony Algorithm J%	Adaptive ant colony Algorithm J%
Fogel50	0.418	0.342
Eil51	0.467	0.387
Eil76	0.591	0.404
Rd100	0.633	0.463
Ch150	1.327	1.109

Obviously, according to the simulation results shown in Table 1, the performance of the adaptive ant colony algorithm is better than that of the conventional ant colony algorithm. Three groups of ants in the adaptive ant colony algorithm play different roles in the process of searching the optimal solutions. Each possible path can be easily found by three groups of ants. Thus, a good initial pheromone trails are provided by three group of ants for the search of the next stage. In this way, the algorithm can avoid to fall into the local minimum and find a global optimal solution. Therefore, the optimization performance can be improved significantly.

Figure 1 and figure 2 show the optimization solutions for 50 cities and 100 cities respectively.

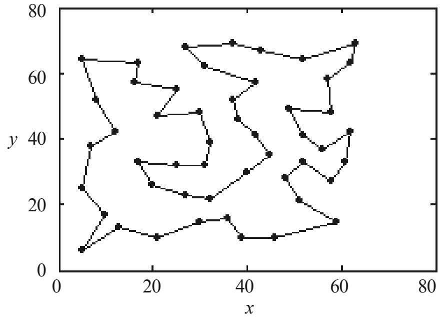

Fig 1. The optimization solution for 50 cities TSP

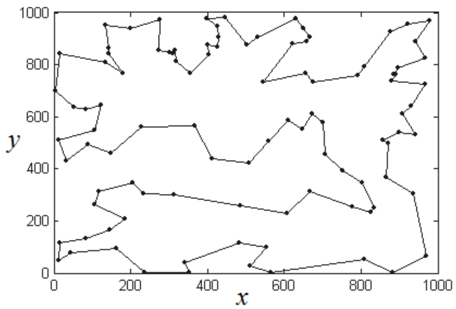

Fig 2. The optimization solution for 100 cities TSP

As far as we know, the solutions given in Fig.1 and Fig.2 are the best solutions. Therefore, the adaptive ant colony algorithm shows its strong global searching ability.

IV. CONCLUSION S

An adaptive ant colony algorithm composed of three groups of ants is proposed to resolve TSP. At the early stage, different ants search paths according to different transition probability rules. Abnormal ants and random ants can easily find new paths with low concentration pheromone which is difficult to be found by the ordinary ants. Thus, all possible paths can be found by the three groups of ants together. All the ants lay their pheromone on the paths that they passed. Thus, the algorithm can obtained a good initial pheromone trails for next search stage. At the late optimization stage, the number of abnormal ants and random ants is decayed to zero, and all the ants become to the ordinary ants. Ants can rapidly concentrate to the global optimal paths according to the positive feedback principle of the ant pheromone. Simulation results show that the adaptive ant colony algorithm has good global optimization ability, and its optimization performance is super to the conventional method.

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