A new Ant Colony Algorithm for solving Traveling Salesman Problem

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***Abstract*—Ant colony optimization (ACO) is a population-based metaheuristic technique to solve combination optimization problems effectively. However, how to improve the performance of ACO algorithms is still an active research topic. Though there are many algorithms solving TSPs effectively, there is an application bottleneck that the ACO algorithm costs too much time in order to get an optimal solution. This paper revised pheromones in local and global update mode。a fast ACO algorithm for solving TSPs is presented in this paper. Firstly, a new pheromone increment model called ant constant, which keeps energy conversation of ants, is introduced to embody the pheromone difference of different candidate paths. Meanwhile, a pheromone diffusion model, which is based on info fountain of a path, is established to reflect the strength field of the pheromone diffusion faithfully, and it strengthens the collaboration among ants. Experimental results on different benchmark data sets show that the proposed algorithm can not only get better optimal solutions but also enhance greatly the convergence speed.**

Keywords-TSP; ACO;Combinatorial optimization problem

I. INTRODUCTION

Ant colony optimization algorithm (ACO) is proposed by Dorigo which is according to the ant group in the process of the foraging reflects the intelligent behavior. After years of development, the ant colony algorithm has become one of the most effective algorithm in solving the swarm intelligence (SI) combinatorial optimization problem, and it has widely typical application in production process, vehicle management, routing addressing, layout planning, resource allocation and data mining, etc. However, slow convergence speed and easy to fall into the local extremum is still the main bottleneck restricting ACO algorithm to be widely used. Therefore, people put forward many kind of improved ant colony algorithm. As a whole, the improvement methods include two basic ways: 1) the improvement of element information update mechanism, namely, it improves optimization ability of the ant colony algorithm through the element information generation and updates the optimization strategy, ameliorate the global convergence of the solution. For example, Gambardella and others propose ant colony system (ACS) to update the pheromones twice with both in global and local to improve the overall convergence ability; Stutzle and others propose Max-min ant system (MMAS) to limit the information upper and lower bound on the path to overcome the stagnation of the solution; Huang Guorui and others propose PDACO algorithm use pheromone diffusion model to modify the pheromones update formula in order to enhance the communication among ants, Ji Junzhong comes up with new incremental model of pheromone, it is the ant constant model. 2) Search mechanism improvement. It adjust the control strategy in the random search process, so as to reduce iteration times and accelerate convergence. Such as WuQingHong and others propose an ant colony algorithm with mutation features, it speed up local search through the mutation strategy. Wu Bin and others propose meeting algorithm, it structure a common solution path with two ants to speed up the process of structural solution. Ding Jianli and others propose the GAAA algorithm; it combines the genetic algorithm and the ant colony algorithm to accelerate solution speed as well. This paper puts forward an ant colony algorithm aimed at a kind of TSP in decreasing the local extremum as far as possible and speeding up the convergence. Firstly, use acceleration factor to choose local optimal path in the adaptive stage, then record the local optimal value in the path, and appropriately reduce the pheromone in collaboration stage until the path was obstructed. Experiment results show that this method not only can rapidly improved ant colony algorithm for searching ability, and also can obtain better search capability in combining with a variety of existing ant colony algorithm.

II. THE BASIC PRINCIPLE OF ANT COLONY ALGORITHM

$C = \{c_1, c_2, ..., c_n\}$ is the set of n city, $L = \{l_{ij} \mid c_i, c_j \in C\}$ is a collection of C elements (city) set of connection Between two elements , $d_{ij}(i, j \in N = (1,2,...,n))$ if said l_{ij} the Euclidean distance, n is the number of ants in colony , $\tau_{ij}(t)$ is said the pheromone when t . When travelling around in the process Ant $k(1 \le k \le m)$ can randomly choose directions according to the stranded pheromone on the feasible candidate path.

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At t time the probability of ant k travelling from city i from city j:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}\times[\eta_{ik}]^{\beta}}{\sum\limits_{l\in U_k}[\tau_{is}]^{\alpha}\times[\eta_{is}]^{\beta}}, j,s\in U_k \\ 0, otherwise\end{cases} \quad (1)$$

Among them, U_k is said a allowed city list that the ant k in the current position can travel , η_{ij} is the expectations of the path l_{ij} from city c_i to city c_j , generally, $\eta_{ij}=1/d_{ij}$. α is the relative importance of path, β is he relative importance of visibility of path l_{ij} .

