An Effective Initialization Strategy of Pheromone for Ant Colony Optimization

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Abstract—Aiming at the poor performance of convergence of ant colony optimization (ACO), in this paper, a novel pheromone initialization strategy of ACO for the traveling salesman problem (TSP) is put forward. More precisely, the pheromone matrix of a specific ACO algorithm is initialized by the minimal spanning tree (MST) information. Simulation results demonstrate that the proposed strategy could improve the convergence performance of ACO both in term of quality of solution and speed of convergence.

Keywords— TSP; MST; Pheromone; ACO

I. INTRODUCTION

The traveling salesman problem (TSP) [1] is a representative combinatorial optimization problem. Given a graph G = (V, E), where V is a set of N vertices and E is a set of edges. Each edge of E is assigned a weight denoting the edge length. The problem is to find a shortest tour that visits each vertex exactly once and then returns to the origin vertex. Despite its simple description, the TSP is a typical NP-hard problem.

Ant Colony Optimization (ACO) was first applied to the TSP. ACO is a meta-heuristic inspired by the foraging behavior of the ants [2]. These ants are able to find the shortest path between the nest and a food source by laying down pheromone on their way. The pheromone is used to mark some favorable paths that could be followed by other members of the colony. ACO similarly builds pheromone trail to learn the best solution to a problem. That is, the procedure of the convergence of ACO is an evolution of the pheromone trail.

So far, many efficient pheromone control methods to improve the performance of ACO are proposed, for example [3] brings forward a new pheromone increment and diffusion model, [4] gives a new pheromone control technique and [5] proposes an ACO algorithm based on mutation and dynamic pheromone updating rule. Though these researches are very successful, they mainly focus on the pheromone updating.

As stated in [6], the different of pheromone initialize parameter setting may result in different solution performance. Namely the pheromone initialize strategy is a factor that influences the performance of ACO. However, there is no success improved pheromone initialization strategy that has been proposed so far. Thus, this paper presents a new pheromone initialization strategy of ACO for TSP, which initializes the pheromone matrix in light of the minimal spanning tree (MST) information. The experimental results on some instances show that the proposed strategy is effective.

II. ANT COLONY OPTIMIZATION

In ant colony optimization, a number of artificial ants build solutions to the considered optimization problem at hand and exchange information on the quality of these solutions via a communication media, pheromone trail, which is reminiscent of the one adopted by real ants. The original ACO algorithm is known as Ant System proposed in the early nineties [2]. Since then, many different ACO algorithms have been proposed. We just describe Ant colony system (ACS) [7] in detail here, because it is one of the most popular ACO algorithms.

In ACS, each ant constructs a solution by repeatedly applying a state transition rule and the solution is improved by a local search algorithm, named 2-opt algorithm [8]. Then the ant modifies the amount of pheromone on the visited edges by applying a local pheromone updating rule. Once all ants have done their operations, the amount of pheromone is modified by applying a global updating rule.

A. The State Transition Rule

The next city j is determined by (1)

$$j = \begin{cases} \arg\max_{u \in J_k(t)} \{\tau_{iu} \cdot \eta_{iu}^{\beta}\}, & \text{if } q \le q_0 \\ J, & \text{otherwise} \end{cases} \tag{1}$$

where τ_{iu} is the pheromone level on edge (i, u), $\eta_{iu}=1/d_{iu}$ is the heuristic information that the inverse of the distance d_{iu} from city i to city u, $J_K(t)$ is the set of cities that remain to be visited by ant k at the t-th step, β controls the relative importance of the heuristic information, q is a random number uniformly distributed in [0, 1], and q_0 is a parameter ($0 \le q_0 \le 1$) that determines the relative importance of exploitation versus exploration. In addition, J is a random variable selection according to the probability distribution, called a random-proportional rule [7].

B. The Local Pheromone Updating Rule

The local pheromone updating rule is shown in

$$\tau_{ij} \leftarrow \tau_{ij} \cdot (1-\varphi) + \varphi \cdot \tau_0 \tag{2}$$

where $\varphi \in (0, 1)$ denotes the local pheromone decay parameter, τ_0 denotes the initial pheromone level on each level on each edge and $\tau_0 = 1 / N \cdot L_{NN}$ where L_{NN} is the tour

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length produced by the nearest neighbor heuristic and N is the number of cities of TSP.

C. The Global Pheromone Updating Rule

The global pheromone updating rule is slightly different from the local one as

$$\tau_{ij} \leftarrow \begin{cases} (1-\rho)\cdot\tau_{ij} + \rho\cdot\Delta\tau_{ij}, & \text{if (i, j)} \in \text{best tour} \\ \tau_{ij}, & \text{otherwise} \end{cases} \quad (3)$$

where $\Delta\tau_{ij} = 1 / L_{best}$ ($L_{best,}$ the best-so-far result) and $\rho \in (0, 1)$ is the evaporation rate.

