Ant Colony Optimization Algorithm using Back-tracing and Diversification Strategy

SeungGwan Lee and SangHyeok An

***Abstract*—We propose a new improved bio-inspired ant colony optimization (ACO) algorithm using the back-tracing strategy of current global path and diversification strategy. In fact, in general, ACO algorithm, the initial position of agents assigned to an each node at randomly. But, when the global optimal value does not change for N iterations, the proposed method assigns the initial position of agent to the end point of current global best tour path, re-initialize the pheromone of current global best tour path, and the agent re-searches the optimal path. And we evaluate the proposed algorithm with original ACS algorithm. The results of a simulation experiment demonstrate that the proposed algorithm is better than, or, at least, as good as, that of original ACS algorithm in most sets.**

***Index Terms*—Ant Colony Optimization, Traveling Salesman Problems, Diversification, Back-tracing, Bio-inspired**

I. Introduction

Ant colony optimization (ACO) is a metaheuristic approach and bio-inspired algorithm that can be used to find approximate solutions to difficult optimization problems[13, 14], including traveling salesman problems (TSP), quadratic assignment, job-shop scheduling, course timetabling, project scheduling, set covering, constraint satisfaction, vehicle routing, sequential ordering, graph coloring and routing in communication networks, etc.

It is a population-based approach that uses an exploitation of positive feedback, distributed computation as well as a greedy heuristic [11, 22].

In recent years, individuals and research groups that are interested in ACO algorithm have increased significantly.

Ant system (AS) was the first ACO algorithm to be proposed by Dorigo et al. for solving the hard combinatorial optimization problems [1, 2, 3]. Ant colony system (ACS) was the first improvement over the ant system to be proposed by Dorigo et al. [5, 6, 7]. And, several individual cases of the ACO metaheuristic have been proposed. Ant system using elitist strategy (ELITIST AS) is another improvement, proposed by Dorigo et al. [2, 3], MAX-MIN ant system (MMAS) is introduced by Stützle et al. [8, 9, 10], Rank-based ant system (RANK-BASED AS) is proposed by Bullnheimer et al. [11, 12], and Gambardella et al. [4, 15] proposed Q-learning based ant system (ANT-Q) over the ant system.

In fact, in addition to these initial basic algorithms, many successful applications of ACO algorithm for many fields to solve complex combinatorial optimization problem have developed continuously. But there are still exists the demerits of time consuming, falling into local minimum quickly. So, in many cases, it does not guarantee to find the global optimum solution. Thus, many researchers have done a lot of researches on it.

Mahi et al. [16] proposed a hybrid method (PSO-ACO-3Opt) which optimizes parameters that affect the performance of the ACO algorithm through PSO and reduces the probability of falling into local minimum with the 3-Opt algorithm. Tseng et al. [17] proposed pattern reduction enhanced ant colony optimization (PREACO) for eliminating the redundant computations of ACO algorithms using the concept of overlapping edges. Liu et al. [18] proposed an improved ACO algorithm based on the idea of PREACO [17]. In this algorithm, the common paths are overlapping edges of the current optimal and suboptimal solution. Also, Lee et al. [19, 20, 21, 22] proposed an improved ACO algorithm using the concept of overlapping edges. This algorithm considering the overlapping edges of a global best path of the previous iteration and the current iteration. Tuba et al. [23] proposed a suspicious elements exclusion pheromone correction strategy (SEE). This approach adds a new heuristic for determining the undesirability of edges belonging to the tour and significantly decreases their pheromone values. Bai et al. [24] proposed a model induced max-min ant colony optimization (MIMM-ACO) to bridge the gap between hybridizations and theoretical analysis. This method exploits analytical knowledge from both the ATSP model and the dynamics of ACO guiding the behavior of ants which forms the theoretical basis for the hybridization. Jun-man et al. [25] proposed an individual variation and routing strategies (IVRS). IVRS introduce the two improvements. The first is a novel optimized implementing an approach which is designed to reduce the processing costs involved with a routing of ants in the ACO. The second, the individual variation is introduced to the ACO, which enables the ants to have different route strategies. In this model, we adjust the routing policy of the ant who worked better, and that is to enhance the impact of pheromones in the route of this ant. Hlaing et al. [26] proposed an improved ant colony optimization algorithm for solving TSP using candidate set strategy and dynamic updating of a heuristic parameter. Dong et al. [27] proposed a new hybrid algorithm, cooperative genetic ant system (CGAS) to improve a performance of ACO for solving TSP. Liu et al. [28] proposed an improved ant colony optimization algorithm

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S.G. Lee is with the Humanitas College, Kyung Hee University, Deogyeong-daero, Giheung-gu, Yongin-si, Gyeonggi-do, 446-701, South Korea. (e-mail: leesg@khu.ac.kr).

