# ANTSYSTEM COMBINED WITH AUTONOMY AND COOPERATIVENESS

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**Abstract** - Ant Colony Optimization (ACO) is well-known as an optimization tool based on Ant System (AS) inspired by real ants' foraging behavior. In ACO, agents in ACO model solve an optimization problem like a traveling salesman problem (TSP) by behaving cooperatively based on information shared by all agents.However, the system of conventional ACO models has an issue for falling into a local solution because of the mechanical and heteronomous behavior of all agents. In this study, we construct a novel ACO model that achieved a balance between the system convergence and the divergence for improving an ability to find better solutions. We name this model ACAS (Ant System combined with Autonomy and Cooperativeness). ACAS is an extended version of AS adding two functions to AS. The behavior of agents in ACAS is in consideration of the fact that real ants realize a balance between convergence to a specific feeding ground and spreading to various feeding grounds. We applied ACAS to various datasets of symmetric TSP and found that ACAS performed better than AS.

**Index Terms** - Ant Colony Optimization, Traveling SalesmanProblem, Exploitation, Exploration

## I. INTRODUCTION

Ant Colony Optimization (ACO) is an optimization model inspired by real ants' foraging. ACO models are known to be effective in solving various combinatorial optimization problems including the traveling salesman problem (TSP)which demands the shortest tour under the condition that travelling agents are allowed to transit each city only once and return to the start city[1].

Inspired by real ants' foraging behavior, Dorigo proposed Ant system (AS) as a solution tool for combinatorial optimization problems like a traveling salesman problem (TSP). Since then, the various models based on AS have been developed. An optimization system using such a model is collectively called Ant Colony Optimization (ACO).

In general, TSP demands the shortest tour under the condition that travelling agents are allowed to transit each city only once and return to the start city. On the other hand, real ants induce their nest-mates to a feeding ground using chemicals elements called pheromones and therefore forage efficiently.Since pheromone is a volatile substance, when the path length is long, it is not possible to obtain a sufficient feedback effect by the nest companion, and as a result, the ant's path disappears.In contrast, when the path length is short, a stable ant path is realized by sufficient feedback.Therefore, the system for the foraging behavior built by real ants can be said to be a kind of computer system that constructs the shortest pathin TSP.

However, if all ants concentrate on a certain feeding ground (solution), they will miss the surrounding unknown feeding ground (solution). Detrain and Deneubourg [2]pointed out that such a feature can be disadvantage of the ant colony.It can be seen that ACO has the same issue, too.

Each agent in ACO models based on AS selects a route probabilistically depending on the pheromone information and distance between cities in TSP.Therefore, agents behave cooperatively since the route-selection of agents is based on information shared by all agents in ACO.At the same time however, the systemin conventional ACO has an issue of falling into a local solutionowing tothe mechanicaland heteronomous behavior of individuals.Agents in conventional ACO cannot find better solutions once the system falls into a local solution because of obeying only global information common to all agents. In order to overcome such an issue, we address a novel AS adopting path memory of each agent to route selection.In this research, it is to verify whether ACO model implementing both autonomy and cooperativeness in behavior of each agent improves the accuracy of Ant System (AS).

Real ants appear to use visual cue and memory as a tool for their navigations [3].For example, ants recall their visual memory and turn their body to match memorized panoramic information and the current scene. Then, they appear to move forward in the best-matched direction. By doing so, ants reliably return to their nest even if chemical cueis not available for them.

The important point is however, ants achieve flexible and adaptive foraging by switching different navigation tools.If ants wouldpersist only in memory, it could be difficult for ant coloniesto switch to a new route that might be gradually established through pheromones [4].The converse is also true.If ants would persist only in pheromone, they might miss the surrounding unknown feeding ground.In other words, in the route search, it can be said that the search behavior based on either pheromone information or memory information means convergence to the local solution.Therefore, in this research, we propose a hybrid ACO model that selectively uses pheromone information and memory information according to the

situation.Recently, it has been reported that ants tended to judge the surrounding area as a useful area when other individuals were present in the surroundings [5]. Therefore, a novel AS proposed in this researchhas a function that if there are more than a certain number of other individuals, route selection based on their own pathmemory is performed, otherwise, route selection based on pheromone information and distance between cities is constructed.This function enables each agent to switch between cooperative behavior and autonomous behavior.

Furthermore, the proposed AS has a function that each agent gives stronger pheromone information to their own tour than conventionalASwhen each agent finds best solution.This function enables each agent to be cooperative.

