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Ant Colony Optimization using Genetic Information for TSP

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Abstract—This study proposes an Ant Colony Optimization using Genetic Information (GIACO). The GIACO algorithm combines Ant Colony Optimization (ACO) with Genetic Algorithm (GA). GIACO searches solutions by using the pheromone of ACO and the genetic information of GA. In addition, two kinds of ants coexist: *intelligent ant* and *dull ant*. The dull ant is caused by the mutation and cannot trail the pheromone. We apply GIACO to Traveling Salesman Problems (TSPs) and confirm that GIACO obtains more effective results than the conventional ACO and the conventional GA.

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 the Traveling Salesman Problem (TSP) [2], the graph coloring problem, the Quadratic Assignment Problem (QAP) 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 the 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.

Genetic Algorithm (GA) [3] is a learning algorithm that mimic the process of biological evolution and is effective to solve problems which solution space is unknown. In GA, the solutions are expressed as the genetic code, and an individual has a genetic code. GA is a collection of individuals and can produce better solution by using crossover, mutation and selection strategies. Several researchers have developed a lot of techniques to improve GA. Those advanced methods are different in the chromosome representation and the genetic operators. GA is also combined with local search algorithms to find better solution [4].

In our previous study [5], we have proposed an Ant Colony Optimization with Intelligent and Dull Ants (IDACO). IDACO is composed of not only the standard ants but also ants called "dull ant" which cannot trail the pheromone. We have confirmed an interesting result that IDACO including the dull ants obtained better results than the conventional ACO which containing only the intelligent ants.

In this study, we propose an Ant Colony Optimization using Genetic Information (GIACO). GIACO is a combination of IDACO and GA. Some ants pass on genetic information to the next generation by "crossover" and "mutation". Therefore, GIACO search solutions using the pheromone and the genetic information. The most important feature of GIACO is that two kinds of ants coexist as IDACO. The one is an *intelligent ant*, and the another is a *dull ant*. The intelligent ant can trail the pheromone and can use the genetic information. In contrast, the dull ant cannot trail the pheromone and cannot use the genetic information. Because we consider that dull ant is similar to the mutation of GA, the dull ant is caused by the mutation in GIACO algorithm.

2. Ant Colony Optimization using Genetic Information

We explain the proposed GIACO algorithm in detail. A flowchart of the GIACO algorithm is shown in Fig. 1. GIACO is a combination of IDACO and GA. Some ants of GIACO pass on genetic information to the next generation by the crossover and the mutation. The most important feature of GIACO is that two kinds of ants coexist; *intelligent ant* and *dull ant*. The intelligent ant can trail the pheromone and can use the genetic information. In constant, the dull ant cannot trail the pheromone and cannot use the genetic information for making the tour. Because we consider that the dull ant is similar to the mutation of GA, the dull ant in GIACO is caused by the mutation. N-city of TSP is denoted as

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

where the data area is normalized from 0 to 1, and P_i denotes the i-th city position ($i = 1, 2, \cdots, N$). Each ant (total