S.H. An is with the Humanitas College, Kyung Hee University, Deogyeong-daero, Giheung-gu, Yongin-si, Gyeonggi-do, 446-701, South Korea. (e-mail: ash@khu.ac.kr).

based on pheromone backtracking algorithm [30]. The backtracking technique is a method that optimizes the search by returning to new selection if it fails to achieve the objectives. [29]

In this paper, we propose a new improved bio-inspired ant colony algorithm using the back-tracing strategy of current global path and diversification strategy.

In fact, in general, ACO algorithm, the initial position of agents assigned to an each node at randomly. But, when the global optimal value does not change for N iterations, the proposed method assigns the initial position of agent to the end point of current global best tour path, re-initialize the pheromone of current global best tour path, and the agent re-searches the optimal path.

The rest of the paper is organized as follows: In Section 2, the basic ant colony optimization algorithms for traveling salesman problem. The proposed method is introduced in Section 3. The results are given in Section 4. Consequently, in Section 5, we conclude the paper with a summarization of results of this research.

II. The Basic Ant Colony Optimization Algorithm for Traveling Salesman Problem

Many ACO algorithms are proposed for solving traveling salesman problem (TSP).

ACO algorithm has emerged recently as a relatively novel metaheuristic for hard combinatorial optimization problems. It is designed to simulate the ability of ant colonies to determine the shortest path to food. In the following, we explain the state transition rule, the local updating rule, and the global updating rule [4, 5, 6, 13, 14, 15, 22, 35, 36, 37, 38, 39, 40].

Let k be an agent whose task is to make a tour: visit all the nodes and return to the starting one. Associated to k there is the list $J_k(r)$ of nodes still to be visited, where r is the current node. An agent(k) situated in node(r) moves to node(s) using the follow rule, called pseudo-random proportional action choice rule(or state transition rule):

$$s = \begin{cases} arg \max_{u \in J_k(r)} \left\{ [\tau(r,u)] \cdot [\eta(r,u)]^{\beta} \right\} & ,if\ q \le q_0 \\ S & ,otherwise \end{cases} \quad (1)$$

Where, $\tau(r,u)$ is the amount of pheromone trail on the edge between nodes. $\eta(r,u)$ is a heuristic function which is the inverse of the distance between nodes r and u, β is a parameter which weighs the relative importance of pheromone trail agents, q is a value chosen randomly with uniform probability in [0,1], $q_0 (0 < q_0 < 1)$ is a parameter, and S is a random variable selected according to the distribution is given by Eq.(2) which gives the probability with which an agent in node r choose the node s to move to.

$$p_k(r,s) = \begin{cases} \dfrac{[\tau(r,s)] \cdot [\eta(r,s)]^{\beta}}{\sum_{u \in J_k(r)} [\tau(r,u)] \cdot [\eta(r,u)]^{\beta}} & ,if\ s \in J_k(r) \\ 0 & ,otherwise \end{cases} \quad (2)$$

While building a solution of the TSP, agents visit edges and change their amount of pheromone trail by applying the following local updating rule:

$$\tau(r,s) \leftarrow (1-\rho) \cdot \tau(r,s) + \rho \cdot \Delta\tau(r,s) \quad (3)$$

Where, $\rho (0 < \rho < 1)$ is the pheromone decay parameter. $\Delta\tau(r,s) = \tau_0 = (n * L_{nn})^{-1}$ is the initial pheromone level, where L_{nn} is the tour length produced by the nearest neighbor heuristic and n is the number of nodes.

Global updating is performed after all agents have completed their tours. The pheromone amount is updated by applying the follow global updating rule:

$$\tau(r,s) \leftarrow (1-\alpha) \cdot \tau(r,s) + \alpha \cdot \Delta\tau(r,s)$$

$$where \quad \Delta\tau(r,s) = \begin{cases} (L_{gb})^{-1} & ,if (r,s) \in global\ best\ tour \\ 0 & ,otherwise \end{cases} \quad (4)$$

$\alpha (0 < \alpha < 1)$ is the pheromone decay parameter, and L_{gb} is the length of the globally best tour from the beginning of the trail.

III. The Back-Tracing Strategy and Diversification Strategy in Ant Colony Optimization

In fact, in general, ACO algorithm, the initial position of agents assigned one agent in an each node at randomly. But, in this paper, we propose a new improved bio-inspired ant colony algorithm using the back-tracing strategy of current global path and diversification strategy.

