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Application of Ant Colony Optimization Using Genetic Information to QAP

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Abstract

This study proposes an Ant Colony Optimization using Genetic Information (GIACO). The GIACO algorithm combines the Ant Colony Optimization (ACO) with the Genetic Algorithm (GA). GIACO searches solutions 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. GIACO algorithm is more similar to the real ant colony than the conventional ACO algorithm. We apply GIACO to Quadratic Assignment Problems (QAPs) and confirm that GIACO obtains more effective results than the conventional ACO and the conventional GA.

1. Introduction

The Ant Colony Optimization (ACO) [1] was proposed to solve difficult combinatorial optimization problems [2], such as a Quadratic Assignment Problem (QAP) [3], a Traveling Salesman Problem (TSP) [4], a graph coloring problem [5] and so on. QAP is a generalization of the TSP, and it is also an NP-hard combinatorial optimization problem. Given two matrices corresponding to a distance and a flow between activities, the task is to assign all activities to different locations with the minimum cost among all of the possible combinations. In the ACO algorithm, multiple solutions called "ants" coexist, and the ants drop a substance called the *pheromone*. Pheromone trails are updated depending on the behavior of the ants. 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 [6]. The dull ant keeps dawdle 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 cosisting of only the intelligent ants. The dull ants are regarded as having task which find the new food sources by dawdle. It means that the coexistence of the intelligent and dull ant improves the effectiveness of the feeding behavior.

Genetic Algorithm (GA) [7] [8] is a learning algorithm that mimics 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 operations. GA is also combined with local search algorithms to find better solution.

In this study, we propose a novel ACO algorithm called an Ant Colony Optimization using Genetic Information (GIACO). GIACO is a combination of ACO and GA. Some ants pass on genetic information to the next generation by "crossover" and "mutation". Therefore, GIACO search solutions using both the pheromone and the genetic information. The most important feature of GIACO 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 can use the genetic information. In contrast, the dull ant cannot trail the pheromone and does not use the genetic information. Because the dull ants are similar to the mutation of GA, we consider that the dull ants are caused by the mutation in GIACO algorithm.

2. Ant Colony Optimization Using Genetic Information (GIACO)

We explain the proposed GIACO algorithm in detail. A flowchart of the GIACO algorithm is shown in Fig. 1. GIACO is a combination of ACO and GA. Some ants of GIACO

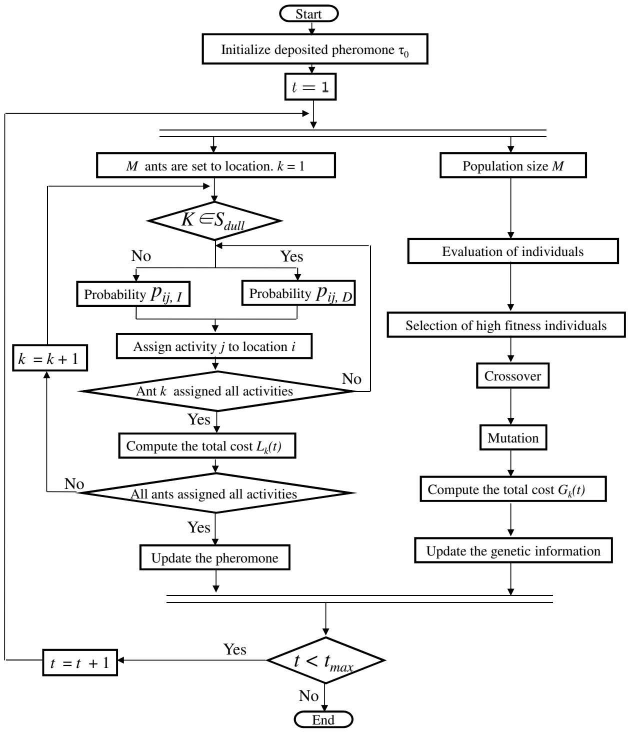

Figure 1: Flowchart of the GIACO.

pass on the 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 does not use the genetic information for making the tour. Because the dull ant is similar to the mutation of GA, we consider that the dull ant in GIACO is caused by the mutation.

In QAP, given two matrices, a distance matrix $\boldsymbol{D}$ and a flow matrix $\boldsymbol{F}$, find a permutation Π which corresponds to the minimum value of the total assignment cost L in Eq. (1).

$$L = \sum_{i=1}^{n} \sum_{j=1}^{n} D_{ij} F_{\pi(i)\pi(j)}, \tag{1}$$

where D_{ij} and F_{ij} are the (i, j)-th elements of $\boldsymbol{D}$ and $\boldsymbol{F}$, respectively. $\pi(i)$ is the i-th element of the vector Π, and n is the size of the problem. The number of ants is denoted by M. $(1 - P_m) \times M$ 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 an amount of pheromone trail on a coupling (i, j) to assign an activity j to the location i, and $\tau_{ij}(0) = \tau_0$. The genetic information $g_{ij}(t)$ is initially set to g_0.

