A Study of a New Multi-ant Colony Optimization Algorithm

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Abstract. This paper introduces the basic ant colony algorithm, the model and its problems in the process of solving the TSP. Ant colony algorithm there are many faults about the slow convergence speed and prone to stagnation. Because the ant colony algorithm to search for to a certain extent, all individuals found the same solutions n in exactly, it can not search the solution space in further, it is not conducive to find better solutions. For the shortcomings of the algorithm, we present a new multiple ant colony algorithms and build the model of the new multiple ant colony algorithm in the paper, the new algorithm through different strategies conducive to the optimal solution obtained by the algorithm of ant colony using different strategies conducive to build mechanism, is to adopt the basic concept of parallel genetic algorithm to search the solution space, this strategy specifically, different groups to avoid solving the problem of local optimum to obtain the global optimum. The simulation results show that the algorithm in solving TSP problems than other algorithms more efficient, have good practical value.

Keywords: ant colony algorithm, multiple ant colony optimization algorithm, algorithm model, convergence speed.

1 Introduction

Ant colony algorithm by the Italian scholar M. Dorigo, who in the 20th century and early 90's ants in nature by simulating the behavior of routing group put forward a heuristic based on biomimetic evolutionary systems population. It consists of two basic stages: stage adaptation stage and Collaboration. In the adaptation stage, the candidate solutions based on the information accumulated continuously adjust its structure. In the collaborative stage, through the exchange of information between candidate solutions to generate performance expectations of a better solution, similar to the learning mechanism of learning automata. Ant colony algorithm was first successfully applied to solve the famous traveling salesman problem (TSP), The algorithm uses a distributed parallel computer system of positive feedback, easy to combine with other methods, but also has strong robustness.

But ant colony algorithm has slow convergence and stagnation of the lack of prone, that the search carried out to a certain extent, all individuals found in exactly the same solution, not further search the solution space is not conducive to find better solutions.

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Therefore, for lack of the algorithm, we present a new ant colony algorithm, called Ant Colony Optimization with Multiple Ant Colony (ACOMAC).The concept of multiple ants Colony is affected by parallel genetic algorithm in solving problems using different populations of the search space to avoid local optimal solution to obtain the global optimal set inspired circumstances.

2 The Model of Multiple Ant Clan Algorithms

In Multiple Ant Clan Algorithm (MACA), the ants that perform labor in the ant colony society are grouped into three classes: scoter ants, seeker ants and worker ants. The task of the scouter ants is to scout local area centering on each city and mark the scouted results by scouting elements, so that they can offer assistant information to the seeker ants to help them select the next city after reaching this city. The task of the seeker ants is to make global search. When they reach a city, they will select the next city according to the scouting elements and the information elements in each path, until they find the optimal path and mark it, so that the worker ants can transport the food to the nest through the optimal path. The task of the worker ants is to transport the food to the nest through the marked optimal path.

Scouter ants: placing m scouter ants in n cities differently, each scouter ant in one city will scout the other n-1 cities centering on current city and combine the scouted results (sorted by the ascending distance) with the priori knowledge already gained (MAXPC: just need to select one city from the rest $\min\{m-x, MAXPC\}$ cities) to make up of the scouting elements. The scouting elements are defined as $S[i][j]$, which are marked in the path from city i to city j. The scouting elements can offer assistance to the seeker ants when they calculate the state transition probability P_{ij}^k and adjust the information content in each path. The formula of $S[i][j]$ is defined as:

$$s[i][j] = \begin{cases} \overline{d_{ij}} \, / \, d_{ij} \ , If \ \ A \ city \ in \ city \ B \ within \ MAXPC \\ 0 \ , \ else \end{cases} \tag{1}$$

In which, $\overline{d_{ij}}$ is the minimum distance to the other $(n-1)$ cities centering on city i. According to the result, we can set the initial information content in each path, the formula is defined as:

$$\tau_{ij}(0) = \begin{cases} C * s[i][j] \ , & if \ \ [i][j] \neq 0 \\ C * \overline{d_{ij}} \Big/ \overline{\overline{d_{ij}}} \ , & else \end{cases} \tag{2}$$

In which, $\overline{\overline{d_{ij}}}$ is the maximum distance to the other $(n-1)$ cities centering on city i, C is the constant denoting initial concentration of the information elements in each path..