ACO algorithm searches the optimal solution through the state transition rule, the local updating rule, and the global updating rule.

ACO algorithm assigns the initial positions of agents randomly. So, a variety of start and end of the paths are generated as figure.1 shows.

After all, agents have completed their tours for N iterations, if the global optimal value does not changed, first, back-tracing strategy, we assign the initial position of agent to the end point of current global best tour path, second, diversification strategy, re-initializes the pheromone value on all edge between nodes. Finally, the agent re-searches the optimal path inversely.

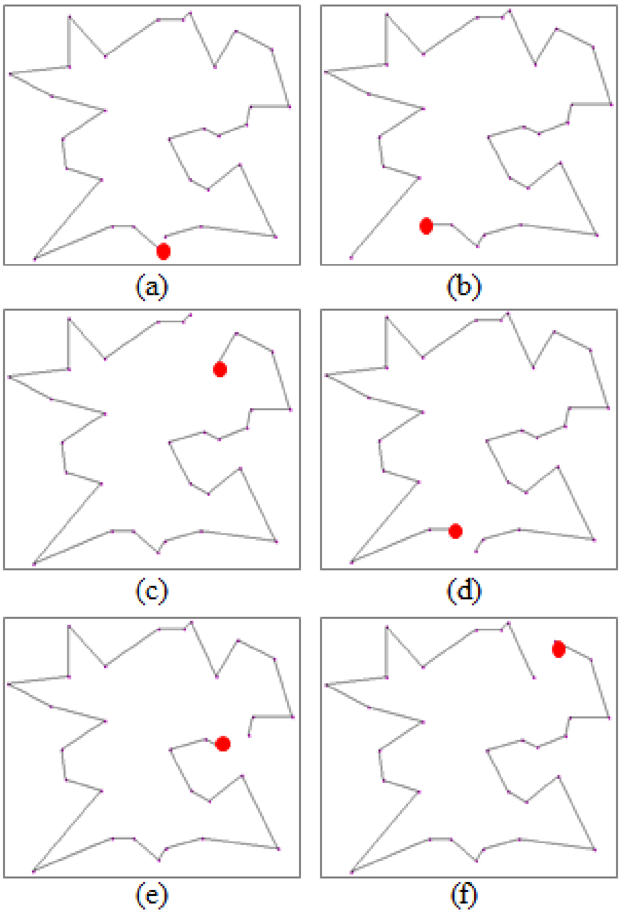

Figure 1. 31-cites best path by ACO

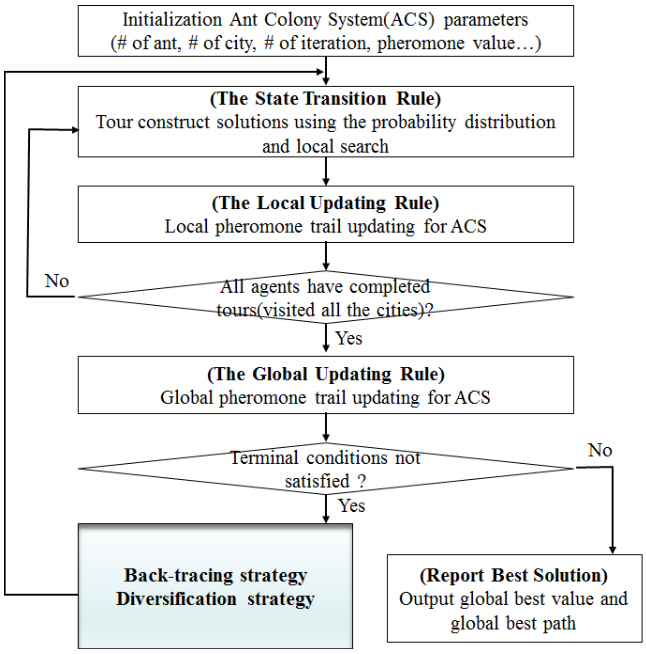

Figure 2. The proposed algorithm

The proposed method reinitializes the amount of pheromone $\Delta\tau(r,s)$ on the edge between nodes r and s by Eq.(5).

$$\Delta\tau(r,s) = \frac{1}{\Delta\tau(r,s)} \tag{5}$$

Next time, to improve the performance, pheromones are updated on updating rules in the ACO algorithm, as given by Eq. (1), (3) and (4), respectively.

IV. The Experimental Results

The running simulation environment: Intel® Core (TM) i-7-4771, 3.50GHz processor; 8.00G RAM, Windows 7 operating system.