[GIACO2](Assign activity): The intelligent and dull ants

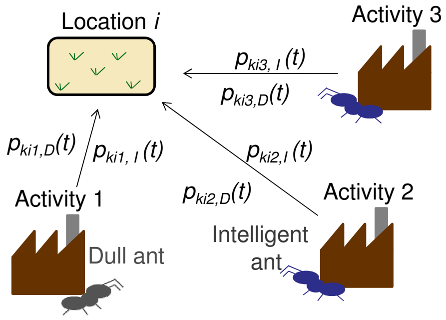

Figure 2: Choice probability $p_{kij}(t)$ of Intelligent and Dull ants. The assigning activity of intelligent ant is chosen by the probability $p_{kij,I}(t)$. The assigning activity of dull ant is chosen by the probability $p_{kij,D}(t)$ which does not include the amount of pheromone and does not include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

assign activity depending on the probability $p_{kij,I}(t)$ and $p_{kij,D}(t)$, respectively, as shown in Fig. 2. GIACO uses the two kinds of choice probabilities. The choice probability $P_{kij}(t)$, that k-th ant ($k = 1, \cdots, M$) assigns activity j to the location i, is decided by

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

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

where η_{ij} is defined as the inverse of the coupling matrix element a_{ij}. The adjustable parameters α and γ control the weight of the pheromone intensity and of the genetic information of the intelligent ant, respectively. The adjustable parameters β_I and β_D control the weight of the coupling matrix element of the intelligent ant and of the dull ant, respectively. 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 $g_{il}(t)$. It means that the dull ants cannot trail the pheromone and does not use the genetic information. Therefore, although the intelligent ants judge the next assigning activity by the pheromone, the coupling matrix element and the genetic information, the dull ants judge the next assigning activity by only the coupling matrix element. The ants repeat the assignment until all the activities are assigned to locations.

[GIACO3](Pheromone update): After all the ants have completed assignment, the total cost $L_k(t)$ are calculated and the amount of the pheromone $\tau_{ij}(t)$ are updated. We should note that the dull ants can deposit the pheromone although they cannot trail the pheromone. The amount of the pheromone

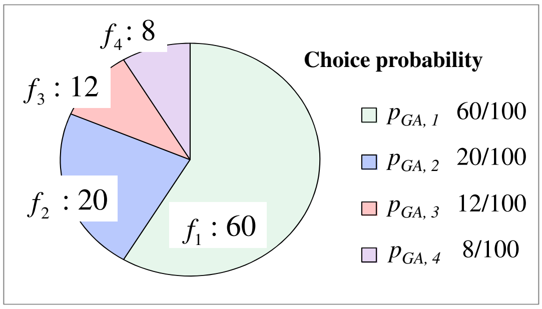

Figure 3: Example of the roulette selection. Individuals, whose genetic information is bequeathed to the next generation, are chosen by the choice probability $p_{GA,k}$. For example, evaluation of 1st individual f_1 is 60, of 2nd individual f_2 is 20, of 3rd individual f_3 is 12 and of 4th individual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

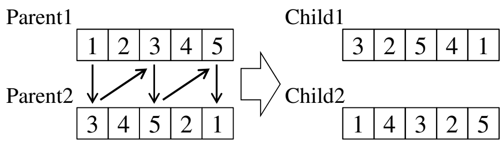

Figure 4: Cycle crossover (CX).

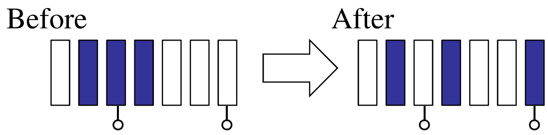

Figure 5: Order changing.

$\Delta\tau_{ij}^k$ deposited by k-th ant on the coupling (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 obtained permutation by k-th ant, and $L_k(t)$ is its total cost. Update $\tau_{ij}(t)$ of each coupling (i,j) depending on its $\Delta\tau_{ij}^k$;

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

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

[GIACO4](Evaluation): GA is performed in parallel with ACO. The solutions of GA are represented as the chromosomes and are performed genetic operation like the evaluation, the crossover and the mutation. The population size U is same as the number of ants, namely $U = M$. The evaluation e_k of k-th individual is decided as

$$e_k = \frac{1}{L_k}, \tag{6}$$

where e_k shows the quality of obtained tour.

