Adaptive Ant Colony Optimization Considering Intensification and Diversification

Masaya Yoshikawa, Tomohiro Nagura

Abstract—**This paper discusses a new adaptive ant colony optimization algorithm and its characteristics are as follows: (1) a novel cranky ant who behaves strangely is introduced to prevent from trapping at the local optima, (2) a new observation technique for searching status is adopted to judge whether it is trapping at local optima. Experimental results using benchmark data prove that the proposed algorithm with the cranky ants and the observation technique enables to control the trade-off between intensification and diversification, in comparison with conventional ACO.**

Index Terms—**Ant Colony Optimization, Cranky ant, Adaptive optimization, Intensification and diversification.**

I. Introduction

Ant Colony Optimization [1],[2] , which is called ACO, is one of the swarm intelligence and has been attracting much attention recently. The ACO represents a general name of the algorithm inspired by feeding behavior of ants. It has been applied to various combinatorial optimization problems such as the travelling salesman problem (TSP) [1],[2], the floorplanning problem[3], the quadratic assignment problem[4], and the scheduling problem [5],[6]. The basic model of the ACO is the ant system (AS) that was proposed by Dorigo et al.[1]. It originally was introduced to solve the shortest path problems on a graph. Therefore, many ACOs [7],[8] applied to TSP are based on the AS.

Ant Colony System [2] is one of the expansion algorithm of AS, and it shows better capability than genetic algorithm and simulated annealing when applying to TSP. Therefore, we adopt Ant Colony System as a base algorithm. Hereafter, ACO indicates Ant Colony System.

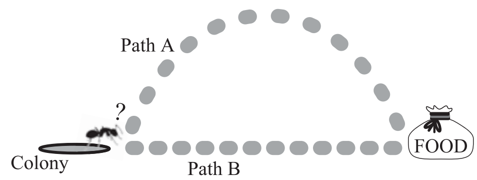
In this paper, we propose a new adaptive ACO algorithm. The characteristics of the proposed algorithm are (1) a novel cranky ant who behaves strangely is introduced to prevent from trapping at the local optima, (2) a new observation technique for searching status is adopted to judge whether it is trapping at local optima. Thus, the proposed algorithm with the cranky ants and the observation technique enables to control the trade-off between intensification (exploitation of the previous solutions) and diversification (exploration of the search space). Experiments using benchmark data prove effectiveness of the proposed algorithm in comparison with the conventional ACO.

This paper is organized as follows: Section 2 describes the search mechanism of ACO and briefly surveys the ACO research. Section 3 indicates the weak points of ACO in terms of the search performance, and explains the proposed algorithm. Section 4 reports the results of computer simulations applied to TSP benchmark data. We summarize and conclude this study in section 5.

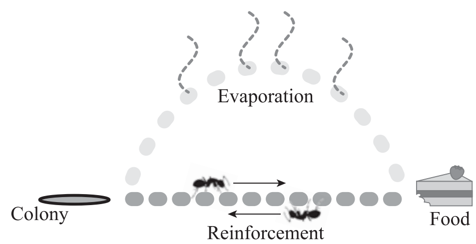
II. Preliminaries

Ant Colony System [2] is one of the expansion algorithm of AS, and it shows better capability than genetic algorithm[10]-[12] and simulated annealing[13] when applying to TSP. Therefore, we adopt Ant Colony System as a base algorithm. Hereafter, ACO indicates Ant Colony System. The search mechanism of ACO utilizes the static evaluation value and the dynamic one. The static evaluation value called heuristic value is peculiar information of the target problem, and usually a reciprocal of the distance between cities is adopted as the heuristic value, when ACO is applied to TSP

On the other hand, the dynamic evaluation value is pheromone amount. A trail of each ant marks by pheromone. The following ants also mark by pheromone. Furthermore, the pheromone evaporates at the same speed. Fig.1 shows an example of the marking by pheromone.



(1) Initial state



(2) Reinforcement

Fig.1 Example of the positive feedback reinforcement using pheromone information

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That is, the shorter trail is marked with pheromones before the longer trail can be marked. This mechanism achieves the positive feedback reinforcement.

In this example, there are two paths, path A and Path B. Since path B is shorter than path A, path B has more pheromone than path A. This difference of pheromone amount causes the reinforcement.