We experiment the proposed ant colony algorithm by using TSPLIB [31, 32] which is a famous TSP example. In this paper, we compare the proposed ant colony algorithm with original ACS [34]. In here, we use the basic ACOTSP [33].

To avoid the effects caused by the randomness of the algorithm, for each set problems have been executed 10 trials independently. The parameters of proposed method are given in Table 1. And, the initial position of agents assigned one agent in an each node at randomly.

Table 1. Parameter setting

Parameter	Value
m	10 *or* 20
α	0.1
ρ	0.1
β	2
q_0	0.95
time	$\{10, 20, 30\}$*sec*
Local search	$3-opt$
$\Delta\tau(r,s)$	$\tau_0 = (n * L_{nn})^{-1}$
N	10

Table 2 shows the performance of *Best*, *Average Best*, *Error Rate*, *Worst*, *Average Time(s)* and *Average Iterations* of each algorithm for each TSP problem considering the maximum time (10, 20, 30 sec) for each trial.

Now, in tables, let *Error Rate* denote the enhancement of *Best* (proposed algorithm) on *Optimal* value in percentage and it is defined as follows:

$$Error\ Rate = \frac{Best\ -\ Optimal}{Optimal} \times 100\% \tag{6}$$

From the bold columns in Table 2, it is observed that the *Best* of proposed algorithm is better than, or, equal, that of ACS.

And, it is noted that the *Average Best* of proposed algorithm outperforms ACS algorithms in many sets. However, the performance may decrease slightly compared to the performance of the *Best*. ACS algorithms outperform proposed algorithm in three sets a little, i.e. att532(30 sec), rat783(20sec) and pr1002(20 sec). Overall, the performance of proposed algorithm is better than, or, at least as good as, that of ACS in the most sets.

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Table 2. The results of simulation and performance comparisions

TSP	Optimal	Iteration Time	Algorithm	Best	Average Best	Error Rate	Worst	Average Time(s)	Average Iterations
pcb442	50778	10	ACS	**50778**	50793.8	0.000%	**50912**	3.62	367.0
			Proposed	**50778**	**50793.1**	0.000%	**50912**	4.28	609.7
		20	ACS	**50778**	50873.1	0.000%	50927	3.31	762.6
			Proposed	**50778**	**50791.4**	0.000%	**50912**	6.29	870.4
		30	ACS	**50778**	50864.3	0.000%	50954	8.55	2089.1
			Proposed	**50778**	**50791.4**	0.000%	**50912**	8.88	1134.4
att532	27686	10	ACS	**27686**	27706.9	0.000%	**27734**	4.78	298.9
			Proposed	**27686**	**27703.5**	0.000%	27736	3.48	266.3
		20	ACS	**27686**	27707.1	0.000%	27742	9.19	487.5
			Proposed	**27686**	**27705.2**	0.000%	**27738**	3.42	254.8
		30	ACS	**27686**	**27696.3**	0.000%	**27706**	12.96	723.7
			Proposed	**27686**	27697.6	0.000%	27708	8.77	729.9
rat783	8806	10	ACS	**8812**	8832.5	0.068%	8851	8.10	148.8
			Proposed	**8812**	**8825.6**	0.068%	**8837**	7.43	379.0
		20	ACS	8810	**8821.8**	0.045%	**8844**	12.66	581.6
			Proposed	**8806**	8828.7	0.000%	8849	11.54	663.1
		30	ACS	**8806**	8825.8	0.000%	8847	18.38	870.0
			Proposed	**8806**	**8814.9**	0.000%	**8824**	17.77	1049.0
pr1002	259045	10	ACS	259757	260516.7	0.275%	261189	9.72	128.3
			Proposed	**259111**	**259967.0**	0.025%	**261066**	8.88	171.8
		20	ACS	**259045**	**259739.7**	0.000%	**260541**	16.29	351.1
			Proposed	**259045**	259794.3	0.000%	260636	17.12	425.3
		30	ACS	**259045**	259681.5	0.000%	260259	23.82	538.6
			Proposed	**259045**	**259542.4**	0.000%	**259898**	20.30	653.5

V. CONCLUSION

In this paper, we propose a new improved bio-inspired ant colony algorithm using the back-tracing strategy of current global path and diversification strategy.

When the global optimal value does not change for N iterations, the proposed method assigns the initial position of agent to the end point of current global best tour path, re-initialize the pheromone of current global best tour path and the agent re-searches the optimal path.

The performance of proposed Algorithm is better than, or, at least, as good as, that of ACS algorithms in the most sets.

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