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Ant Colony Optimization with Intelligent and Dull Ants

Sho Shimomura†, Masaki Sugimoto†, Taku Haraguchi†, Haruna Matsushita‡ and Yoshifumi Nishio†

†Department of Electrical and Electronic Engineering, Tokushima University
2-1 Minami-Josanjima, Tokushima 770-8506, Japan
‡Department of Electrical and Electronics Engineering, Hosei University
3-7-2 Kajino-cho, Koganei-city, Tokyo 184-8584, Japan
Email: †{s-sho, sugimoto, nishio}@ee.tokushima-u.ac.jp, ‡haruna.matsushita.pd@k.hosei.ac.jp

Abstract—This study proposes a new Ant Colony Optimization (method; ACO) with Intelligent and Dull Ants (IDACO). In IDACO algorithm, two kinds of ants coexist: *intelligent ants* and *dull ants*. IDACO algorithm is nearer to the real ant colony than the standard ACO algorithm. We apply IDACO to Traveling Salesman Problems (TSPs) and confirm that IDACO obtains more effective results than the standard ACO which consists of only the intelligent ants.

1. Introduction

Ant Colony Optimization (ACO) [1] is a biologically inspired optimization algorithm with pheromone effect of ants and is effective to solve difficult combinatorial optimization problems, such as Traveling Salesman Problem (TSP) [2], graph coloring problem [3], Quadratic Assignment Problem (QAP) [4] and so on. TSP is a problem in combinatorial optimization studied in an operations research and a theoretical computer science. In TSP, given a list of cities and their pairwise distances, the task is to find the shortest possible tour that each city exactly visited once. In ACO algorithm, multiple solutions called "ants" coexist, and the ants drop pheromone on the path connecting the cities. Pheromone trails are updated depending on the behavior of the ants. The ants find a food source through paths having strong pheromone. By communicating with other ants according to the pheromone strength, the algorithm tries to find the optimal solution. However, ACO has a problem which is to fall into local solutions. Therefore, it is important to enhance the algorithm performances by improving its flexibility.

Meanwhile, it has been reported that about 20 percent of the ants are unnecessary ants called "dull ant" in the real ant's world [5]. The dull ant keeps still around its colony whereas the other ants in the colony perform feeding behavior. In a computational experiment, the researchers performed the feeding behavior by using intelligent ants, which can trail the pheromone exactly, and dull ants which cannot trail the pheromone. From results, the ants group including the dull ants can obtain more foods than the group containing only the intelligent ants. It means that the coexistence of the intelligent and dull ant improves the effectiveness of the feeding behavior.

In this study, we propose a new type of ACO algorithm called Ant Colony Optimization with Intelligent and Dull Ants (IDACO). The important feature of IDACO is that two kinds of ants coexist. The one is an *intelligent ant* and the another is a *dull ant*. The intelligent ant can trail the pheromone and the dull ants cannot trail the pheromone. Because their features are essentially similar to the real ant's world, we can say that IDACO algorithm is nearer to the real ant colony than the standard ACO algorithm.

2. Ant Colony Optimization with Intelligent and Dull Ants (IDACO)

We explain the proposed IDACO algorithm in detail. In the IDACO algorithm, the most important feature of IDACO is that two kinds of ants coexist; *the intelligent ants* and *the dull ants*. The intelligent ant is the same as the ant of the standard ACO, and it can exactly trail the pheromone. In constant, the dull ant cannot trail the pheromone.

N-city of TSP is denoted as

$$S \equiv \{P_1, P_2, \cdots, P_N\}, P_i \equiv (x_i, y_i), \tag{1}$$

where a data area is normalized from 0 to 1, and P_i is an i-th city position ($i = 1, 2, \cdots, N$). Each ant (total M) is deposited on a city selected at random. $(1-d)\times M$ ants and $d \times M$ ants are classified into a set of the intelligent ants S_{Intel} and of the dull ants S_{dull}, respectively. d is a rate of dull ants in all the ants.

[Step1](Initialization): Let an iteration number $t = 0$. $\tau_{ij}(t)$ is an amount of pheromone deposited on a path (i, j) between the city i and the 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 the probability $p_{ij,I}(t)$ and $p_{ij,D}(t)$, respectively, as shown in Fig. 4. The probability of k-th ant moving from the city i to the city j is decided by

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

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

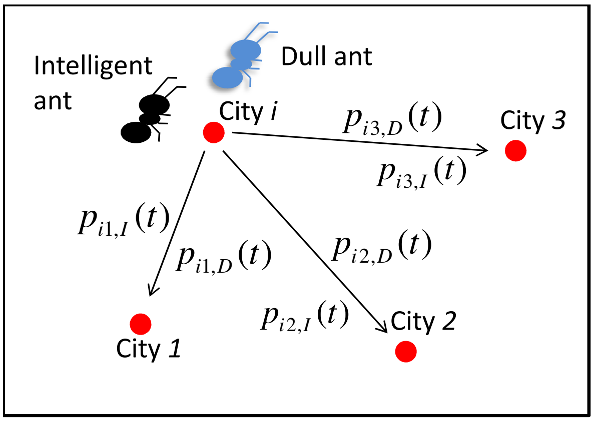


Figure 1: Probability $p_{ij}(t)$ of Intelligent and Dull ants.The visiting city of intelligent ant is chosen by the probability $p_{ij,I}(t)$. The visiting city of dull ant is chosen by the probability $p_{ij,D}(t)$ which does not include the amount of pheromone $\tau_{ij}(t)$ and $\tau_{il}(t)$.

