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Behavior of Ant Colony Optimization with Intelligent and Dull Ants

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***Abstract*— In this study, we investigate Ant Colony Optimization (ACO) containing two kinds of ants: intelligent ants and dull ants. Algorithm of the proposed method is more near to the real ant colony than algorithm of the conventional ACO. We apply the proposed method to Traveling Salesman Problem (TSP), and confirm that the proposed method obtains the effective results than the conventional ACO in solving optimization problem.**

I. Introduction

Ant Colony Optimization (ACO) [1] is an evaluational optimization algorithm inspired by pheromone effect of ants and is effective to solve difficult combinatorial optimization problems, such as graph coloring problem, routing in communications networks, Quadratic Assignment Problem (QAP) and so on [2]-[4]. It has also been used to produce near-optimal solutions to the traveling salesman problem (TSP) [5]. TSP is a problem in combinatorial optimization studied in operations research and theoretical computer science. Given a list of cities and their pairwise distances, the task is to find a shortest possible tour that each city exactly once. In algorithm of ACO, the ants drop pheromones on the path connecting cities. The pheromones are updated depending on behavior of the ants to find a food source through path having strong pheromone deposits. Referring to the pheromone strength and communication among ants, the algorithm tries to find the optimal solution. However, ACO has the problem which is to fall into local solution. It means that the balance of the decentralization and the centralization is bad. Therefore, it is important to enhance the algorithm performances for flexible and adaptive.

Meanwhile, it is believed that God does not create an unnecessary thing even if it seems to useless. This story was backed by a report about the ant's world [6]. This report has confirmed that about 20 percent of the ants are unnecessary ants. The unnecessary ants keep still or stay around their colony whereas the other ants in a colony perform feeding behavior. We consider that the ants are seemingly unnecessary, however, the researchers consider the unnecessary ants have certain roles. Because, the idea was backed by a computational experiment of feeding behavior in trailing the pheromone. In the experiment, the researchers performed the feeding behavior by using the intelligent ants, which can trail the pheromone exactly, and the dull ants which can not trail the pheromone exactly. From the results, the ants group including a certain amount of the dull ants, can obtain more foods than the group containing only the intelligent ants. The intelligent ants can effectively carry the discovered foods to the colony, however, it may be difficult to discover new foods just because they consider the efficiency. On the other hand, the researchers consider that the dull ants work as the searcher of the new foods or have the effect to discover the shortest route. In order words, the coexistence of the intelligent and the dull ants improves the effectiveness of the feeding behavior.

In this study, we investigate ACO containing two kinds of ants, which are intelligent ants and dull ants. The intelligent ants can trail the pheromone exactly and the dull ants can not trail the pheromone exactly. Their features are essentially similar to the real ant's world. Therefore, the proposed method is more near to the real ant colony than the conventional ACO. We apply the proposed method to TSP problem and confirm the effectiveness.

II. Ant Colony Optimization with Intelligent and Dull Ants

We explain the proposed method in detail. The important feature of the proposed method is that two kinds of ants exist; intelligent ants can exactly trail pheromone, and dull ants can not trail the pheromone. S denotes the input space of N city positions as

$$S \equiv \{P_1, \cdots, P_N\}, P_i \equiv (x_i, y_i), \tag{1}$$

where the input area is normalized as the unit square and P_i is the i-th city position. M ants are deposited on each city at random. $d \times M$ ants are classified into a set of the dull ants S_{dull}. d is rate of the dull ants on all the ants.

[Step1](Initialization): Let iteration number $t = 0$. $\tau_{ij}(t)$ is the amount of pheromone trail on the path (i, j) between city i and city j at time t, and $\tau_{ij}(t)$ is initially set to τ_0.

