An ACO Algorithm with Adaptive Volatility Rate of Pheromone Trail

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Abstract. Ant colony optimization (ACO) has been proved to be one of the best performing algorithms for NP-hard problems as TSP. The volatility rate of pheromone trail is one of the main parameters in ACO algorithms. It is usually set experimentally in the literatures for the application of ACO. The present paper proposes an adaptive strategy for the volatility rate of pheromone trail according to the quality of the solutions found by artificial ants. The strategy is combined with the setting of other parameters to form a new ACO algorithm. Finally, the experimental results of computing traveling salesman problems indicate that the proposed algorithm is more effective than other ant methods.

Keywords. Ant colony optimization, pheromone trail, adaptive volatility rate

1 Introduction

ACO was first proposed by M. Dorigo and his colleagues as a multi-agent approach to deal with difficult combinatorial optimization problems such as TSP [1-2]. Since then, many applications to the NP-hard problems have shown the effectiveness of ACO [3].

The main parameters of ACO may conclude: k is the number of artificial ants, ρ is the parameter for volatility of pheromone trail and α, β determine the relative importance of pheromone value and heuristic information [2]. All of the parameters are usually set with experimental methods in the application of ACO [3]. There have been also several works [4-7] for the adaptive parameter setting of ACO algorithms.

This paper presents a tuning rule for ρ based on the quality of the solution constructed by the artificial ant. Then, the adaptive rule is used to form a new ACO algorithm, which is tested to compute several benchmark TSP problems. The experimental result indicates that the proposed ACO algorithm with adaptive ρ performs better than other ACO algorithms [2, 8].

2 Adaptive Volatility Rate of Pheromone Trail

In ACO algorithms [3], each ant builds a tour (i.e. a feasible solution to the TSP problem) by repeatedly applying the state transition rule as Equation 1 shows.

$$P_{gs}^{(m)}(t) = \begin{cases} \frac{[\tau_{gs}(t)]^\alpha [\eta_{gs}]^{\beta(g,t)}}{\sum_{r \in J_m(g)} [\tau_{gr}(t)]^\alpha [\eta_{gr}]^{\beta(g,t)}} & \text{if } s \in J_k(g) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where P_{gs}^m is the probability with which the m -th ant moves from city g to city s in the t -th iteration, τ is the pheromone, $\eta = 1/d$ is the reciprocal of distance d_{gs} , and $J_m(g)$ is the set of cities not visited when ant m is at city g .

After constructing its tour, an artificial ant also modifies the amount of pheromone on the visited edges by applying the pheromone updating rule:

$$\tau_{gs}(t+1) = (1 - \rho)\tau_{gs}(t) + \rho\Delta\tau_{gs}(t) \quad (2)$$

where $\Delta\tau_{gs}(t)$ is the increment for the pheromone of edge (g, s) at the t -th iteration, and $\rho = 0.1$ is the volatility rate of the pheromone trail [2-3].

In order to update the pheromone according to the quality of solutions found by ants, an adaptive rule for volatility of the pheromone trail is designed as follows:

$$\rho_m = L_m^{-1} / (L_m^{-1} + L_p^{-1}) \quad (3)$$

where L_m is the length of the solution S_m found by the m -th ant, and L_p is the length of the solution built based on the pheromone matrix (Equation 4).

$$s = \arg \max_{u \in J_m(r)} \{[\tau(r, u)]\} \quad (4)$$

where s is the city selected as the next one to city r for any $(r, s) \in S_p$.

The motivation of the proposed rule is: better solutions should contribute more pheromone, and the worse ones contribute less. We use this rule to design a new ACO algorithm, which is similar to ant colony system (ACS) [2] except for the updating rule [2] (Equation 5). For $i = 1, \dots, k+1$ (k ants and the best-so-far ant),

$$\tau_{gs}(t+1) = (1 - \rho_i)\tau_{gs}(t) + \rho_i L_i^{-1} \quad (5)$$

where $\forall (g, s) \in S_i$ and $\rho_i = L_i^{-1} / (L_i^{-1} + L_p^{-1})$ for the t -th iteration.

3 Numerical Results

This section indicates the numerical results in the experiment that the proposed ACO algorithm is used to solve TSP problems [9]. Other ant approaches ACS [2] and the ACO [8] are also tested in the same machines as the comparison with the proposed ACO. Several TSP instances are computed by the three algorithms on a PC with an Intel Pentium 550MBHz Processor and 256MB SDR Memory, and the results are shown in Table 1. It should be noted that every instance is computed 20 times. The algorithms would not stop until a better solution could be found in 500 iterations.

Table 1 shows that the proposed ACO algorithm (PACO) performs better than ACS [2] and the ACO [8]. The shortest lengths and the average lengths obtained by PACO are shorter than those found by ACS and the ACO in all of the TSP instances. Furthermore, it can be concluded that the standard deviations of the tour lengths obtained by PACO are smaller than those of another algorithms. Therefore, we can conclude that PACO is proved to be more effective and steady than ACS [2] and the ACO [8]. Computation time cost of PACO is not less than ACS and ACO in all of the instances because it needs to compute the value of volatility rate $k+1$ times per iteration. Although all optimal tours of TSP problems cannot be found by the tested algorithms, all of the errors for PACO are much less than that for another two ACO approaches. The algorithms may make improvement in solving TSP when reinforcing heuristic strategies like ACS-3opt [2] are used.

Table 1. Comparison of the results in TSP instances

Problem	Algorithm	best	Ave	time(s)	Standard deviation
kroA100	ACS	21958	22088.8	65	1142.77
	ACO	21863	22082.5	94.6	1265.30
	PACO	21682	22076.2	117.2	549.85
ts225	ACS	130577	133195	430.6	7038.30
	ACO	130568	132984	439.3	7652.80
	PACO	130507	131560	419.4	1434.98
pr226	ACS	84534	86913.8	378.4	4065.25
	ACO	83659	87215.6	523.8	5206.70
	PACO	81967	83462.2	762.2	3103.41
lin105	ACS	14883	15125.4	88.8	475.37
	ACO	14795	15038.4	106.6	526.43
	PACO	14736	14888	112.2	211.34
kroB100	ACS	23014	23353.8	56.2	685.79
	ACO	22691	23468.1	102.9	702.46
	PACO	22289	22728	169.6	668.26
kroC100	ACS	21594	21942.6	54.8	509.77
	ACO	21236	21909.8	78.1	814.53
	PACO	20775	21598.4	114.8	414.62
lin318	ACS	48554	49224.4	849.2	1785.21
	ACO	48282	49196.7	902.7	2459.16
	PACO	47885	49172.8	866.8	1108.34

4 Discussions and Conclusions

This paper proposed an adaptive rule for volatility rate of pheromone trail, attempting to adjust the pheromone based on the solutions obtained by artificial ants. Thus, a new ACO algorithm is designed with this tuning rule. There is a special pheromone updating rule in the proposed algorithm whose framework is similar to Ant Colony System. There are some experimental comparisons among the proposed ACO approach and other methods [2, 8] in solving TSP problems. The results show the effectiveness of the proposed algorithm.

Further study is suggested to explore the better management for the optimal setting of the parameters of ACO algorithms, which will be very helpful in the application.

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