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Performance of Ant Colony Optimization Changing Characteristics of Pheromone Reaction

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Abstract

Recently, nature-inspired metaheuristic optimization algorithms such as Ant Colony Optimization (ACO) is developed. ACO is based on the feeding behavior of ant herds.

In this study, we propose a new ACO in which the pheromone's reaction improve on increasing at the number of repetition for Traveling Salesman Problem (TSP). The standard ACO has constant pheromone's reaction. However, the pheromone's reaction of the propose method has changing state and constant state. We compare the solution with ACO and the proposed method. We find optimal rate of repetition times of changing pheromone's reaction. Then, we investigate characteristic of algorithm according to rate of repetition times. Average of solutions that ACO has two states is better than average of solutions that ACO has only changing state.

1. Introduction

Optimization is to search optimal solution under condition. Advantage of optimization is high efficiency. Optimization is needed in various scenes. Combinatorial optimization problem is often solved by metaheuristic optimization algorithms.

Many combinatorial optimization problems are often trapped in a local optima. Metaheuristic optimization algorithms are solved high performance in these problems. These algorithms are developed to solve more efficiency and larger problems. Metaheuristic optimization algorithms have Evolutionary Algorithm (EA), Swarm Intelligence (SI) algorithm, local search, etc. In our study, we choose the SI because research has been conducted actively.

SI is one of the artificial intelligence techniques. SI was born from swarm of insect. Examples existing in nature are ant, bee and firefly, etc. In insect colonies, each insect has its the group in total appears to be highly organized. The applications of SI technique are a self-driving car and data mining. The good points of this technique are smaller control system and multi control by simple systems. SI algorithms have Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Firefly Algorithm (FA), etc [1]. The ACO is used by our propose method.

ACO is idealized the social behavior of ants based on their feeding characteristics. ACO was developed by Marco Dorigo in 1992 [2]. Artificial intelligence algorithms have been demonstrated to show effectiveness and efficiency to solve difficult optimization problems [3]. ACO performs higher ability in discrete optimization problem than other SI algorithms. For example, routing problem, allocation problem, and scheduling problem [4]. However, demerit of ACO is easy to trap in local optima in large search range [5]. The reason is a re-search of route occurs hard since the route stabilizes as the search progresses [6].

In this study, we propose ACO in which the pheromone's reaction improves by increasing at the number of repetition. We compare the accuracy of the solution with ACO and the proposed method. We can find optimal rate of change of pheromone's reaction. Moreover, we investigate characteristic according to more increasing times of constant pheromone's reaction. We show the superiority of the propose method.

2. Ant Colony Optimization

First, we introduce the behavior of ants. Ant communicates a variety of information to another ant by pheromone. Ants can find the shortest route from a nest to place of bait. The reason is each ant follow two rules:

- All ants leave volatile pheromone on the route while they move;
- Most ants choose the strong pheromone route.

Each ant searches bait. After each ant finds bait, it carries bait to nest. While each ant moves, it remains pheromone on each route. As a result, each ant leaves pheromone on the route from a nest to place of bait. This pheromone evaporates by gradation. Therefore, the shortest route is remained pheromone. When another ant starts to search bait from nest, it chooses route according to the second rule. Thus, most ants can find the shortest route. Figure 1 shows feeding behavior of ant.

ACO is based on these characteristics. ACO is simple little rule system. However, ACO is high search performance. This point is benefit of ACO. Implementation steps of the algorithm are summarized below:

Step1. Initialize the total number of ants k, reaction of pheromone α, responding to heuristic information β and evaporation rate of pheromone ρ.

Step2. Calculate the evaluation value α by Eq. (1) when each ant moves from city i to city j. Then, select a route according to the probability p by Eq. (2).

Step3. Add pheromone to the route that the ant found. The value of pheromone τ can be obtained by Eqs. (3) and (4).

Step4. Repeat steps 2 to 3 until times of maximum iteration t_{max} and output the solution.