where $k = 1, 2, \cdots, M$, and $1/\eta_{ij}$ is a distance of the path (i, j). The adjustable parameters β_I and β_D control the weight of the city information of the intelligent ant and of the dull ant, respectively. Therefore, the searching ability goes up and down by changing α and β. As Eq. (2) does not include the amount of deposited pheromone $\tau_{ij}(t)$ and $\tau_{il}(t)$, the dull ants cannot trail the pheromone. In contrast to the intelligent ants which judge next city by the pheromone and the distance from a present location, the dull ants judge next city depending on only the distance from a present location. N_k is a set of cities that k-th ant has never visited. The ants repeat choosing next city until all the cities are visited.

[Step3](Pheromone update): After all ants have completed their tours, the amount of deposited pheromone on each path is updated. We should note that the dull ants can deposit the pheromone on the path, though, they cannot trail the pheromone. Then, the tour length $L_k(t)$ is computed for both the intelligent and dull ants, and the amount of pheromone $\Delta\tau_{k_{ij}}(t)$ deposited by k-th ant on the path (i, j) is decided as

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

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

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

where $\rho \in [0, 1]$ is the rate of pheromone evaporation.

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

3. Numerical Experiments

In order to evaluate a performance of IDACO and to investigate its behavior, we apply IDACO to two TSPs and compare IDACO with different rates of dull ants with the standard ACO.

In the experiments, the number of ants M in the standard ACO and IDACO are set to the same as the number of cities. The standard ACO contains only the intelligent ants whose choice probability is decided by Eq. (3). IDACO includes $d \times M$ dull ants, and $(1-d) \times M$ intelligent ants in each simulation. The rate of dull ants d is set to 0.2 and 0.5 in each simulation. We repeat the simulation 10 times for all the problems. The parameters of the standard ACO and IDACO were set as follows;

$$\tau_0 = 10,\ \rho = 0.3,\ \alpha = 1,\ \beta = \beta_I = \beta_D = 5,\ t_{\max} = 2000,$$

where the evaporation rate ρ, the weight of pheromone α, the weight of distance β, β_I and β_D and the search limit $t = t_{\max}$ are fixed values.

In order to compare obtained solutions with the optimal solution, we use an error rate as follow;

$$\text{Error rate[\%]} = \frac{\text{(obtained solution)} - \text{(optimal solution)}}{\text{(optimal solution)}} \times 100. \tag{6}$$

This equation shows how close to the optimal solution the ACOs obtain the tour length. Thus, the error rate nearer 0 is more desirable. Furthermore, in order to evaluate how well the solution of IDACO are improved from that of ACO, we use an improved rate as follow;

$$\text{Improved rate[\%]} = \frac{\text{(Avg. of Error of ACO)} - \text{(Avg. of Error of IDACO)}}{\text{(Avg. of Error of ACO)}} \times 100. \tag{7}$$

3.1. Simulation 1: att48

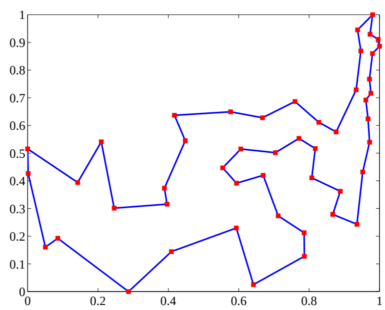
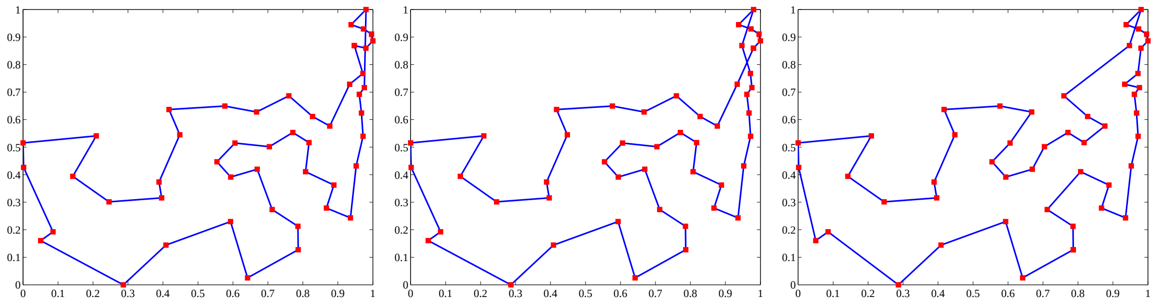


Figure 2: Benchmark problem *att48* and its optimal tour.