In order to reduce the probability of the algorithm to a certain extent in local optimum solution , Gambardella etc [9] put forward a improved ant colony algorithm,

$$j=\begin{cases}\{\arg_{u\in U_k}\max\{[\tau_{iu}(t)]^{\alpha}.[\eta_{iu}]^{\beta}\}, q<q_0 \\ \text{j from(1)}, otherwise\end{cases} \quad (2)$$

q_0 is the initial parameters, q is a random sampling number $q_0, q\in[0,1]$.

When structuring the solution, an ant update local pheromones with Equation(3) on the path :

$$\tau_{ij}(t+1)=(1-\zeta)\times\tau_{ij}(t)+\zeta\times\Delta\tau_0, \zeta\in(0,1) \quad (3)$$

$$\tau_0=1/(nl_{\min}) \quad (4)$$

ζ is said the Volatile degree of pheromones , $l_{\min}$ is said the distance between two recent elements in C.

$$\tau_{ij}=(1-\rho)\times\tau_{ij}+\rho\times\Delta\tau_{ij}, \rho\in(0,1) \quad (5)$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \quad (6)$$

ρ is the volatile coefficient, $\Delta\tau_{ij}^{k}(t)$ is the increment of the pheromones on l_{ij} in this circulation , $\Delta\tau_{ij}^{k}$ is the pheromone amount on the iteration k in this followed remained in the path l_{ij} , Dorigo, etc have defined 3 kinds of pheromone incremental model [1-2],including the ant-quantity, the ant-density and the ant-cycle . One of the most easy ant model is ant-density,the pheromone increment Q is a constant pheromone strength .In the ant-quantity the pheromone and the path length is inverse ratio (Q/d_{ij}) .In the ant-cycle , the pheromone and the ant traveled length is inverse ratio (Q/L_k).

III. New Ant Colony Algorithm

Standard ACO inevitably makes search tend to temporary optimal solution, by means of successive information element accumulation process finished the optimal path search. Although it can change the position of the next hop through the roulette wheels algorithm according to specified probability , it was unable to build a new optimal path. This paper ,using penalty factor, weights the distance between the two cities , and joins the pheromones in the renewal. The farther between two of cities, the lower the pheromones .

A. Pheromones local update

$$\tau_{ij}(t+1)=\tau_{ij}(t)\times(1-\xi_k)+Q$$

ξ_k :From i the distance to j the $k-1$ iteration is completed with minimum value of the ratio of the known path

B. Pheromones global update

$$\tau_{ij}(t+1)\begin{cases}=\tau_{ij}(t)\times\zeta_k & \text{new best path when the K iteration} \\ =\tau_{ij} & \text{otherwise}\end{cases}$$

ζ_k : the ratio of The original minimum path and the new minimum path.

IV. Experimental Results and Comparative Analysis

A. Basic parameter Settings

Experimental environment:Windows XP;

CPU: Penium Dual Core for 2.8 GHz;

memory:2GB;

experimental platform: MATLAB7.0.

STPs:

To avoid differences caused by different codes, the results of Standard ACO are shown as Table 1.

TABLE I. THE BEST ITINERARY MAPS FOR ACS ALGORITHM

Instances	Optimum Solution	ACS Algorithm		
		Best length	Run times	Error%
Berlin52	7542	8165	22.1	8.3
Pr76	108159	129562	41.6	19.8
Pr152	73682	77969.7	1249	5.818
Tsp225	3919	5287	315.8	39.9
Pr226	80369	85254.5	3393	6.079
Pcb442	50778	53384.3	5762	5.13

The results of improved ACO is table 2,and Figure1-6 are the best itinerary maps of 6 instances from TSPLIB :

TABLE II. THE BEST ITINERARY MAPS FOR ACS ALGORITHM

Instances	Optimum Solution	ACS Algorithm		
		Best length	Run times	Error%
Berlin52	7542	8022.1	36.2	6.3
Pr76	108159	118209.2	36.4	10.2
Pr152	73682	81914.2	90.6	11.2
Tsp225	3919	4707.2	355.2	20
Pr226	80369	90906.8	196.2	13.1
Pcb442	50778	62600.2	2313.1	23.2