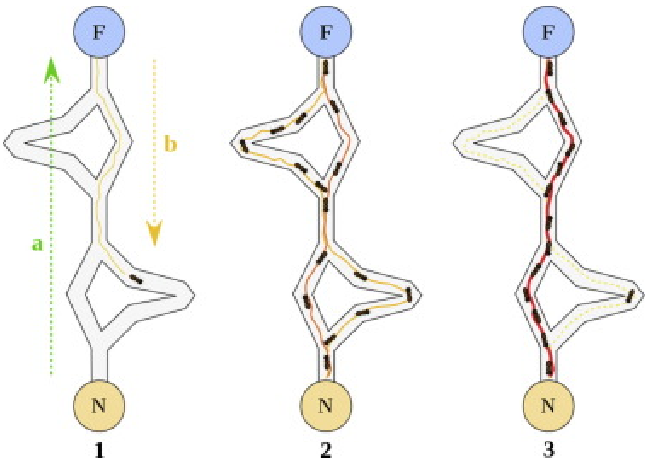

Figure 1: Ant behavior.

Pheromone values τ and evaluations value a are given by following equations:

$$a_{ij}^k(t) = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_k} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta}, \quad (1)$$

$$p_{ij}^k(t) = \frac{a_{ij}^k(t)}{\sum_{l \in N_k} a_{il}(t)}, \quad (2)$$

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^k(t), \quad (3)$$

$$\Delta\tau_{ij}^k(t) = 1/L_k(t)(if\ i,j \in L_k), \quad (4)$$

where, L_k expresses the length of the route that each ant visited.

3. Proposed method

We propose a ACO Changing Pheromone's Reaction (ACO-CPR). The reaction of pheromone is constant value in the standard ACO. ACO-CPR is that the pheromone's reaction (α) has two states. At the beginning of the simulation α varies linearly with repetition by using Eq. (5).

$$\alpha = \frac{1}{h} t \quad (5)$$

where h corresponds to the gradient of changing α and t denotes the repetition time. After α reaches to 1.0, α keeps the constant value (α=1.0). We compare 6 kinds of pheromone's reaction by changing the parameter h (h=1000, 1500, 2000, 2500, 3000 and 3500). Figures 2 to 4 show some examples of the pheromone's reaction which has two states; changing state and constant state. We also change the total repetition time (t_{max}) for each pheromone's reaction. Namely the ratio of the changing state and the constant state is changed.

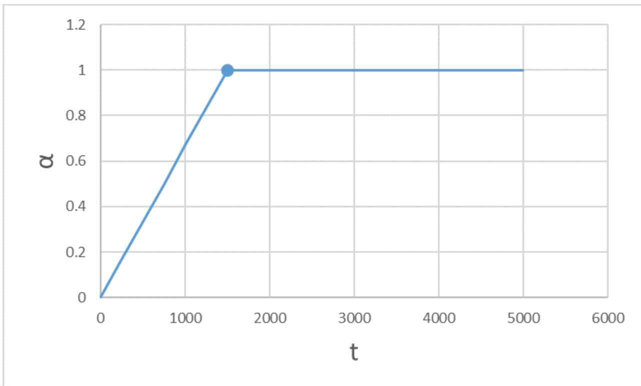

Figure 2: Changing pheromone's reaction (h=1500).

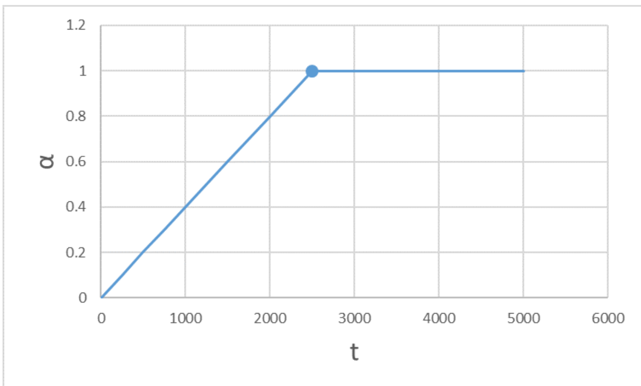

Figure 3: Changing pheromone's reaction (h=2500).