Therefore, two functionsenable each agent to spread to various solutions while enabling each agent to promote convergence to an optimal solution as a whole system.Therefore, we propose a new ACO model called Ant System combined with Autonomy and Cooperativeness (ACAS).

We apply ACAS proposed in this researchand conventional AS to benchmark problems of various TSPs and analyzed solutions obtained by both models. As a result, we verified that proposed ACAS has higher ability to find better solutions compared to conventionalAS.

## II. ANT SYSTEM

We explain conventional AS which is the most basic model of ACO to be compared in this research.

First, an agent is introduced on each city. Agent $k$ is located in city $i$ at step $t$ within a tour $z$ . At this time, the probability that agent $k$ selects city $j$ from the set of unvisited citiesfor the agent $k$ is calculated using following equation:

$$p_{ij}^{k}(t)=\frac{\left[\tau_{ij}(z)\right]^{\alpha}\left[\eta_{ij}(z)\right]^{\beta}}{\sum_{l\in N_t^k}\left[\tau_{il}(z)\right]^{\alpha}\left[\eta_{il}(z)\right]^{\beta}}, \qquad (1)$$

where $\tau_{ij}$ is the pheromoneinformation defined in the path between city $i$ andcity $j$ , while $\eta_{ij}$ is the heuristic information defined as the inverse of the distance between city $i$ and city $j$ in the path between the two cities.The parameters $\alpha$ and $\beta$ respectively control the influence of pheromone information and heuristic information. Generally, when combining parameters of $\alpha=1$ and $\beta=5$ , ability to find solutions is high [1].Next, after all agents have constructed tours, each agent adds $\Delta\tau_{ij}^{k}(z)$ as additional pheromone information like followings:

$$\Delta\tau_{ij}^{k}(z)=\begin{cases}\dfrac{1}{u^{k}(z)}, & if\ (i,j)\in T^{k}(z),\\ 0, & otherwise.\end{cases} \qquad (2)$$

In equation (1), $T^{k}(z)$ represents a set of pairs of paths that the agent $k$ selects during $z$-th tour, while $u^{k}(z)$ represents the total distance of the tour $z$ .

Finally, pheromone information is updated based on the following equation:

$$\tau_{ij}^{k}(z+1)=(1-\rho)\,\tau_{ij}(z)+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(z), \qquad (3)$$

where $\rho\,(0<\rho<1)$ represents pheromone evaporation rate and $m$ represents the total number of agents.

## III. ANTSYSTEM COMBINED WITH AUTONOMY AND COOPERATIVENESS

We explain ACAS proposed in this research. Two important functions of ACAS arefollowings. One is the individual-memory function based on the best solution route memory. The other one is the pheromone deposition function, i.e., agent deposit stronger pheromone than usual updated pheromone when it finds the best solution.The following shows the algorithm of the ACAS.

### STEP1: INITIAL SETTING

Every agent is introduced on each city. The total number of cities is defined as $a$ , and the pheromone information between cities $i$ to $j$ is defined as $\tau_{ij}$ .The initial pheromone information is $\tau_{ij}=1.0$ on all possible paths.

### STEP2: CALCULATING THE NUMBR OF AGENTS

The parameter $number^{k}(s^{k}(t))$ is calculated in STEP2. Here,the city where the agent is located at step $t$ within a tour is defined as $s^{k}(t)$ . At step $t$ , the number of other agents present in $s^{k}(t)$ is defined as $number^{k}(s^{k}(t))$ .

### STEP3: ROOTING

A parameter $judge^{k}(x)$ represents whether or not the agent $k$ has already visited city $x$ . If the agent has visited city $x$ , then that parameter can be replaced from 0 with 1 . Furthermore, the threshold on the number of agents in the same city is defined as $\omega$ .The next city is selected as follows:

If $judge^{k}(x)=0$ and $number^{k}(s^{k}(t))\geq\omega$ , thenext city is selected based on the best solution route memory held in each agent.

On the other hand, that is, if $judge^{k}(x)=1$ or $number^{k}(s^{k}(t))<\omega$ ,the next city is selected based on equation (1).

Remark that in proposed ACAS a path is selected autonomously based on its own memory in accordance with the surrounding environment, as well as the

mechanical and heteronomous selected behavior in AS.In this way, each agent realizes "autonomy" based on the individual-memory function.

**STEP4: TOTAL DISTANCE CALCULATION**

The total distance of the tour $z$ , i.e., $u^k(z)$ is calculated.