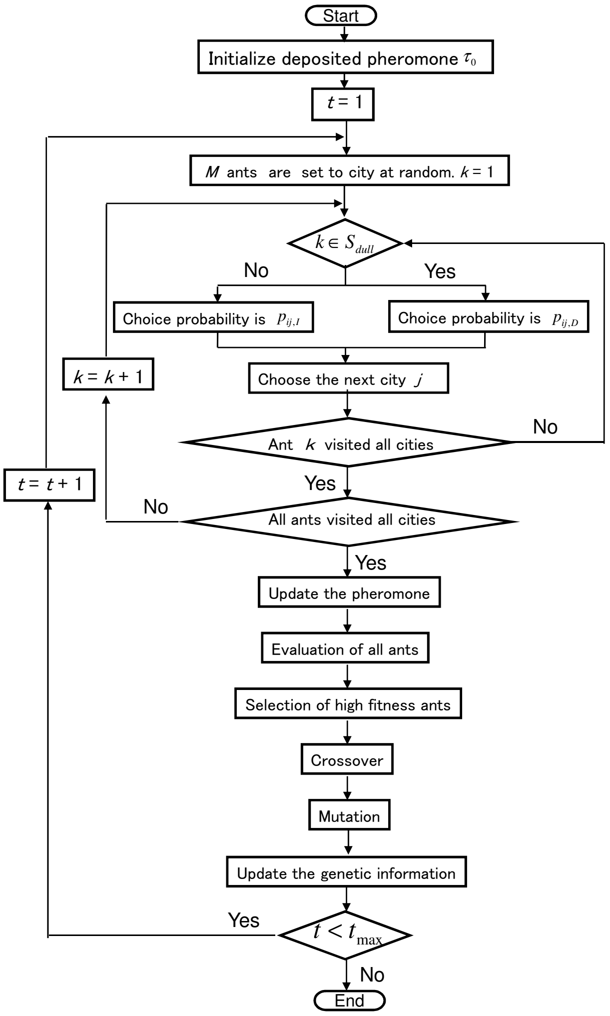

Figure 1: Flowchart of the GIACO.

M) is deposited on a city selected at random. $(1 - P_m) \times M$ ants and $P_m \times M$ ants are classified into a set of the intelligent ants S_{Intel} and of the dull ants S_{dull}, respectively.

[GIACO1](Initialization): Let the iteration number $t = 0$. $\tau_{ij}(t)$ is the amount of pheromone deposited on the path (i, j) between the city i and j at time t, and $\tau_{ij}(t)$ is initially set to τ_0. The genetic information $g_{ij}(t)$ is initially set to g_0.

[GIACO2](Find tour): The visiting city of each ant is chosen by the probability $p_{ij,I}(t)$ and $p_{ij,D}(t)$ as shown in Fig. 2. The probability of k-th ant moving from the city i to j is decided by

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

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

The adjustable parameters α, β_I and β_D control the weight of the city information of the intelligent ant and of the dull

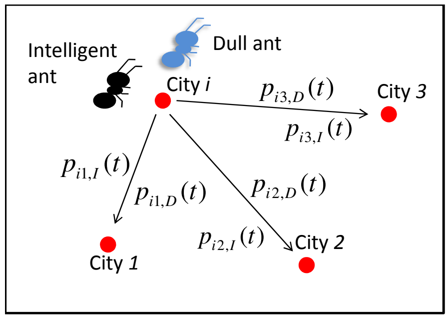

Figure 2: Probability $p_{ij}(t)$ of Intelligent and Dull ants.The visiting city of intelligent ant is chosen by the probability $p_{ij,I}(t)$. The visiting city of dull ant is chosen by the probability $p_{ij,D}(t)$ which does not include the amount of pheromone and does not include the genetic information.

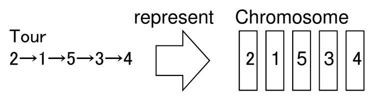

Figure 3: Example of the representation. The tour obtained by respective ant is represented as a chromosome.

ant, respectively. As Eq. (2) does not include the amount of deposited pheromone $\tau_{ij}(t)$ and $\tau_{il}(t)$, and the genetic information $g_{ij}(t)$ and $g_{il}(t)$, the dull ants cannot trail the pheromone and cannot use the genetic information. The dull ants judge next city depending on only the distance from the present location. In contrast, the intelligent ants which judge next city by the pheromone, the distance and the genetic information from the present location.

[GIACO3](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

$$\Delta\tau_{k_{ij}}(t) = \begin{cases} 10/L_k, & \text{if } (i, j) \in T_k(t) \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

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

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

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

[GIACO4](Evaluation): The solutions obtained by ants are represented as the chromosomes, and it is shown in Fig. 3.

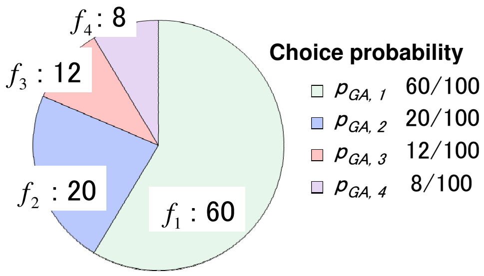

Figure 4: Example of the roulette selection. Individuals, whose genetic information is bequeathed to the next generation, are chosen by the choice probability $p_{GA,k}$. For example, evaluation of 1st individual f_1 is 60, of 2nd individual f_2 is 20, of 3rd individual f_3 is 12 and of 4th individual f_4 is 8. It shows that it is easy for the individual with high fitness to be selected when the roulette spins.