Seeker ants: the calculation formula of the state transition probability of ant $k(k=1,2,\cdots,m)$ in the movement from city i to city j at the time of t is defined as:

$$p_{ij}^{k'}(t)=\begin{cases}(\tau_{ij}^{\alpha}(t)*\eta_{ij}^{\beta}(t))\Big/\sum\limits_{s\neq tabu_k}\tau_{is}^{\alpha}*\eta_{is}^{\beta}(t),\\ \quad(\text{ if } j[0,1]\neq tabu_k \ and\ s[i][j]\neq 0)\\ 0,\ else\end{cases}\tag{3}$$

After all the ants complete a loop, the concentration of information elements in each path needs to be adjusted according to (4)

$$t_{ij}(t+1)=\begin{cases}(1-\rho)*\tau_{ij}(t)+\rho*\triangle\tau_{ij},\ \ if\ \ s[i][j]\neq 0\\ (1-\rho)*\tau_{ij}(t),\ \ else\end{cases}\tag{4}$$

In which, $\triangle\tau_{ij}$ is the sum of information content released by all ants in the path in this loop, and $\triangle\tau_{ij}=\sum_{k=1}^{m}\triangle\tau_{ij}^{k}$ is the information content in the path (i,j) left by ant k in this loop, and its value can be defined by (5)

$$\triangle\tau_{ij}^{k}=\begin{cases}Q*(\overline{d_{ij}}/d_{ij})/L_k,\\ \quad(if\ \ the\ ant\ k\ passed\ \ (i,j),\ and\ \ s[i,j]\neq 0)\\ 0,\ \ else\end{cases}\tag{5}$$

From the above formula (5), we know that according to the scouting elements, each seeker ant only leaves the right amount of information elements (the combination of the local information $\overline{d_{ij}}/d_{ij}$ and the global information L_k) in the path, which may be a constituent part of the optimal solution. Is it a constituent part of the optimal solution or not, decided by if $s[i][j]$ is 0 or not.

3 ACOMAC Algorithm

MACA algorithm is a relatively new use of the communication in ant behavior in the principle of solving the meta-heuristic search optimization methods. Ants can pass through the path of the pheromone left on the method to exchange information on their food source found in the path of information that can guide other ant's prime tracks to find food sources. So far, many studies have concentrated on solving several benchmark problems, such as the TSP problem, JSP issues, and QAP problem. Here, we present a new ant colony algorithm, it is Ant Colony Optimization with Multiple Ant Clan(ACOMAC), ACOMAC algorithm to solve the problem, we use this algorithm not only requires the solution of problems, and requires a solution close to the optimal solution .ACOMAC algorithm through different strategies conducive to the optimal solution obtained by the algorithm of ant colony using different strategies conducive to build mechanism, is to adopt the basic concept of parallel genetic algorithm to search the solution space, this strategy specifically, different groups to avoid solving the problem of local optimum to obtain the global optimum.

