A New Ant Colony Optimization Method Considering Intensification and Diversification

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Abstract. Ant colony optimization (ACO) is a meta-heuristic algorithm inspired by foraging behavior of ants and is one of the most well known swarm intelligence algorithms for solving the Traveling Salesman Problem (TSP) because of its simpleness and quality. In this paper we will propose an ACO based algorithm called ASwide that adds simple but powerful factors in the pheromone updating formula. To check the efficiency of our algorithm we did several computer experiments and confirmed that ASwide generates an acceptable solution stably compared with other methods.

Keywords: Ant Colony Optimization, Traveling Salesman Problem, Swarm Intelligence, Combinatorial Optimization.

1 Introduction

Ant Colony Optimization (ACO) is a method inspired by the foraging behavior of ants used and studied in various types of complicated problems including the Traveling Salesman Problem (TSP) with significant efficiencies [1,6]. For these metaheuristic algorithms the balance between intensification and diversification will play an important roll in the quality of its solution. In recent studies lots of significant research has been done by adjusting the pheromone tables or by setting several colonies using $\mathcal{MAX}-\mathcal{MIN}$ Ant System [17,14,18,22]. But using $\mathcal{MAX}-\mathcal{MIN}$ Ant System has a problem in that it needs a preliminary preparation by using another method such as nearest neighbour algorithm [9], 2-opt [3] to the pheromone table which greatly affects solution's quality.

In this paper we will propose a method called ASwide which outputs solutions with high precision in an acceptable time aiming in the field of car navigations and network routings. ASwide which is an improvement of ACO adds a ratio of the best solution the system found so far and the length of the trail the ant agents moved to the ACO's pheromone updating formula. In addition, we will also propose a method to make the system converge faster with maintaining diversification using λ-branching factor. In the next section, we will explain the ACO algorithm and some other algorithms improved form the ACO. In Section

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Algorithm 1. A typical ACO algorithm

- Initialize all ant agents and the pheromone

while Termination condition are not satisfied **do**

1. Every ant agents selects the next city to move stochastically using the city selection formula
2. Calculates the amount of pheromone each ant agent secrete to the trail using the pheromone calculation formula
3. Updates the pheromone field using the pheromone updating formula

end while

- Outputs the best ant's trail found in the system

3 and Section 4 we will do some computer experiments and consideration with our proposed method and other traditional methods. Finally in Section 5 we will conclude our study.

2 An Outline of ACO

Recently, studies on swarm intelligence which models the habits and behaviours of a particular creature especially social insects and natural phenomenons are commonly done [21,15]. One of the major and famous method in swarm intelligence is the Ant Colony Optimization (ACO) which ant agents secrete pheromones to communicate and cooperate food retrieval with other ant agents.

The most basic and common ACO named as the Ant System (AS) was introduced by Dorigo to solve complex combinatorial optimization problems especially the TSPs [5].

Traveling Salesman Problem (TSP) is one of the typical NP-hard problem in combinatorial optimization which you need to find the shortest possible route that visites each city exactly once and return to the origin city when the list of cities and the distances between each pair of cities are given.

Most studies on ACOs done today such as ASelite [8], ASrank [2], Ant Colony System [7], $\mathcal{MAX}-\mathcal{MIN}$ Ant System [17] is a method improved from the Dorigo's Ant System. Algorithm 1 shows the basic Ant System's algorithm.

3 ASwide

In Bullnheimer's study [2] the pheromone value of ASrank is weighted $(\sigma - \mu)$ times according to the rank of the elite ants. In addition to that the ratio of the maximum pheromone value that a single ant agent can secrete and the ant agent's tour length is also weighted the the pheromone calculation. We think there is a problem in this method. There is a bad influence on the system when all the elite ant's evaluation were not good since it will be weighted $(\sigma - \mu)$, not considering the tour length found beforehand.

So in our proposed method ASwide, we will add another weighting to the ASrank to solve the problem mentioned above. The added weight will be the

Table 1. Comparison Using eil51.tsp at Tour 300 (Best solution:426)

	ACO	ASelite	ASrank	ASwide
Best Solution	450	437	**429**	431
Relative Error	5.33	2.52	**0.67**	1.16
Average	474.2	458.9	444.6	**440.4**
Relative Error	10.16	7.17	4.18	**3.27**
Worst Solution	487	475	472	**451**
STDEV	9.73	11.86	9.39	**5.98**

Table 2. Comparison Using qa194.tsp at Tour 300 (Best solution:9352)

	ACO	ASelite	ASrank	ASwide
Best Solution	11814	11392	9883	**9855**
Relative Error	20.84	17.91	5.37	**5.10**
Average	12134.0	11838.5	10171.9	**10124.4**
Relative Error	22.93	21.00	8.06	**7.63**
Worst Solution	12373	12187	10656	**10463**
STDEV	**161.09**	229.03	227.95	162.61

ratio of the best solution the system found so far and the tour length the elite ant traveled. By adding this weight the system can give the ant agents proper rewards either negative or in positive even if all the elite ants' evaluation were no good. The system can also give extra pheromone to the ant agent that has broken the record of the best solution found so far. We think by this ASwide could do the weighting better than ASrank and other methods and reflects it to the solution's quality. ASwide's pheromone calculation formula $\Delta\tau_{ij}^{\mu}$ is shown in Formula (1).

$$\Delta\tau_{ij}^{\mu} = \begin{cases} (\sigma - \mu)\frac{Q \cdot L^*}{(L_\mu(t))^2} & \text{if } (i,j) \in T^\mu(t) \\ 0 & \text{else} \end{cases} \tag{1}$$

Where μ represents the rank of the elite ants which is ranked by the length of their route, σ as a value added one to the number of the elite ants, L^* as the best length of the route the system found so far, $L_\mu(t)$ as the μ-th elite ant's length of the route at the t-th tour, Q as the maximum value of pheromone a single ant can secrete in a single tour, $T^\mu(t)$ as the μ-th elite ant's route at the t-th tour.