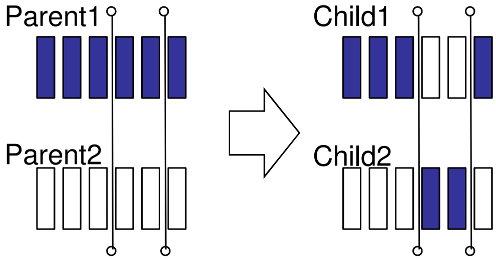

Figure 5: Partially-mapped crossover operator (PMX).

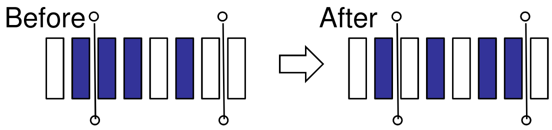

Figure 6: The inverse mutation.

The evaluation e_k of k-th ant is decided as

$$e_k = \frac{N}{L_k}, \tag{6}$$

where e_k shows the quality of obtained tour.

[GIACO5](Selection): The GIACO algorithm bequeaths the ants with high fitness to next generation, to obtain better solution. We perform scaling and leading of the fitness f_k from the evaluation. The scaling is decided as

$$f_k = \frac{[\chi(e_k - e_{ave}) + (e_{max} - e_k)]e_{ave}}{e_{max} - e_{ave}}, \tag{7}$$

where χ is the scaling parameter, e_{ave} is the average of the ant evaluation and e_{max} is the best evaluation in the population. The individuals, whose genetic information is bequeathed to the next generation, are chosen by according to the probability p_{GA} as shown in Fig. 4, and this rule is called roulette selection.

The choice probability of k-th ant is decided by

$$p_{GA,k} = \frac{f_k}{\sum_{k=1}^{M} f_k}. \tag{8}$$

It should be noted that it is possible for the dull ant to be chosen as the ant whose genetic information is bequeathed to the next generation, although the dull ant cannot use the genetic information to choose the next visit city as [GIACO2].

[GIACO6](Crossover): Parents are chosen from the population, and these parents produce their children. This operation is repeated until the number of children is same as the population. However, the number of parents participating in the crossover is decided by a crossover rate P_c. There are various ways of the crossover, in this paper, we use Partially-mapped crossover operator (PMX). PMX is two-point crossover and is shown in Fig. 5. PMX selects two cut points along the strings, which represent the parent tours, at random. The substrings between the cut points are exchanged for genes of the other parents.

[GIACO7](Mutation): After a crossover is performed, the mutation is taken place. The probability of the mutation is decided by the mutation rate P_m. In this paper, we use the inverse mutation, and it is shown in Fig. 6. This mutation selects two cut points along the strings, which represent the tours, at random. The substrings between the cut points are inversed.

[GIACO8](Update the genetic information): After the genetic operators, the obtained tour length $G_k(t)$ is calculated. The genetic information $\Delta g_{k_{ij}}(t)$ bequeathed to the next generation by k-th ant is decided as

$$\Delta g_{k_{ij}}(t) = \begin{cases} 10/G_k, & \text{if } (i,j) \in T_k(t) \\ 0, & \text{otherwise,} \end{cases} \tag{9}$$

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

$$g_{ij}(t+1) = g_0 + \sum_{k=1}^{M} \Delta g_{k_{ij}}(t), \tag{10}$$

where the genetic informations are initialized to g_0 at every iteration t.

[GIACO9] Let $t = t + 1$. Go back to [GIACO2] and repeat until $t = t_{\max}$.