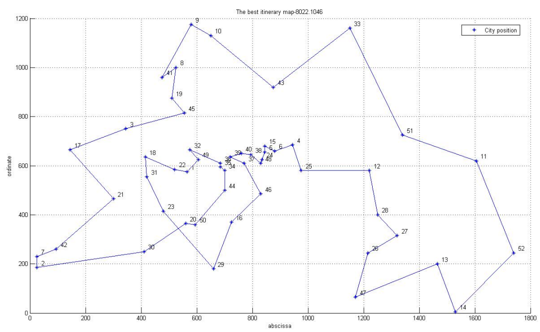

Figure 1. The best itinerary map of Berlin52

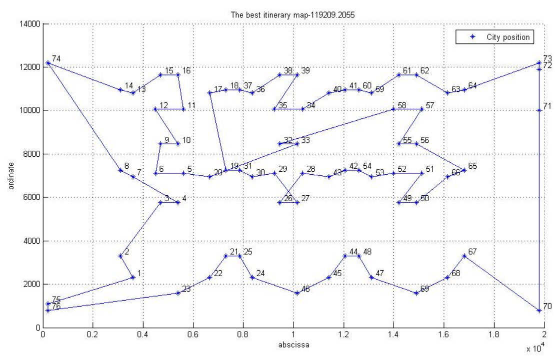

Figure 2. The best itinerary map of pr76

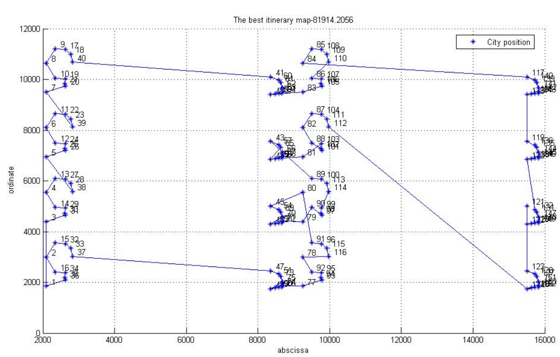

Figure 3. The best itinerary map of pr152

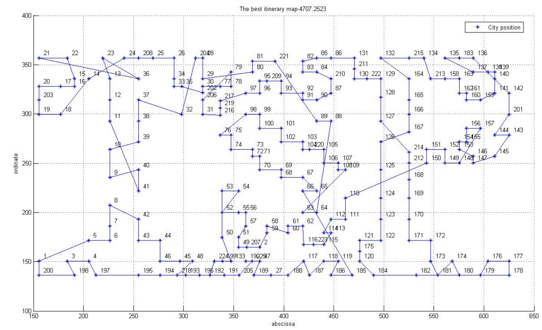

Figure 4. The best itinerary map of Tsp225 355.2 4707.2

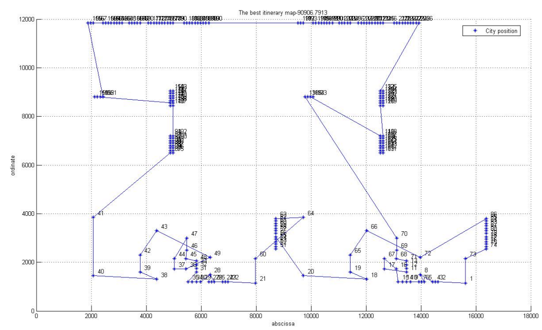

Figure 5. The best itinerary map of pr226

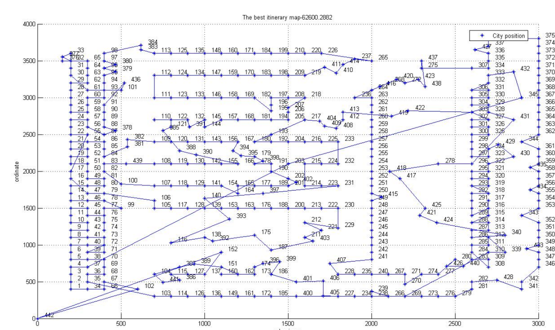

Figure 6. The best itinerary map of pcd442

V. CONCLUSION

The improved algorithm can be more effective ACO global search, for bad Clustering instances ,it could also find relatively good path, and improve the searching efficiency.

When the number of cities increases, there need more time and more cost to improve the global search ability .In the future,we should find more efficient pheromone update model to solve this problem.

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