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Investigation of Behavior of Bee Colony Optimization with Role and Responsibility

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***Abstract*—In previous study, we proposed Bee Colony Optimization with Role and Responsibility (BCOR&R) as new Bee Colony Optimization (BCO). BCOR&R has two kind of search methods like an actual honeybee. One is the global search to do a wide area search, another is the local search to do a small area search. In this study, we investigate the behavior of BCOR&R by changing the range of local search and the formation time of local search (after a period of time, initialization and re-formation) for solving Traveling Salesman Problem (TSP).**

I. Introduction

Traveling Salesman Problem (TSP) is known as one of the combinatorial optimization problems, the task is to find the shortest possible tour that each city exactly once. Although small number of cities is easy to solve the problem, many number of cities become more difficult to solve. By swarm intelligence, Ant Colony Optimization (ACO) [1] [2] and Particle Swarm Optimization (PSO) [3] are often generally used for solution of TSP. In this time, we use Bee Colony Optimization (BCO) [4]- [6]for solve TSP. BCO has two kind of lists, Personal tour List (*PL*) and Global tour List (*GL*). *PL* is the optimal tour list of each bee. When better tour is discovered, *PL* is updated. And, *GL* is the optimal tour list of all bees. In the all *PL*, the best evaluation *PL* become *GL*.

In our previous study, we have proposed Bee Colony Optimization with Role and Responsibility (BCOR&R) as new Bee Colony Optimization algorithm for TSP. The feature of BCOR&R is to have two kind of search methods, global search and local search. Global search is the same as the standard BCO's. Local search is new search method in BCOR&R. In local search, the cities of all are divided into a small group. The optimal tour of the group is searched. When the optimal tour of the group is updated, the tour information of local search is exported to global search. BCOR&R can be to explore to all the corners of large area by combining the two types of search.

In this study, we investigate the influence of the local search by changing the range of local area.

II. Bee Coloy Optimization with Role and Responsibility (BCOR&R)

For comparison with the standard BCO, the important feature of BCOR&R has two kind of search methods, global search and local search. At initial phase, search-bees $M_i(i = 1, 2, ..., m_i)$ do global search. And, the evaluated tour in *GL* and *PL* are updated. After a fixed period of time ($t < t_{limit}$), recruit-bees M_i do local search using *GL*. The number of search cities is reduced ($N_l = N * LS_{range}$) using the *GL* of global search. As shown in a Fig. 1, the starting point and a terminal point are fixed, and a local search is performed in two points. N-city of TSP denoted as follows.

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

City coordinates are normalized from 0 to 1, and P_i is the city coordinate of i-th ($i = 1, 2, ..., N$)D

Step. 1 (Initialization): BCOR&R lets a generation step $t = 0$ and the initialization count of local search $t_R = 0$.

Step. 2 (Find tour): The global tour of M bees is created. A local search is started after ($t > t_{local}$).

$$p_{ij,n}(t) = \frac{[\rho_{ij,n}]^\alpha \cdot [\frac{1}{d_{ij}}]^\beta}{\sum_{j\in A_{i,n}} [\rho_{ij,n}]^\alpha \cdot [\frac{1}{d_{ij}}]^\beta} \tag{2}$$

Where $\rho_{ij,n}$ is the arc fitness from city i to city j after n transitions and d_{ij} represents the distance between city i and city j. Note that the d_{ij} is inversely proportional to the city distance. In other words, the shorter the distance, the higher is the likelihood of that city to be selected. Where α and β are control parameters.

Arc fitness $\rho_{ij,n}$ is defined as blow. ($0 \le \lambda \le 1$)

$$\rho_{ij,n} = \left\{ \begin{array}{ll} \lambda & , j \in F_{i,n}, |A_{i,n}| > 1 \\ \frac{1-\lambda|A_{i,n}\cap F_{i,n}|}{|A_{i,n}-F_{i,n}|} & , j \notin F_{i,n}, |A_{i,n}| > 1 \\ 1 & , |A_{i,n}| = 1 \end{array} \right\} \tag{3}$$

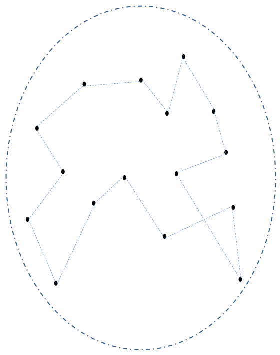
Step. 3 (Evaluation): Evaluate tours, and the probability of following a waggle dance is calculated.

$$Pf_i = \frac{1}{L_i}, \quad L_i = tour\ length \tag{4}$$

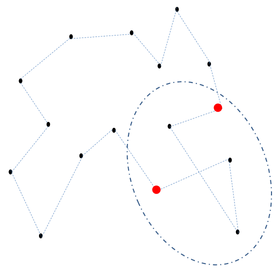
$$Pf_{colony} = \frac{1}{N_{bee}} \sum_{i=1}^{M_i} Pf_i, \quad GL(t) = \frac{Pf_i}{Pf_{colony}} \tag{5}$$

Where Pf_i is the profitability score of bee i and Pf_{colony} is the bee colony's average profitability and is updated after each bee completes its tour.