**STEP5: UPDATING MEMORY INFORMATION**

When tour length $u^k(z)$ is smaller than the best-so-far tour length $u^k_{\min}$ for the agent $k$ , $u^k_{\min}$ is replaced with $u^k(z)$ .

**STEP6: UPDATING PHEROMONE INFORMATION**

When the best tour memory is updated in STEP 5, the agent $k$ adds pheromones 100 times as large as pheromones calculated by equation (2) like following equation.

$$\Delta\tau^k_{ij}(z) = \frac{100}{u^k(z)} \quad if\,(i,j) \in T^k(z). \qquad (4)$$

Otherwise, the pheromone update is occurred using equation (2) in the usual way. After the pheromone update amount is calculated, the pheromone information is updated based on equation (3). The above updating rule is for enhancing the guidance to the best solution found and increasing the search capability of the optimal solution while each agent is distributed to various solutions.

**STEP7: OUTPUT OF OPTIMAL SOLUTION**

After loop processing from STEP 1 to STEP 6 by an arbitrary number of times, the best-so-far is selected.Then, the search is finished.

## IV.RESULTS

### A. Experimental method

In applyingproposedACAS and conventionalAS to TSP, we set the number of tours to 1000 per trial. In addition, eil51, berlin52, st70, eil76, pr76, and rat99in [7]are used as benchmarks of TSP. These are data sets frequently used for analysis in the benchmark in which the distance definition of the symmetric TSP data sets is represented by a two-dimensional Euclidean.

The values of the parameters in both models areshown in Table 1. Furthermore, for all benchmark problems, the threshold (parameter: $\omega$ ) are shown in Table 2.This value was chosen from preliminary experiments. In the preliminary experiment, the bestsolution was derived from 10 trials for each threshold in all benchmarks.

**Table1: Setting parameters**

| parameter | AS | ACAS |
|---|---|---|
| $\rho$ | 0.5 | 0.5 |
| $\alpha$ | 1 | 1 |
| $\beta$ | 5 | 5 |

**Table 2: Setting thresholds**

| TSP | Threshold $\omega$ |
|---|---|
| eil51 | 1 |
| berlin52 | 1 |
| st70 | 1 |
| pr76 | 1 |
| eil76 | 1 |
| rat99 | 1 |

For reference, the resultsin the preliminary experiments are shown in Table 3. We decided to use the threshold at the time when the best solution average was the best in the preliminary experiments.

### B. Verification of improvement of solving ability to find better solutions

In order to evaluate the performance of each system(proposed ACAS and conventional AS), the averaged best-so-far obtained from 10 trials were calculated.Here best-so-far solution means the best solution obtained from each trial using each ACO model.

The Shapiro-Wilk test was used to checkthe normality of the data distributionof 10 best solutions obtained from 10 trials.After using this test, t test or U test was applied, which was dependent on whether the data distribution confirmed the normality or not.These tests were conducted to verify whether there was a significant difference in the average value of the solutions betweenproposedACAS and conventionalAS.

The results are shown in Table 4. As you can see, significant differences are found in all benchmarks. Furthermore,proposedACAS appears to perform better than conventionalAS.

In order to evaluate the difference between the optimum solution and the best solution in each benchmark dataset, we additionally conducted following analysis.The error $\varepsilon$ between the obtained solution and the optimal solution of the benchmark is evaluated by Eq. (5) with the obtained solution as $M$ and the optimal solution as $T$ :

**Table 3: Comparison of thresholds in ACAS**

| TSP | Threshold $\omega$ | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| eil51 | 428.982 | 431.946 | 432.187 | 430.600 | 441.119 |
| berlin52 | 7544.366 | 7544.366 | 7544.366 | 7545.291 | 7545.784 |
| st70 | 681.066 | 692.224 | 685.158 | 685.937 | 685.919 |
| pr76 | 110156.227 | 111715.968 | 112488.406 | 112918.763 | 113490.576 |
| eil76 | 548.812 | 550.116 | 552.295 | 553.292 | 553.238 |
| rat99 | 1234.379 | 1245.299 | 1254.345 | 1257.239 | 1259.597 |

**Table 4: The averaged best solution calculated from 10 trials**

| TSP | average | | U test (p-value) | t test (p-value) |
|---|---|---|---|---|
| | AS | ACAS | | |
| eil51 | 451.480 | 429.679 | 1.74E-04 | |
| berlin52 | 7546.775 | 7544.366 | 5.94E-05 | |
| st70 | 705.940 | 679.673 | | 8.75E-09 |
| pr76 | 115487.69 | 109966.557 | | 1.07E-11 |
| eil76 | 561.274 | 549.048 | | 1.05E-08 |
| rat99 | 1282.93 | 1231.353 | | 9.62E-13 |

$$\varepsilon\,[\%] = \frac{(M - T)}{T} \times 100. \quad (5)$$

The closer the error rate $\varepsilon$ is to $0$, the higher the ability to find better solutions is.