Regarding the selection of ant's move, the concretely procedure is as follows. First, the random number q between from 0 to 1 is generated. Next, q is compared with benchmark (parameter) q_0. When q is smaller than q_0, the city that has the largest value of the product of the static evaluation and the dynamic one is selected as the next destination. Otherwise, ant k in city i selects the move to city j according to probability p^k and it is defined as follows.

$$p^k(i,j) = \frac{[\tau(i,j)][\eta(i,j)]^\beta}{\sum_{l \in n^k} [\tau(l,j)][\eta(l,j)]^\beta} \quad (1)$$

Where, $\tau(i,j)$ is a pheromone amount between city i and city j, $\eta(i,j)$ is a reciprocal of the distance between city i and city j, β is a parameter which controls the balance between static evaluation value and dynamic one, and n^k is a set of un-visit cities. Therefore, the selection probability is proportional to the product of the static evaluation and the dynamic one as shown in Fig.2.

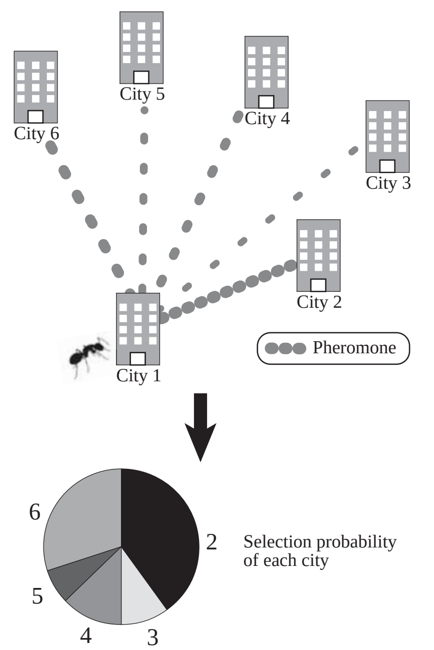

Fig.2 Example of the selection probability

Moreover, a pheromone amount on each path is calculated by using two pheromone update rules. One is local update rule and the other is global update rule. The local update rule is applied to the path which is selected by equation (1), and it is defined as follows.

$$\tau(i,j) \leftarrow (1-\psi)\tau(i,j) + \psi\tau_0 \quad (2)$$

Where, ψ is a decay parameter in local update rule, $\tau 0$ is the initial value of pheromone. Thus, local update rule add the pheromone to the selected path between two points, when the ant moves. The global update rule adds pheromone to the best tour (the completed path) of all tours. The best tour usually indicates the shortest tour. The global update rule is defined as follows.

$$\tau(i,j) \leftarrow (1-\rho)\tau(i,j) + \rho\Delta\tau(i,j)$$

$$\Delta\tau(i,j) = \begin{cases} 1/L^+ & \text{if } (i,j) \in T^+ \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Where, T^+ is the best tour, and L^+ is the distance of the best tour.

Regarding previous work of which ACO is applied to TSP, many works including hybrid approach [14] and pheromone control technique [15] have been reported. G.Shang [14] proposed a hybrid approach which combined ant colony algorithm with genetic algorithm. S.G.Lee [15] introduced a pheromone control technique using a curve-fitting algorithm. However, no studies have ever seen, to our knowledge, adaptive ACO algorithm which introduces the cranky ants.

III. Adaptive Ant Colony Optimization

The searching process of ACO is based on the positive feedback reinforcement using pheromone information. Thus, the escape from the local optima is more difficult than the other meta-heuristics. Therefore, the recognition of searching status and the escape technique from the local optima are important to improve the search performance of ACO.

Regarding the recognition of searching status, the proposed algorithm utilizes a transition of the distance of the best tour (the shortest tour). A period of which each ant builds a tour represents one generation.

The proposed algorithm judges to be trapped at the local optima if the best tour is not improved across several generations. In contrast, it judges not to be trapped at the local optima while the best tour is improved.

Regarding the escape technique from the local optima, the proposed algorithm introduces a cranky ant. Usually, the ant selects the path which is short distance and has a lot of pheromones as shown in equation (1). The path which has a lot of pheromones indicates the many-selected path.

The cranky ant adopts a reciprocal of the pheromone amount as the dynamic evaluation in the contrary. Thus, the cranky ant chooses the path with few pheromones as shown in Fig. 3.