The TSP conducted on *att48* (composed of 48 cities) shown in Fig. 2. The simulation results of the standard ACO and IDACO are shown in Table 1. Figure 3 shows



(a) (b) (c)

Figure 3: The best tours of the three ACOs for att48. (a) The standard ACO. (b) IDACO with $d = 0.2$. (c) IDACO with $d = 0.5$.

Table 1: Results of the standard ACO and IDACO for *att48*.

		ACO	IDACO	
		$d = 0$	$d = 0.2$	$d = 0.5$
Error rate	Average	2.87%	2.62%	3.84%
	Minimum	2.43%	1.46%	2.09%
Improved rate from ACO		-	8.7%	−33.8%

the best tours of *att48* obtained by the standard ACO and IDACO.

In Table 1, IDACO with $d = 0.2$ obtained better result than the standard ACO. We should note that the result of IDACO with $d = 0.5$ was worse than the standard ACO. This result suggest that too many dull ants make the result bad.

3.2. Simulation 2: kroA100

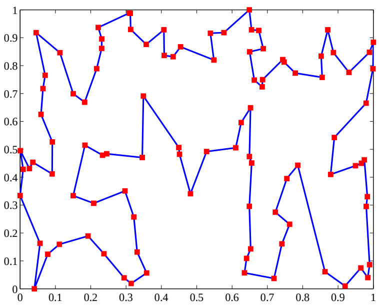


Figure 4: Benchmark problem *kroA100* and its optimal tour.

Furthermore, we considered the TSP conducted on *kroA100* (composed of 100 cities) shown in Fig. 4. The simulation results of the standard ACO and IDACO are shown in Table 2. Figure 5 shows the best tours of *kroA100* obtained by the standard ACO and IDACO.

In Table 2, IDACO obtained better results than the standard ACO. Furthermore, as the result of *att48*, IDACO with $d = 0.2$ obtained better results than IDACO with $d = 0.5$. From the results of the Simulation 1 and 2, we can confirm that IDACO obtains the effective results when the rate of dull ants is same as that in the real ant world. Especially in case of TSP containing many cities, IDACO greatly improves the result of the standard ACO.

Table 2: Results of the standard ACO and IDACO for *kroA100*.

		ACO	IDACO	
		$d = 0$	$d = 0.2$	$d = 0.5$
Error rate	Average	1.27%	1.12%	1.13%
	Minimum	1.22%	1.12%	1.12%
Improved rate from ACO		-	11.81%	11.02%

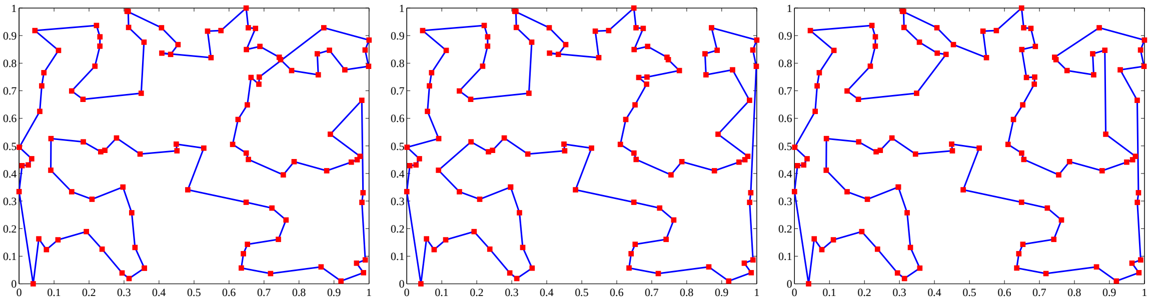
4. Conclusions

In this study, we have proposed Ant Colony Optimization with Intelligent and Dull Ants (IDACO). We have investigated the performances by applying it to two TSPs. We have confirmed that IDACO including the dull ants obtained better results than ACO which containing only the intelligent ants because the dull ants help in getting out of the local optima. Furthermore, we have confirmed that IDACO with $d = 0.2$ obtained better results than the standard ACO for all the cases. From these results, we can say that IDACO is nearer to the real ant colony than the standard ACO and is effective algorithm in solving TSP.

References

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

[2] M. Dorigo and L. M. Gambardella, “Ant Colonies for



(a) (b) (c)

Figure 5: The best tours of the three ACOs for kroA100. (a) The standard ACO. (b) IDACO with $d = 0.2$. (c) IDACO with $d = 0.5$.

the Traveling Salesman Problem," *BioSystems*, vol. 43, pp. 73–81, 1997.

[3] M. Dorigo, G. D. Caro and L. M. Gambardella, "Ant Algorithms for Discrete Optimization", *Artificial Life* vol. 5 no. 2, pp. 137-172, 1999.

[4] V. Maniezzo and A.Colorni, "The ant system applied to the quadratic assignment problem", *IEEE Transactions on Knowledge and Data Engineering* vol. 11 no. 5, pp. 769-778, 1999.

[5] H. Hasegawa, "Optimization of GROUP Behavior," *Japan Ethological Society Newsletter*, no. 43, pp. 22–23, 2004 (in Japanese).