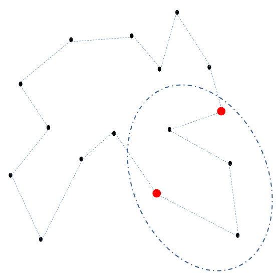
The following Table I shows the probability which each bee M use $GL(t)$ or $PL_i(t)$, at the time of $(t+1)$.



(a) Global search.



(b) Local search.



(c) Exportation of global search from local search.

Fig. 1. Search methods of BCOR&R.

Step. 4 (Local search): After ($t > t_{local}$), carry out the following tasks. Thereafter, a local search is performed instead of a global search. A local search is performed in a small number of city M_l ($M_l = M * LS_{range}$) using the GL of global search. After $t_R(t) > t_{limit}$, initialize current local search group and $t_R(t) = 0$, and re-formation new local search group.

Step. 5 BCOR&R let $t = t + 1$ and $t_R(t + 1) = t_R(t) + 1$. BCOR&R goes back to [Step. 2], and repeats until $T = t$.

TABLE I
PROBABILITY OF FOLLOWING WAGGLE DANCE

Profitability Scores	P_{follow}
$Pf_i < 0.95Pf_{colony}$	0.80
$0.95Pf_{colony} \leq Pf_i < 0.975Pf_{colony}$	0.20
$0.975Pf_{colony} \leq Pf_i < 0.99Pf_{colony}$	0.02
$0.99Pf_{colony} \leq Pf_i \leq Pf_i$	0

III. SIMULATION

In order to investigate the behavior of BCOR&R, we apply BCOR&R to att48 ($N = 48$) and kroA100 ($N = 100$) of two TSPs. In this study, we carry out the simulation 100 times with 2000 generations. The number of bee M is same as the number of city N. The parameter of standard BCO and BCOR&R is shown below.

$$\lambda = 0.95, \alpha = 1, \beta = 10, R = 0.65$$

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

$$Errorrate[\%] = \frac{(obtainedsolution) - (optimalsolution)}{(optimalsolution)} \times 100 \quad (6)$$

where this equation shows how close to the optimal solution the standard BCO obtains the tour length. Thus, the error rate nearer 0 is more desirable.

A. Investigation of the initialization count t_{limit}

First, we investigate the value of t_{limit} that is updated at each range of local search LS_{range}. Where t_{limit} is initialization count of local search, LS_{range} is search range of local search. At this time, determined by the random location of the local search.

TABLE II
THE RESULT OF t_{limit}

		$LS_{range}=$	0.2	0.3	0.5	0.7
att48	t_{limit}	Number of updates[time]	19	22	4	0
		min[]	2	3	100	-
		max[]	107	131	137	-
kroA100	t_{limit}	Number of updates[time]	53	4	0	0
		min[]	3	2	-	-
		max[]	179	39	-	-

As shown in a Table II, $LS_{range} = 0.3$ is the most number of updates at $N = 48$. The number of updates shows 150 or less times at the longest in the time of every LS_{range}. However, the update could not confirm $LS_{range} = 0.7$. Thus, the local search can consider that $LS_{range} = 0.3$ is a peak, and is decreasing gradually from there. In $N = 100$, $LS_{range} = 0.2$ is the most number of updates. As in common with $N = 48$,

$$N = 48 : N \times LS_{range} = 48 \times 0.3 = 14.4 \quad (7)$$

$$N = 100 : 100 \times 0.2 = 20 \quad (8)$$

In a local search, it can be guessed that about 15-20 cities are the optimal number of cities.

$$N = 48 : 48 \times 0.7 = 33.6 \tag{9}$$

$$N = 100 : 100 \times 0.2 = 50 \tag{10}$$

In an above case, there was no updating. Local search is not influential at the time of at least 33 or more cities. The number of updates is same maximum 150 times as $N = 48$ except $LS_{range} = 0.1$.

The value of t_{limit} which considers these results and is used by the following simulations is shown in table III.

TABLE III
DETERMINATION OF t_{limit}

	LS_{range}=	0.2	0.3	0.5	0.7
att48	t_{limit}	150	150	150	-
kroA100		200	150	-	-

B. Investigation of the local search range LS_{range}

Next, we investigate behavior when the local search range LS_{range} is changed. Optimal LS_{range} of every N is determined using t_{limit} optimized above section.

TABLE IV
THE RESULT OF LS_{range}

		LS_{range}=	0.2	0.3	0.5	0.7
att48	Error rate	avg[]	2.28	**1.89**	2.35	2.56
		min[]	1.37	1.17	1.56	1.37
		deviation[]	0.67	0.47	0.46	0.83
kroA100	Error rate	avg[]	**11.38**	13.27	13.68	12.51
		min[]	7.42	11.83	11.79	10.75
		deviation[]	2.21	0.91	1.3	1.37

As shown in a Table IV, for $N = 48$, the best result is obtained with $LS_{range} = 0.3$, and for $N = 100$, the best result is obtained with $LS_{range} = 0.2$. From these results, it turned out that the number of updates by local search is greatly related to a result. In order to increase the number of updates of a local search, it turned out that a suitable range setup is required. This position of the local search was also determined randomly, there is a possibility of better results by improving the methods of positioning

IV. CONCLUSIONS

In this study, we investigated about behavior of the local search of BCOR&R. The local search was very effective as a method of improving TSP. However, local search has much influence on the results by changing range. We have discovered the optimal parameter of the local search this time. In the future work, we want to discover new positioning method of local search.

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