That is, the cranky ant selects the path which has not been selected. It enables to change the searching area, and to escape from the local optima as shown in Fig.4.

Using the recognition of searching status and the escape technique, the proposed algorithm achieves the control of the trade-off between intensification and diversification.

Specifically, the cranky ants increase when the proposed algorithm judges to be trapped at the local optima. In the proposed algorithm, the normal ants decrease when the cranky ants increase because the total number of ants is constant. Fig.5 shows the relationship between the local optima and the number of the cranky ants.

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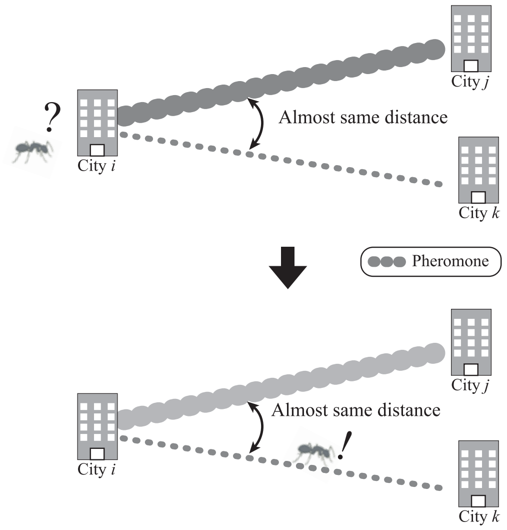

Fig.3 Example of selection of the cranky ant

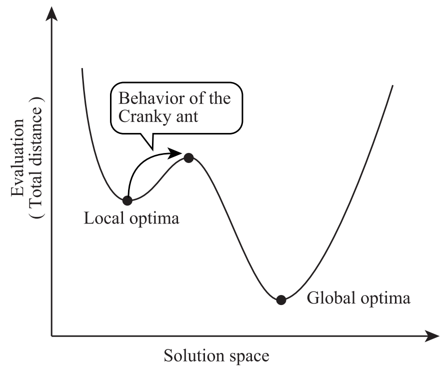

Fig.4 Example of the escape from the local optima

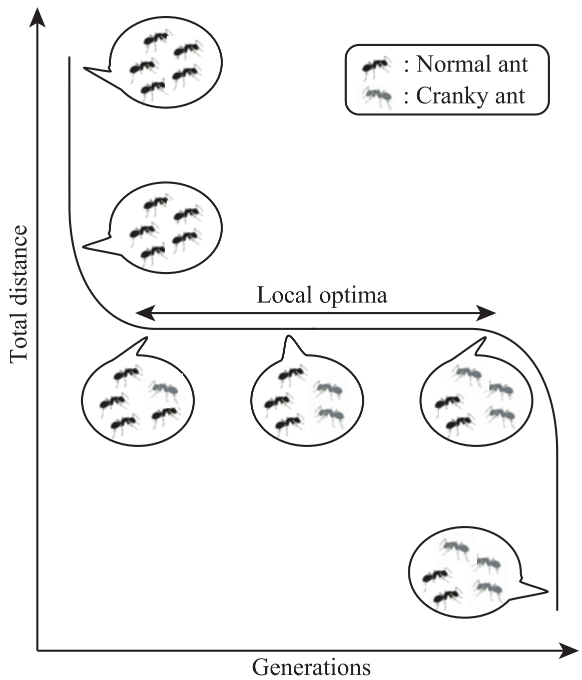

Fig.5 Example of relationship between the local optima and the number of the cranky ants

IV. Experiments And Discussions

In order to evaluate the proposed algorithm, we conducted several experiments in comparison with the conventional ACO. The experimental platform is Pentium Core 2 Duo with 2G byte memory and the program is described by C language. As experimental data, the travelling salesman library (TSP.LIB) benchmark data of 51 cities (eil51) and that of 100 cities (kroA100) are used. The number of the cranky ants at the initial generation is the several kinds in these experiments.

Experimental results of 10 trials are shown in Tables.1 and 2. In these tables, #cranky indicates the number of the cranky ants, #normal indicates that of the normal ants, and the value with squares brackets represents the optimal solution in each benchmark data.

The parameter q is different in both experiments. The parameters of Tables.1 and 2 are 0.25 and 0.50, respectively.