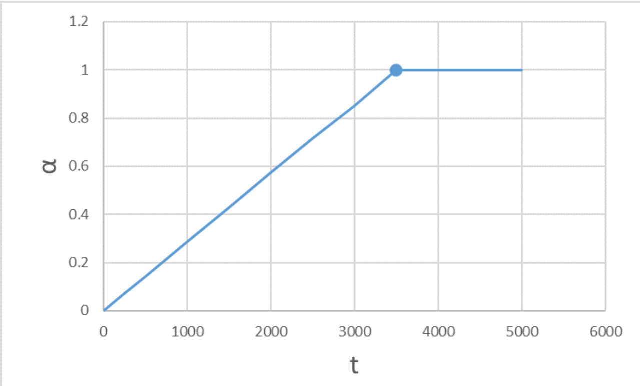

Figure 4: Changing pheromone's reaction (h=3500).

4. Simulation result

In order to evaluate the performance of ACO-CPR, we compare the simulation results with the standard ACO for applying Traveling Salesman Problem (TSP). The purpose of this problem is to find the shortest route which is visited once to all cities. The applications of TSP are design of electric circuit and optimal assembling plan of robot. The problem eil51 is used for the computer simulations. The number of cities is 51 and the optimal solution is 426 [7].

We set the parameters of ACO and ACO-CPR as follows.

$$k = 51,\ \beta = 2.0,\ \rho = 0.2, \tag{6}$$

$$\alpha = 1.0\ (\text{ACO}),\ \alpha_0 = 0.001\ (\text{ACO-CPR}) \tag{7}$$

First, we investigate the performance of ACO-CPR when pheromone's reaction has only changing state. The simulation results of 25 averages are summarized in Table 1. We can see that ACO-CPR obtains best performance when the parameter h is fixed with h=3000.

Table 1: Solution of only changing α

h	best	worst	average
1000	435	463	444.5
1500	448	474	462.9
2000	453	489	468.3
2500	435	494	443.1
3000	435	463	442.9
3500	435	462	444.7

Next, we apply the pheromone's reaction with two states (changing and constant states) for ACO-CPR by changing the parameter h and the ratio of two states. Table 2 summarizes the simulation results. By increasing the parameter h, the performance of ACO-CPR obtains better results when the total repetition number is small. The good performance can be obtained when the total repetition number is fixed around 2000 to 3000 for all cases of the parameter h. The best values when ACO-CPR is used each h indicated in boldface.

Table 2: Simulation results by changing rates

h	t_{max}	rate	best	worst	average
1000	2000	1:1	435	463	440.9
	1666	3:2	435	462	439.2
	1500	2:1	435	448	**438.5**
	1400	5:2	435	456	442.4
	1333	3:1	434	458	440.7
	1285	7:2	426	471	441.7
	1250	4:1	431	478	441.7
	1222	9:2	431	457	441.7
	1200	5:1	426	461	440.6
1500	3000	1:1	435	463	440.7
	2500	3:2	435	463	440.9
	2250	2:1	435	463	442.3
	2100	5:2	431	452	**438.1**
	2000	3:1	426	450	439.3
	1928	7:2	435	456	438.9
	1875	4:1	435	463	442.1
	1833	9:2	435	463	441.6
	1800	5:1	426	466	448.0
2000	4000	1:1	435	461	439.6
	3333	3:2	435	467	445.7
	3000	2:1	435	463	441.2
	2800	5:2	435	458	**439.2**
	2666	3:1	434	463	**439.2**
	2570	7:2	435	465	441.7
	2500	4:1	435	449	439.5
	2444	9:2	435	465	439.5
	2400	5:1	435	463	441.4
2500	5000	1:1	435	467	460.3
	4166	3:2	435	467	445.7
	3750	2:1	435	467	449.9
	3500	5:2	435	467	445.8
	3333	3:1	435	464	443.6
	3215	7:2	435	465	**441.7**
	3125	4:1	435	464	445.0
	3055	9:2	435	464	443.2
	3000	5:1	435	467	443.5
3000	6000	1:1	435	469	459.3
	5000	3:2	436	467	459.9
	4500	2:1	435	467	452.9
	4200	5:2	435	467	455.1
	4000	3:1	435	467	450.3
	3856	7:2	435	467	450.9
	3750	4:1	435	467	447.7
	3666	9:2	435	467	447.8
	3600	5:1	435	464	**445.2**
3500	7000	1:1	435	479	465.5
	5832	3:2	436	479	461.5
	5250	2:1	435	470	460.1
	4900	5:2	435	467	453.6
	4666	3:1	435	467	449.5
	4500	7:2	435	479	450.5
	4375	4:1	436	467	455.0
	4276	9:2	435	467	449.9
	4200	5:1	435	467	**448.9**