[Step2](Find tour): For the Intelligent ants and the Dull ants, the visiting city is chosen by probability $p_{ij,I}(t)$ and $p_{ij,D}(t)$ as shown in Fig. 1. The probability with which k-th ant ($k = 1, \cdots, M$) chooses to go from city i to city j is as following equations;

$$p_{k_{ij},D}(t) = \frac{\eta_{ij}}{\sum_{l \in N_k} \eta_{il}}, \quad \text{if } k \in S_{\text{dull}} \tag{2}$$

$$p_{k_{ij},I}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\Sigma_{l\in N_k}[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}}, \quad \text{otherwise}, \tag{3}$$

where $1/\eta_{ij}$ is the distance of path (i, j). The adjustable parameters α and β control the weight of pheromone intensity and city information, respectively. Therefore, Searching ability goes up and down by changing α and β. Dull ants can not trail the pheromone. Because, the equation of the dull ants does not include the amount of pheromone trail $\tau_{ij}(t)$. Therefore, intelligent ants judge next city by the pheromone and the distance from the present location, however, dull ants judge next city by only the distance from the present location. N_k is a set of cities that k-th ant has not yet visited. The ants repeat choosing next city until all the cities are visited.

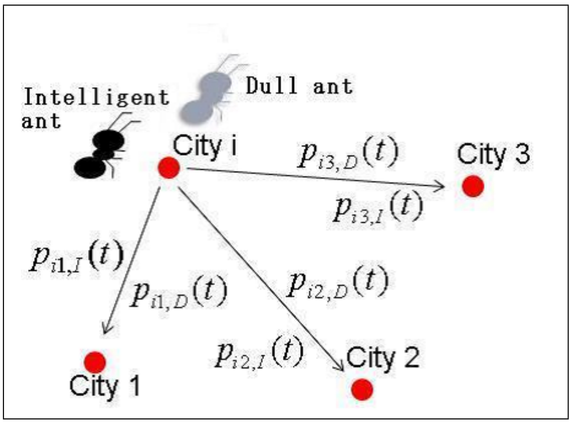


Fig. 1. Probability $p_{ij}(t)$ of Intelligent and Dull ants

[Step3](Pheromone update): After all ants have completed their tour, pheromone is updated by all ants. Dull ants can not trail pheromone, however, can deposit pheromone on the path. Then, compute the tour length $L_k(t)$, how k-th ant deposits pheromone $\Delta\tau_{k_{ij}}(t)$ between city i and city j at iteration t is as following equations;

$$\Delta\tau_{k_{ij}}(t) = \begin{cases} 1/L_k, & \text{if } (i,j) \in T_k(t) \\ 0, & \text{otherwise}, \end{cases} \tag{4}$$

where $T_k(t)$ is obtained tour by the k-th ant and $L_k(t)$ is its length. All ants finished the tour, updated the $\tau_{ij}(t)$ of each path (i,j) depending on its $\Delta\tau_{k_{ij}}(t)$;

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{M} \Delta\tau_{k_{ij}}(t), \tag{5}$$

$\rho \in [0, 1]$ is the pheromone trail decay coefficient.

[Step4] Let $t = t + 1$. Go back to [Step2] and repeat until $t = t_{\max}$.

III. Numerical Experiments

In order to investigate feasibility and effectiveness of the proposed method, we apply the proposed method to TSP problem. The TSP problem is conducted on bayg29 (composed of 29 cities).

In the experiments, the number of ants M in the proposed methods and the conventional ACO are the same as the number of cities, respectively. The conventional ACO contains only the intelligent ants. The proposed method 1 contains the dull ants, which are 10 percent of all the ants and the intelligent ants which are the others. The proposed method 2 contains the dull ants, which are 20 percent of all the ants and the intelligent ants which are the others. We repeat the simulation 5 times. The parameters of the two proposed methods and the conventional ACO were set to the following;

$$\rho = 0.3, \ \alpha = 1, \ \beta = 5, \ t_{max} = 2000, \tag{6}$$

where evaporation rate ρ, weight of pheromone α, weight of distance β and search limit $t = t_{max}$ are fixed value. In order to compare the obtained solution with the optimal solution, we use the error rate as follow;