III. THE NEW PHEROMONE INITIALIZATION STRATEGY

In this section, we propose a new strategy of pheromone initialization. First, we advance the general idea of the new strategy and show our motivation. Then, for showing how the strategy works, a specific one for ACS is described as an example.

The new pheromone initialization strategy is to initialize the pheromone matrix of ACO by means of the MST, structural information obtained from TSP problem. The MST is a spanning tree of a weighted graph whose sum of edge weights is minimal. The minimum spanning tree describes the cheapest network to connect all of a given set of vertices. The purpose of this strategy is to give the edges belonging to the MST more probability to be chosen by ants at the beginning of the algorithm running. There are several reasons why our pheromone initialization strategy employs the MST information.

Firstly, pheromone matrix is the basic communication media for ants in the ACO and its appropriate initialization at the beginning is crucial to the performance of the ACO. But in specific ACO algorithm such as ACS, the initial pheromone values for all edges are always set by the same value. A disadvantage of this strategy may be a factor which causes the slow convergence of ACO.

Secondly, examining the solutions of TSP and MST on a same graph, a great number of edges are identical, about 70–80%. Therefore, as structure information obtained from problem, the MST is well suited for initializing the pheromone matrix of ACO.

Thirdly, for some information from the MST may be misleading, pheromone initialization could be a good method for exploiting the MST information, as in this way the misleading MST information is not permanent but can be forgotten over time through evaporation.

Finally, the MST computing is only run once and not in the iterative part. Thus our strategy does not influence runtime crucially.

In a word, this strategy is proper approach to exploiting the MST information and enhancing the convergence performance of ACO.

In order to evaluate the effectiveness of the new strategy conveniently, we take ACS as an example here to show how the strategy works. We name the new ACS, which exploits the strategy, as MST-ACS in contrast to the standard ACS. A pseudo-code of MST-ACS is shown in Fig.1.

```
Procedure MST-ACS {
    Read the TSP data;
    Initialize the system;
    Compute a MST using the algorithm of Kruskal;
    Initialize the pheromone matrix using distance and MST
    information;
    Repeat {
        For each ant {
            Construct a TSP tour;
            Apply a 2-opt algorithm to the tour;
            Update the best found solution;
            Update the pheromone matrix locally;
        }
        Update the pheromone matrix globally;
    } until the pre-specified stopping criterion is met;
    Return the best found solution;
}
```

Figure 1. The pseudo-code for MST-ACS

Before the iterative part of MST-ACS, an MST is computed using the well known algorithm of Prim algorithm [9] and the pheromone is initialized using the MST information as (4),

$$\tau_{ij}^{\ 0} = \begin{cases} (\tau_0)^{1/\theta}, & \text{if}\,(i,j) \in \text{MST} \\ \tau_0, & \text{Otherwise} \end{cases} \tag{4}$$

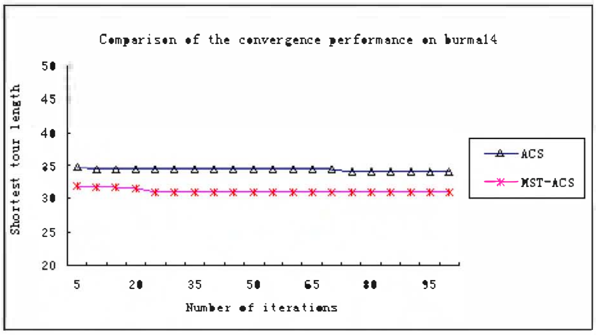
where τ_0 is the same as the one of ACS and θ is a parameter which denotes the relative weight associated to the MST information. As $0 \leqslant \tau_0 \leqslant 1$, the greater θ, the higher τ_{ij}^{0}. It means that the edges belonging to MST receive higher pheromone amount at the beginning of the algorithm running. Therefore, they have more opportunity to be chosen by artificial ants than others, according to (1). Here, we take θ = β which is determined by experiment.

The computation complexity of the proposed strategy is $O(N^2)$, where N is the num of city, and the iteration part of MST-ACS is $O(N_c \cdot N^2 \cdot m)$, equaling to ACS [2]. So the MST-ACS is $O(Nc \cdot N^2 \cdot m)$. Therefore, MST-ACS and ACS have the same computation complexity.

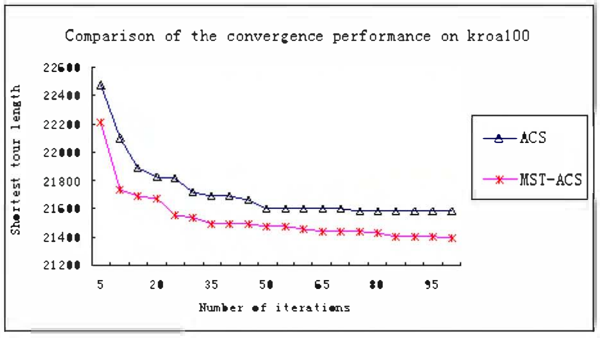
IV. EXPERIMENT

All experiments are realized in VC2005 and run on a DELL GX260 PC (CPU Pentium 2.8GHz, 512MB RAM) with Windows XP Professional Operating System. To validate the effectiveness of the novel strategy of pheromone initialization, all the algorithms are tested 10 times on benchmark problems which can be downloaded from TSPLIB at http://elib.zib.de/ pub/mp-testdata/tsp/tsplib/tsp/index.html.