Next, we compare the two pheromone's reactions as shown in Table 3. From this result, we confirm that the pheromone's reaction with the both of changing and constant states obtains better results than another one.

Table 3: Comparison of solution of only changing α and two states

h		best	worst	average
1000	only change	435	463	444.5
	two states	435	448	438.5
1500	only change	448	474	462.9
	two states	431	452	438.1
2000	only change	453	489	468.3
	two states	434	463	439.2
2500	only change	435	494	443.1
	two states	435	465	441.7
3000	only change	435	463	442.9
	two states	435	469	440.3
3500	only change	435	462	444.7
	two states	435	467	449.5

Finally, the results of the standard ACO and ACO-CPR are compared in Table 4. Furthermore, Table 4 shows results of ACO and ACO-CPR when we use more large TSP. The standard ACO and ACO-CPR solve 3 TSPs (eil51, eil76, eil101). The number of cities of eil76 is 76 and the optimal solution is 538 [7].The number of cities of eil101 is 101 and the optimal solution is 629 [7]. ACO-CPR of Table 4 is set the best parameters of Table 3 (h = 1500, t_{max} = 2100). The simulation results of 25 averages are summarized in Table 4.

Table 4: Comparison of solution of ACO and ACO-CPR

	ACO		ACO-CPR	
	best	average	best	average
eil51(428)	435	444.5	431	438.1
eil76(538)	544	584.8	553	580.6
eil101 (629)	678	722.5	685	722.2

From the Table 4, it is clear that the average of ACO-CPR is better than the average of ACO. When we use more large TSP, ACO-CPR is easier to trap in local optima than the stndard ACO.

5. Conclusion

This study introduced at the Ant Colony Optimization Changing Pheromone's Reaction (ACO-CPR). The reaction to pheromone of ACO-CPR is reinforced according to the number of repetitions. In the proposed ACO-CPR, the pheromone's reaction has two states; changing and constant states. By applying the proposed ACO-CPR to TSP, we confirmed that ACO-CPR obtained good results when the parameter h and the number of repetition are fixed appropriately.

In the future work, we would like to investigate the mechanism of the proposed ACO-CPR in detail. Furthermore, we will use ACO of nonlinear changing pheromone.

References

[1] X. S. Yang, "Nature-Inspired Metaheuristic Algorithms Second Edition," Luniver Press, 2010.

[2] V. Maniezzo and A. Colorni, "The ant system applied to the quadratic assignment problem," IEEE Transactions on Knowledge and Data Engineering, vol. 11, pp. 769-778, 1999.

[3] M. Dorigo and L. M. Gambardella, "Ant Colonies for the Traveling Salesman Problem," BioSystem, vol. 43, pp. 73-81, 1997.

[4] M. Dorigo and T. Stützle, "Ant Colony Optimization," The MIT press, 2004.

[5] D. Maruyama and R. Yamaguchi and N. Noguchi and Y. Kohno and T.Takahashi, "Addition of the social cognitive characteristic to ACO," The 27th Annual Conference of the Japanese Society for Artificial Intelligence, 2013.

[6] K. Yosuke and K. Hitoshi, "Solution to Traveling Saleman Problem by Ant Colony Optimization Applying Local Optimum Solutions to Initiazation," MPS, vol. 19, pp. 109-112, 2007.

[7] "TSPLIB -Zuse Institute Berlin," http://elib.zib.de/pub/mp-testdata/tsp/tsplib/tsp/