As shown in both tables, the proposed algorithm found the optimal solution, although the conventional ACO couldn't find it in the case of KroA100.

Table.1 Results of parameter q = 0.25

(1) Result of eil51 (51cities)

	# ants	Best	Worst
Conventional ACO	#normal:51 #cranky:0	[426]	433
Cranky ACO (Constant)	#normal:41 #cranky:10	427	437
	#normal:26 #cranky:25	427	438
	#normal:10 #cranky:41	428	459
Cranky Ant (Adaptive)	#normal:41 #cranky:10	[426]	432
	#normal:26 #cranky:25	427	441
	#normal:10 #cranky:41	437	459

(2) Result of kuroA100 (100cities)

	# ants	Best	Worst
Conventional ACO	#normal:100 #cranky:0	21792	22458
Cranky ACO (Constant)	#normal:80 #cranky:20	21406	22601
	#normal:50 #cranky:50	[21282]	21543
	#normal:40 #cranky:60	[21282]	21706
	#normal:20 #cranky:80	21476	22547
Cranky Ant (Adaptive)	#normal:80 #cranky:20	21370	21767
	#normal:50 #cranky:50	[21282]	21470
	#normal:40 #cranky:60	[21282]	21877
	#normal:20 #cranky:80	21597	22824

Table.2 Results of parameter q = 0.50

(1) Result of eil51 (51cities)

	# ants	Best	Worst
Conventional ACO	#normal:51 #cranky:0	[426]	433
Cranky ACO (Constant)	#normal:41 #cranky:10	[426]	435
	#normal:26 #cranky:25	427	440
	#normal:10 #cranky:41	430	452
Cranky Ant (Adaptive)	#normal:41 #cranky:10	[426]	432
	#normal:26 #cranky:25	428	444
	#normal:10 #cranky:41	434	476

(2) Result of kuroA100 (100cities)

	# ants	Best	Worst
Conventional ACO	#normal:100 #cranky:0	21678	22211
Cranky ACO (Constant)	#normal:80 #cranky:20	21540	21821
	#normal:50 #cranky:50	[21282]	21694
	#normal:40 #cranky:60	[21282]	22095
	#normal:20 #cranky:80	21505	22587
Cranky Ant (Adaptive)	#normal:80 #cranky:20	21340	21635
	#normal:50 #cranky:50	[21282]	21694
	#normal:40 #cranky:60	[21282]	21646
	#normal:20 #cranky:80	21453	23229

Fig.6 shows the relationship between the total distance and the transition of the number of the normal ants and that of the cranky ants in the case of KroA100. The number of the cranky ants has increased as the generation advances. It means that the cranky ants work to expand the searching area. Thus, the proposed algorithm enables to improve the searching performance, and it achieves to control the trade-off between intensification and diversification effectively.

V. Conclusion

In this paper, we proposed a new adaptive ant colony optimization algorithm with the cranky ants. It enabled the search to prevent from trapping at the local optima and achieved the control of the trade-off between intensification and diversification. Experiments using benchmark data prove effectiveness of the proposed algorithm in comparison with the conventional ACO.

In relation to future work, experiments using large scale data are the most important priority. We will also apply it to other combinattorial optimization problems.

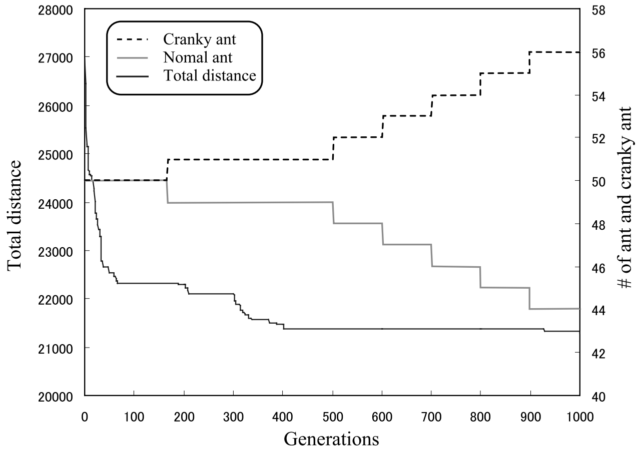

Fig.6 Relationship between the total distance and the transition of the number of the normal ants

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