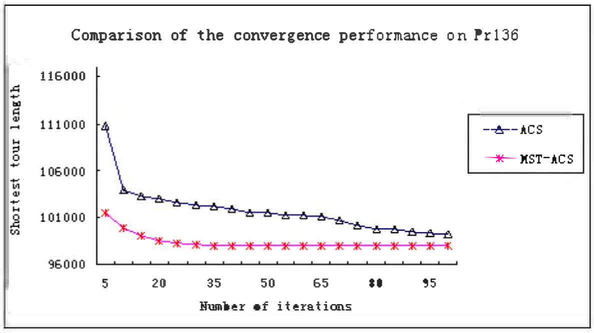
We first compare the performance of MST-ACS and ACS for TSP in terms of speed of convergence. Most of parameter settings of the two algorithms are in common, i.e. that M = N (number of city), β=2, ρ=0.2, φ=0.2 ,N_C=100 (number of iterations) and θ=2 in MST-ACS. The average convergence curves of ACS and MST-ACS on four TSP instances are given respectively in Fig. 2. These charts show obviously that MST-ACS performs significantly better than ACS at the each number of iterations. Consequently, MST-ACS has a faster convergence speed than ACS.



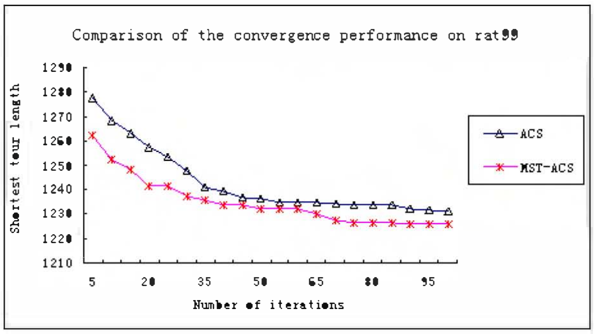
(a) burma14



(b) kroa100



(c) pr136



(b) rat99

Figure. 2 Comparisons of the convergence performance curves between MST-ACS and ACS for different instances

TABLE I. THE RELATIVE PERCENTAGE DEVIATION FROM THE OPTIMAL SOLUTION

Instance	ACS			***MST-ACS***			NN-Ants			***MST-NN-Ants***		
	Best	Mean	Time	***Best***	***Mean***	***Time***	Best	Mean	Time	***Best***	***Mean***	***Time***
Kroa100	0.88	1.42	33	***0.08***	***0.55***	***16***	0	0.01	1.6	***0***	***0***	***0.6***
Pr136	1.32	2.50	42	***0.40***	***1.33***	***18***	0	0.16	3.2	***0.02***	***0.15***	***1.9***
Rat99	0.99	1.65	30	***0.83***	***1.24***	***14***	0	0.03	1.2	***0***	***0.02***	***0.8***
Rd100	0.29	1.43	35	***0.06***	***0.72***	***28***	0	0.13	1.8	***0***	***1.04***	***0.9***
Pr124	0.22	0.52	40	***0.22***	***0.45***	***21***	0	0	2.1	***0***	***0***	***0.7***
Ch130	0.75	1.46	39	***0.74***	***1.21***	***26***	0	0.33	3.0	***0***	***0.20***	***1.9***

To testify the solution quality and the convergence time of MST-ACO which ACO adopts the proposed initialization strategy, we list Table I, where it gives the best and average relative percentage deviation (RPD) from the optimal solution and average convergence time of ACS, MST-ACS, NN-Ants [3] as well as MST-NN-Ants (NN-Ants exploiting the proposed strategy). The new pheromone initialization equation of MST-NN-Ants is as (5)

$$\tau_{ij} = \begin{cases} 1, & \text{if } (i, j) \in \text{MST} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

and the parameter settings of NN-Ants and MST-NN-Ants are identical and same as [3]. The table displays that MST-ACS and MST-NN-Ants have better solution quality performance than ACS and NN-Ants and cost less convergence time.

The experiment results above verify clearly that the new strategy of pheromone initialization proposed in this paper can improve the convergence performance of the ACO with respect to both quality of solution and speed of convergence

V. CONCLUSION

This paper proposes a novel strategy of pheromone initialization of ACO for TSP. That is, the pheromone trail is initialized using the MST information. The experiment results are promising and demonstrate that the proposed pheromone initialization strategy can improve both the solution quality and the convergence speed.

Although the performance of the strategy is promising, it is not suitable to large scale problem. And it is worth noting that it may be better to initialize the pheromone matrix with other information. In relation to future work, we will study these works.

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