3. Numerical Experiments

In order to evaluate a performance of GIACO and to investigate its behavior, we apply GIACO to various TSPs. In addition, in order to confirm the effectiveness of the dull

Table 1: Results of the conventional ACO and GA, GA-ACO and GIACO.

		eil51	kroC100
ACO	Average	7.43%	10.21%
	Minimum	6.09%	9.79%
GA	Average	7.52%	13.92%
	Minimum	4.16%	4.08%
GA-ACO	Average	6.32%	9.86%
	Minimum	4.91%	9.55%
GIACO	Average	**5.15%**	**9.48%**
	Minimum	3.34%	8.38%
Improved rate of GIACO from ACO		30.7%	7.15%

ants, we consider GA-ACO whose algorithm is same as GIACO containing no dull ants. We compare GIACO with the conventional ACO, the conventional GA and GA-ACO.

In the experiments, the number of ants M in the conventional ACO, GIACO and GA-ACO are set to the same as the number of cities, namely $M = N$. The number of individuals U in the conventional GA is fixed as $U = 1024$. The conventional ACO contains the ants whose choice probability is decided by

$$p_{k_{ij}}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\Sigma_{l \in N_k}[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}}. \tag{11}$$

GIACO contains $P_m \times M$ dull ants and $(1 - P_m) \times M$ intelligent ants. We repeat the simulation 10 times for all the problems. The parameters of three methods are set as follows;

$$\tau_0 = 10,\ g_0 = 1,\ \rho = 0.3,\ \alpha = 1,\ \beta = \beta_I = \beta_D = 5,$$

$$\gamma = 5,\ \chi = 100,\ P_c = 0.8,\ P_m = 0.05,\ t_{\max} = 2000,$$

where the evaporation rate ρ, the weight of pheromone α, the weight of distance β, β_I and β_D, the weight of genetic information γ, the scaling parameter χ, the crossover rate P_c, the mutation rate P_m 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;

$$\text{Error rate[\%]} = \frac{\text{(obtained solution)} - \text{(optimal solution)}}{\text{(optimal solution)}} \times 100. \tag{12}$$

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 GIACO are improved from that of ACO, we use an improved rate as follow;

$$\text{Improved rate[\%]} = \frac{\text{(Avg. of Error of ACO)} - \text{(Avg. of Error of GIACO)}}{\text{(Avg. of Error of ACO)}} \times 100. \tag{13}$$

The TSPs are conducted on *eil51* (composed of 51 cities), *kroC100* (composed of 100 cities).

The simulation results of the conventional ACO, the conventional GA, GA-ACO and GIACO are shown in Table 1. We can see that GA-ACO, which is the combination method of ACO and GA but does not include the dull ants, obtained better results than the conventional ACO and GA, for most problems. This result means that the combination method of ACO and GA is more effective than using only ACO or GA. In addition, in comparison with GA-ACO, GIACO containing the dull ants obtained better results than GIACO including no dull ant, in all the problems. This result means that the dull ants help in getting out of the local optima.

4. Conclusions

In this study, we have proposed Ant Colony Optimization using Genetic Information (GIACO). GIACO optimizes the tour of TSP by using not only pheromone but also the genetic information as GA. GIACO is composed of the intelligent ants and the dull ants, and the dull ants are caused by the mutation of GA. We have investigated the performances of GIACO by applying it to two TSPs. We have confirmed that GIACO including the dull ants obtained better results than GIACO which containing only the intelligent ants because the dull ants help in getting out of the local optima.

Acknowledgment

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References

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

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

[3] L. Homaifar, C. Guan, and G. Liepins, "A New Approach to the Traveling Salesman Problem by Genetic Algorithms," *Proc. 5th Int. Conf. On Genetic Algorithms*, Morgan Kaufmann, pp.460-466, 1993.

[4] B. Freisleben and P. Merz, "A Genetic Local Search Algorithm for Solving Symmetric and Asymmetric Traveling Salesman Problems," *Proceedings of the 1996 IEEE International Conference on Evolution Computation* , pp. 616-621, 1996.

[5] S. Shimomura, M. Sugimoto, T. Haraguchi, H. Matsushita and Y. Nishio "Ant Colony Optimization with Intelligent and Dull Ants" *Proceedings of International Symposium on Nonlinear Theory and its Applications (NOLTA'10)*, pp. 504-507, Sep. 2010