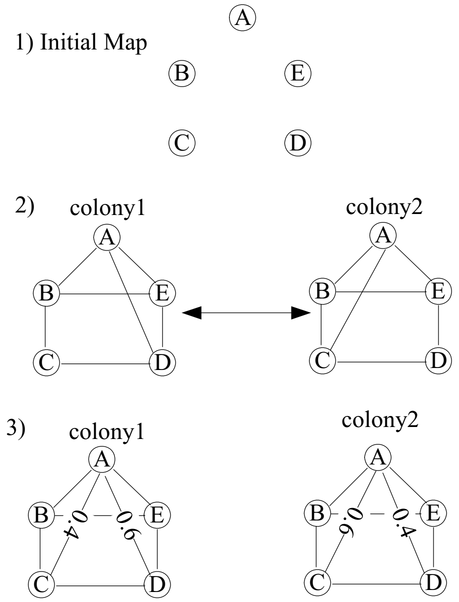

Fig. 1. Multi-ant colony's social rules

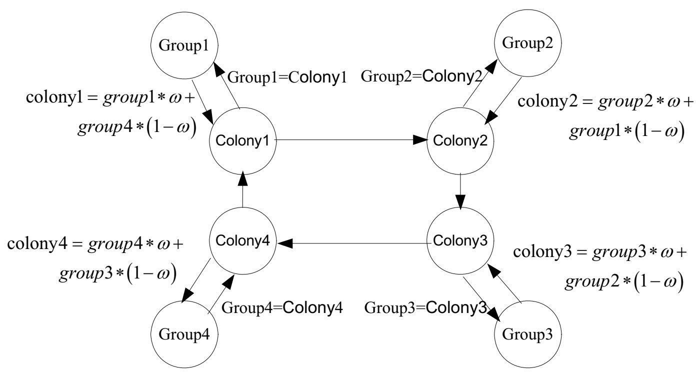

Fig. 2. Multiple ant colonies Society of the rules

Assumes that all the ants are in the same map or area, they are formed according to the different preferences of different groups and communicate with each other, but sometimes a group will obtain information from other groups to get knowledge, so that it can improve the survival competitiveness.Fig.1 shows the social rules of multi-ant colony. Fig. 1(1) describes the initial map, Fig. 1(2) represent two cycles after the colony through the children, their pheromone values in the table each side has different initial pheromone value (each side of the initial value of pheromone equal to 1.0),The equivalent of two different ant pheromone left on the ground, and then left in the path trajectory marking pheromone, that is, the two groups of ants in the group where only know their own knowledge about the shortest path, do not know where the other group of knowledge about the shortest path (local search).Fig.1 (3) describes the circumstances for the information communication group 1, in addition to the length of side equal to 0.4, the other side length is equal to 1.0; For Group 2 is concerned, in addition to the length of side AD is equal to 0.4, the other side length is equal to 1.0.After a few steps, the group and the group will communicate with each other and get all the knowledge about the shortest path or a global search. For more detailed concept of the social rules of colony shown in Fig. 2,Figure 2 describes the concept of local search and global search for the concept, First, all groups will be to search for solutions in each cycle; Second, they will be fixed in a few cycles to build information and communication, At the same time, each group should put it to use the pheromone path mapping the way to their records in, and then using Eq. 6 for information and communication; it is worth noting that the formula represents a group and another about an exchange of information elements of a group situation.

$$\begin{cases} Clan_i = Clan_k * (1-w) + Clan_i * w & (\text{if } i=1) \\ Clan_i = Clan_{i-1} * (1-w) + Clan_i * w & (\text{else}) \end{cases} \tag{6}$$

Where, i represents the i group, k represents group number, w represents a group of pheromone table weight (local weight), $(1-w)$ on behalf of another group of pheromone table weight (external weight). $0 \le w \le 1$.

In Fig.1(1) is the initial map, Fig.1(2) Suppose there are two ant, After several cycles, which pheromone values in the table is different, each edge of the initial pheromone value is equal to 1.0,Fig. 1(3) describes the situation about information and communication: For group 1 is, AC is equal to the length of side 0.4, AD edge lengths equal to 0.6, the other side of the length 1.0; in it for the group 2, AD is equal to the length of side 0.4, AC edge lengths equal to 0.6, the other side The length is equal to 1.0.

ACOMAC algorithm is described as follows:

```
// For solving TSP problems ACOMAC Algorithm
Set parameters, initialize pheromone track
While (termination condition not met) do
    While (termination condition not met) do
        Construction Solutions
        Application local search
        Update local pheromone
        After T time adjustment, the local information elements
        P_a * (1 - w) + (P_i * w)
         Loop
    Global pheromone update
Loop
End
```

4 The Simulation Results

To test the algorithm performance, simulation of the algorithm in the experiment, the algorithm's parameters are: $q_0 = 0.9$, $\beta = 2$, $\rho = \alpha = 0.1$, $m = 10$, $\tau_0 = (n * L_{nn})^{-1}$, L_{nn} represents the nearest neighbor produced by the journey length, n represents the number of sites, the computer simulation run 30 times, local weight w = 0.6, external weight $(1-w) = 0.4$, Table 1 shows the result between ACOMAC algorithms and M. Dorigo's ACS algorithm in solving problems of comparing different TSP.