Table 5 shows the best solution found from 10 trials in both systems. From Table 5, we can see that ACAS has better solution than AS in all benchmark problems. Therefore, it was found that ACAS performed better than AS.

### C. Verification of relationship between improvement of ability to find better solutions and escaping from local solution

In this section,we examine whether the improvement of proposed ACAS is related to the system ability of escaping from the local solution. In concrete, we compared the number of best-so-far updates in ACAS with the number of best-so-far updates in AS.

The best-so-far update means that agents can derive a new solution without falling into the local solution.Here, we calculated the number of best-so-far update during each trial.Then, we applied U testto compare the number of best-so-far updates in ACAS with the number of best-so-far updates in AS.Results are shown in Table 6.

From the results in Table 6, significant differences were found between ACAS and AS in all benchmark datasets.Furthermore, from the average of the best solution update counts, it is found that ACAS has a larger number of best solution update counts than AS. Therefore, since ACAS can escape from local solution, it is inferred that ACAS improves the ability to find better solutions.

### D. Verification of relationship between improvement of ability to find better solutions and the balance between convergence and diversity

In the section C, we calculated the average number of best-so-far updates in both models to verify the system ability for getting away from falling into a local solution. In this section,we examined whether ACAS realized the balance between convergence and diversity and checked the ability escaping from a local solution in ACAS.

Here, we compared the standard deviation of the tour length of each agent in the search processof ACAS with the standard deviation of AS. The reasons for focusing on the standard deviation areas follows:

(i)the magnitude of the standard deviation of the tour length of each agentindicates that each agent builds various tours,

(ii) the smallness of the standard deviation of the tour length of each agent indicates that each agent islikely to converge to one tour.

Figure 1 shows the fluctuation ofthe standard deviation of the tour length before and after 50time steps when the best-so-far solution was updated. According to Figure 1, the standard deviation of ACAS was smaller than that of AS before the best-so-far update occurred. However, the standard deviation in ACASwas replaced with higher value around the best-so-far update. Such behavior cannot be appeared in the case of AS.It was seen that ACAS as a whole systemsuccessfully switched the behavior of convergence to optimal solution and the behavior of dispersion to various solutions, which resulting in realizing the balance between convergence and diversity.

Finally, we examined whether or not the ACAS performed in a same manner if one of two functions were removed from the system. As we already mentioned, two important functions of ACAS are followings: the individual-memory function and pheromone-deposition function. We developed two additional models called ACAS-memory / ACAS-pheromone in which only the pheromone-deposition / the individual-memory function was included. Then, we calculated the averaged best-so-far solutions from 10 trials by comparing these two models with ACAS and AS.

**Table 5:Best solution in 10 trials**

| TSP | optimum | AS | | ACAS | |
|---|---|---|---|---|---|
| | | best | $\varepsilon[\%]$ | best | $\varepsilon[\%]$ |
| eil51 | 426 | 444.944 | 4.447 | 428.982 | 0.700 |
| berlin52 | 7542 | 7549.891 | 0.105 | 7544.366 | 0.030 |
| st70 | 675 | 696.495 | 3.184 | 677.111 | 0.313 |
| pr76 | 108159 | 113970.970 | 5.376 | 108478.994 | 0.296 |
| eil76 | 538 | 556.203 | 3.384 | 544.478 | 1.204 |
| rat99 | 1211 | 1268.783 | 4.771 | 1223.451 | 1.028 |

**Table 6: The averages of best solution update count in 10 trials and result of t test and U test**

| TSP | average | | U test (p-value) |
|---|---|---|---|
| | AS | ACAS | |
| eil51 | 2.9 | 7.1 | 2.35E-04 |
| berlin52 | 4.1 | 6.6 | 4.98E-03 |
| st70 | 4.0 | 7.4 | 1.53E-04 |
| pr76 | 3.5 | 7.3 | 1.45E-04 |
| eil76 | 4.1 | 7.2 | 1.12E-03 |
| rat99 | 4.9 | 6.7 | 1.65E-03 |

Tables 7 and 8 represents that the averaged best-so-far solutions. From the results of Tables7 and 8, it can be seen that ACAS-pheromone and ACAS-memory have a significant solution difference from AS and ACAS.It can be found that the average of the 10 best solutions in ACAS-pheromoneand ACAS-memory is inevitably better than AS and is worse than ACAS.