$$\text{error rate} = \frac{(\text{obtained solution}) - (\text{optimal solution})}{(\text{optimal solution})}, \tag{7}$$

where this equation shows how near to the optimal solution the conventional ACO obtains the tour length. Furthermore, in order to investigate how well the solution of the proposed method are improved from the solution of the conventional ACO, we use the improved rate of AVG of the proposed method from AVG of the conventional ACO as follow;

$$\text{Improved rate} = \frac{(\text{AVG of ACO}) - (\text{AVG of Proposed method})}{(\text{AVG of Proposed method})}. \tag{8}$$

Table I shows the simulation results of the conventional ACO and the two proposed methods. In this table, Min shows the shortest value of the whole simulation, namely 10 times. AVG shows the average value of Min for each simulation. We can confirm that the two proposed methods obtain better results than the conventional ACO for AVG and Min, and the proposed method has a good performance to find near optimal solutions. Furthermore, in the improved rate, the two proposed methods have greatly improved than the conventional ACO. As the results, we can say that the proposed method near to the real ant colony are effective in solving TSP problem. Figures 2 show the best tour of bayg29 obtained by the conventional ACO and the proposed method, respectively. From these results, we can visually confirm that the crossover path of the proposed method is less than the crossover path of the conventional ACO. Therefore, we can say that the proposed method is more effective than the conventional ACO.

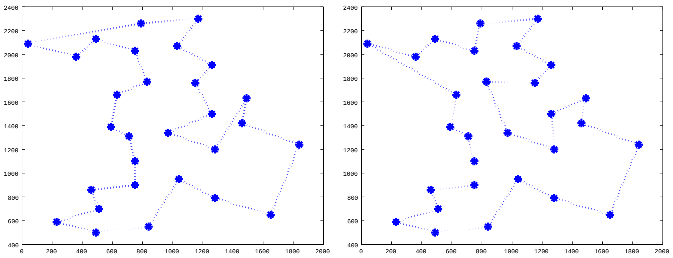
IV. Conclusions

In this study, we have investigated Ant Colony Optimization (ACO) containing the intelligent ants and the dull ants, and applied to the TSP problem. We have confirmed that the proposed method obtains better results than the conventional ACO for various performances. From these results, we can say that the proposed method is more near to the real ant colony

TABLE I

RESULTS OF CONVENTIONAL ACO AND PROPOSED METHODS FOR BAYG29.

TSP problem		bayg29
The total number of ants		29
The number of dull ants of Proposed method1		2
The number of dull ants of Proposed method2		5
ACO	AVG	2.76%
	Min	1.82%
ADAGE1	AVG	2.35%
	Min	1.54%
ADAGE2	AVG	2.00%
	Min	1.15%
Improved rate of Proposed method1 from ACO		17%
Improved rate of Proposed method2 from ACO		38%



(a) (b)

Fig. 2. The best tour of bayg29. (a) Conventional ACO. (b) Proposed method

than the conventional ACO and obtains the effective results in solving TSP problem.

REFERENCES

[1] M.Dorigo and T.Stutzle, Ant Colony Optimization, Bradford Books, 2004.

[2] Blum and Merkel (eds.), Swarm Intelligence, Springer, 2008

[3] Inspiration for optimization from social insect behaviour. E. Bonabeau1,2, M. Dorigo3 and G. Theraulaz4

[4] Stutzle, Thomas and Dorigo, Marco (1999) ACO Algorithms for the Quadratic Assignment Problem. New Ideas in Optimization.

[5] M. Dorigo and L.M. Gambardella, “Ant Colonies for the Traveling Salesman Problem,” BioSystems, vol. 43, pp. 73–81, 1997.

[6] H. Hasegawa, “Optimization of GROUP Behavior,” Japan Ethological Society Newsletter, no. 43, pp. 22–23, 2004.

[7] M.Dorigo and T.Stutzle, Ant Colony Optimization, Bradford Books, 2004.