Table 1. Algorithm for computing the results

TSP Problems	ACS	ACOMAC
Ei151	452.27	439.75
Ei176	562.43	557.92
Kroa100	21780.82	21265.3
D198	17026.7	16873.8

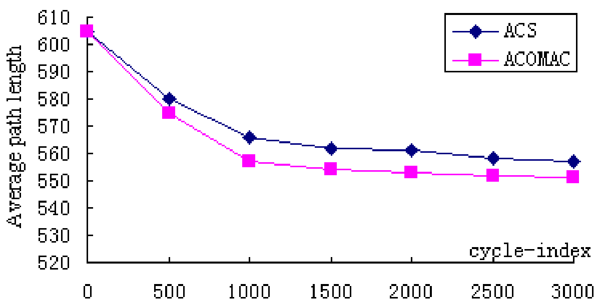

Fig. 3. The comparision of the evolution curves in solving problems Eil 176

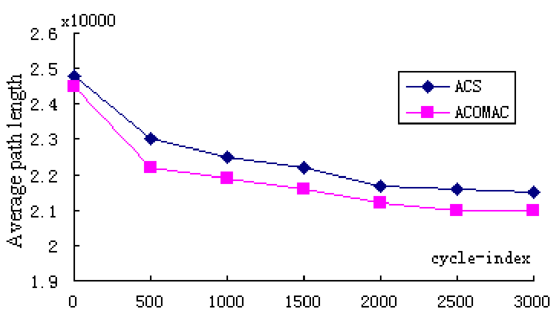

Fig. 4. The comparison of the evolution curves in solving problems Kroa100

Fig. 3 describes the comparison of the evolution curves between ACOMAC algorithm and M. Dorigo's ACS algorithm in solving problems Ei176 (76 nodes, running the number 30.). Fig.4 describes the comparison of the evolution curves between ACOMAC algorithm and M. Dorigo's ACS algorithm in solving problems Kroal00 (100 nodes, running the number 30.);The results show that, ACOMAC algorithm for solving TSP problems in the performance has been significantly improved than the ACS algorithm, we can obtain global optimal or near global optimal solution.

5 Conclusions

Many studies have shown that ant colony algorithm has a strong ability to find better solutions, because the algorithm exploits the positive feedback principle, to a certain extent, can speed up the evolutionary process, but the essence is a parallel algorithm, different ongoing exchange of information between individuals and the transmission, which can work together, is conducive to find better solutions.

This paper presents a new problem to solve TSP algorithm-ACOMAC algorithm, the concept of multiple ant colony is affected by parallel genetic algorithm for solving TSP problems in different populations of the search solution space in order to avoid local optimum conditions to obtain the global optimum inspired and created. Simulation results show that, ACOMAC algorithm for solving TSP problems more effective than the ACS algorithm.

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References

[1] Dorigo, M., Di Caro, G., Gambardella, L.M.: Ant algorithms for discrete optimization. Artiticial Life 5(2), 137–172 (1999)

[2] Baterina, A.V.: Image edge detection using ant colony optimization. WSEAS Transactions on Signal Processing 6(2), 58–67 (2010)

[3] Matthews, D.C.: Improved Lower Limits for Pheromone Trails in Ant Colony Optimization. In: Rudolph, G., Jansen, T., Lucas, S., Poloni, C., Beume, N. (eds.) PPSN 2008. LNCS, vol. 5199, pp. 508–517. Springer, Heidelberg (2008)

[4] Jin, Y., Zhao, Y.: Optimization of ship principal parameters with improved ant colony algorithm. Journal of Huazhong University of Science and Technology 36(11), 99–102 (2008)

[5] Nonsiri, S.: Modifying ant colony optimization. In: Proceedings of the 2008 IEEE Conference on Soft Computing on Industrial Applications, pp. 95–100 (2008)

[6] Yoshikawa, M.: A new pheromone control algorithm of ant colony optimization. In: International Conference on Smart Manufacturing Application, pp. 335–338 (2008)

[7] Gao, W.: New continuous ant colony algorithm. In: Proceedings of the World Congress on Intelligent Control and Automation, pp. 1275–1279 (2008)