[GIACO5](Selection): The GIACO algorithm bequeaths the individuals with high fitness to next generation to obtain better solution. The individuals, whose genetic information is bequeathed to the next generation, are chosen by according to the probability p_{GA} as shown in Fig. 3, and this rule is called roulette selection. The choice probability of k-th individual is decided by

$$p_{GA,k} = \frac{e_k}{\sum_{k=1}^{M} e_k}. \tag{7}$$

[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 size. 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 the Cycle crossover (CX) shown in Fig. 4. CX exchanges the first locus of Parent 1 with the first locus of Parent 2. Next, CX searches same value as Parent 2 from Parent 1 and exchanges the locus of Parent 1 with the locus of Parent 2 which is the same as the locus of Parent 1. Repeat same operation until CX searches a locus which has been exchanged once.

[GIACO7](Mutation): After a crossover is performed, the mutation is carried out. The probability of the mutation is decided by the mutation rate P_m. In this paper, we use the order changing shown in Fig. 5. This mutation selects two numbers and exchanges them. The number of dull ants is same as the number of mutated individuals.

[GIACO8](Update the genetic information): After the genetic operation, 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 individual is decided as

$$\Delta g_{k_{ij}}(t) = \begin{cases} 10/G_k, & \text{if } (i,j) \in T_k(t) \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

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

$$g_{ij}(t+1) = g_0 + \sum_{k=1}^{M} \Delta g_{k_{ij}}(t), \tag{9}$$

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

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

Table 1: Results of the conventional ACO, IDACO and IDACO-CR for Nug12, Scr12, Nug20, Had20 and lipa20a.

	Nug12	Tai 12	Scr12	Nug20	Had20	lipa20a
The conventional ACO	3.17%	5.54%	5.36%	11.39%	3.44%	3.92%
The conventional GA	1.82%	5.13%	3.13%	**7.46%**	3.45%	4.14%
GA-ACO	1.97%	**4.87%**	3.69%	7.51%	3.37%	4.1%
GIACO	**1.73%**	4.97%	**2.84%**	**7.46%**	**3.16%**	**3.04%**

3. Simulation Results

In order to evaluate a performance of GIACO and to investigate its behavior, we apply GIACO to various QAPs. In addition, in order to confirm the effectiveness of the dull ants, we consider GA-ACO whose algorithm is same as GIACO but containing no dull ants. We compare GIACO with the conventional ACO, the conventional GA and GA-ACO. In the experiments, GIACO include $Pm \times M$ dull ants and $(1-Pm) \times M$ intelligent ants in each simulation. The QAPs are conducted on *Nug12*, *Tai12* and *Scr12* (composed of 12 locations and activities), *Nug20*, *Had20* and *lipa20a* (composed of 20 locations and activities).

We repeat the simulation 20 times. The parameters of GIACO, the conventional ACO, the conventional GA and GA-ACO were set to the follows;

$$\begin{aligned} &\tau_0 = 10, \rho = 0.9,\ \alpha = 1,\ \beta_I = \beta_D = 1,\ \gamma = 1, \\ &M = U = 100,\ t_{max} = 4000,\ P_c = 0.4,\ P_m = 0.05 \end{aligned} \tag{10}$$

where the evaporation rate ρ, the weight of pheromone α, the weight of coupling matrix element β_I and β_D, the weight of genetic information γ, the search limit t_{max}, the crossover rate P_c and the mutation rate P_m are fixed value. In order to compare the obtained result with the optimal solution, we use the error rate as follow;

$$\text{Error rate} = \frac{(\text{obtained solution}) - (\text{optimal solution})}{(\text{optimal solution})}, \tag{11}$$

where this equation shows how close to the optimal solution the conventional ACO obtains the total cost. Thus, the error rate nearer 0 is more desirable. The simulation results of the conventional ACO, the conventional GA, GA-ACO and the proposed GIACO are shown in Table I.

We can see that GIACO, which is the combination method of ACO and GA including the dull ants, obtained better results than the conventional ACO and GA, for most the 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 including the dull ants obtained better results than GIACO including no dull ant, in most problems. This result means that the dull ants affect the colony in a positive way. In fact, the dull ants help the colony even if they look like unnecessary. From these results, we can say that the algorithm which similar to the real ant colony obtained effective results.

4. Conclusions

In this study, we have proposed Ant Colony Optimization using Genetic Information (GIACO). GIACO optimizes the cost of QAP 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 six QAPs. We have confirmed that GIACO including the dull ants obtained better results than GIACO which containing only the intelligent ants. Therefore, we can say that the algorithm which similar to the real ant colony obtained effective results.

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