Tables9 and 10 show the best solution among all agents' solutions obtained from ten trials of ACAS, ACAS-pheromone, ACAS-memory and AS. The closer the error rate $\varepsilon$ is to 0 , the higher the ability to find better solutions is. Therefore, from Tables9 and 10, it was found that ACAS-pheromone and ACAS-memoryhad higher ability to find better solutions than AS and lower ability than ACAS.

From the above results, it can be said that the two functions in proposed ACAS are contributed to improving the ability to find better solutions. Since the two functions are related to the realization of the balance between convergence and diversity, it can be concluded that the ACAS improves the ability to find better solutions by realizing the balance between convergence and diversity.

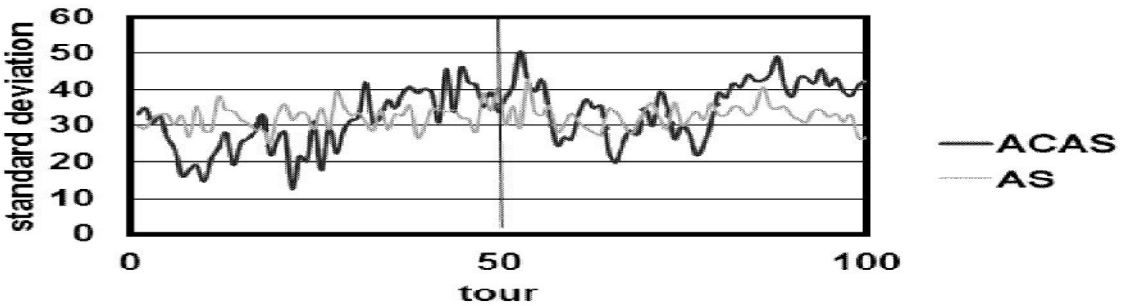



**Figure 1. The fluctuation of the standard deviation of the tour length**

**Table 7: The averages of best solution update count in 10 trials and result of U test**

| TSP | average | | | U test(p-value) | |
|---|---|---|---|---|---|
| | AS | ACAS-pheromone | ACAS | vs AS | vs ACAS |
| eil51 | 451.48 | 440.537 | 429.679 | 1.83E-04 | 1.74E-04 |

**Table 8: The averages of best solution update count in 10 trials and result of U test**

| TSP | average | | | U test(p-value) | |
|---|---|---|---|---|---|
| | AS | ACAS-memory | ACAS | vs AS | vs ACAS |
| eil51 | 451.48 | 431.947 | 429.679 | 1.83E-04 | 2.72E-03 |

**Table 9: Best solution in 10 trials**

| TSP | optimum | AS | | ACAS-pheromone | | ACAS | |
|---|---|---|---|---|---|---|---|
| | | best | $\varepsilon[\%]$ | best | $\varepsilon[\%]$ | best | $\varepsilon[\%]$ |
| eil51 | 426 | 444.944 | 4.447 | 431.979 | 1.404 | 428.982 | 0.700 |

**Table 10: Best solution in 10 trials**

| TSP | optimum | AS | | ACAS-memory | | ACAS | |
|---|---|---|---|---|---|---|---|
| | | best | $\varepsilon[\%]$ | best | $\varepsilon[\%]$ | best | $\varepsilon[\%]$ |
| eil51 | 426 | 444.944 | 4.447 | 429.530 | 0.822 | 428.982 | 0.700 |

## CONCLUSIONS

In this research, we proposed ACAS that combines autonomy and cooperativeness with the aim of improving ability to find better solutions by escaping from the local solution. By adapting proposed ACAS

and AS to benchmark problems of various TSPs and by analyzing the solutions obtained respectively, the effectiveness of ACAS was verified.We guess that AS is falling into a local solution by selecting agents' selective behavior to depend only on agent cooperativity. While, It can be considered that ACAS realizes a balance between convergence to an optimal solution as a whole system of agents and divergence behavior to various solutions and got an excellent solution without falling into a local solution by combining the autonomy and cooperation of agents.Therefore, ACAS is considered to be more effective to solve TSP than AS.

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