3.1 Computer Experiments

In this section we would have done some experiments focusing on intensification to confirm the effectiveness of ASwide by comparing the results with other ACOs using few TSP problems. For our computer experiments we used eil51.tsp which has 51 cities provided from the "TSPLIB" [20] and qa194.tsp which has 194 cities provided from the "The Traveling Salesman Problem" [19]. For our comparative approach we used ACO, ASelite and ASrank which all of the methods promotes intensification. Defining the number of cities in the TSP as x, parameters for our computer experiments are as follows: number of ant agents m are $x-1$, number of elite ants σ are $x/10$, α and β are both 1, maximum pheromone value Q is 100 and the evaporation rate ρ is 0.005. In this paper we considered 300 tours as a reasonable time to solve the problem which is an early searching period for the ACOs. Each simulation resultes until 300 tours are shown in Table 1 and Table 2. The best solution, worst solution, average, standard deviation (STDEV) are the results from 30 simulations and the relative error is calculated from the best known solutions from each benchmark, 426 for the eil51.tsp and 9352 for the qa194.tsp.

From the two tables Table 1 and Table 2 we can confirm that ASwide outperforms other methods when solving both eil51.tsp and qa194.tsp. This is because we think ASwide was able to give an appropriate reward both negative and positive to the elite ants which lead to the results. In addition other than the best average and the best solution, the standard deviation was in the smaller which means ASwide can output good solutions stably compared to other methods.

From the computer experiments we confirmed that ASwide outperforms other methods with a stable and a good quality of solution, only adding a simple ratio of the maximum pheromone value that a single ant agent can secrete and the ant agent's tour length to the pheromone calculation formula.

4 Control in Diversification

In ACO's searching process ant agents secrete pheromone to the path they traveled to communicate the route with other ant agents. But there is a problem with ACO that in the latter stage of the search it easily falles into a localized solution which makes the system to stop searching. Maintaining diversity is a very important factor for improving the ACO and a lot of studies have been done to maintain diversity mainly by making some ants randomly select cities [13,16,11,10,12]. Selecting the suitable random rate for the system in very difficult since the best random selection rate differs in every problem. So, in this paper we will introduce a method applying random selection after the system converges instead of applying the random selection from the beginning of the search which most of the studies have done.

4.1 Introducing Random Selection

Random selection enables the system to maintain diversity by ant agents randomly selecting their next city to travel. Randomly selecting the next city means not to use heuristic, pheromone information nor the length between the two cities, but to select the next city to visit all in the same probability.

In Nakamichi's study [13] the random selection above is held at the beginning of the search, but in this paper random selection will be introduced only after it satisfies the convergence inequality. We will use the λ-branching factor [4] which examines the deviation of the pheromone in the field for our convergence inequality.

4.2 Lambda-branching Factor

λ-branching factor [4] was introduced by Dorigo to verify whether the system needs to continue the search by checking the convergence to set the termination condition automatically. In this paper we will use λ-branching factor for our convergence inequality to determine the timing to apply random selection. λ-branching factor is a method that calculates the deviation of the pheromone by taking the average number of the cities from city i to city j which exceeds the threshold a user defines.

The formula which $\Lambda(t)$ represents the average number of cities exceeding the threshold in time t is shown in Formula (2).

$$\Lambda(t) = \frac{1}{n} \sum_{1 \leq i \leq n} \sum_{1 \leq j \leq n, j \neq i} \epsilon_{ij}(t) \tag{2}$$

Where n represents the number of cities, ϵ_{ij} as a function determining whether the pheromone from city i and city j exceeds the threshold which is detailed in Formula (3).

$$\epsilon_{ij}(t) = \begin{cases} 1 & \text{if } \tau_{ij}(t) > \lambda(\tau_i^{max}(t) - \tau_i^{min}(t)) + \tau_i^{min}(t) \\ 0 & \text{else} \end{cases} \tag{3}$$

Where τ_{ij} represents the value of pheromone secreted in cities between i and j, λ as a constant on how severely you want to make the convergence that satisfies $(0 \leq \lambda \leq 1)$, $\tau_i^{max}(t)$ as the maximum pheromone value that goes out from city i in time t and $\tau_i^{min}(t)$ as the minimum pheromone value that goes out from city i in time t.

4.3 Sensitivity Experiments Using Random Selection

In this section we will examine how diversity control will affect to the system. We prepared 4 methods for the computer experiments. $\text{ASwide}_{\text{RS}}$ and $\text{ASrank}_{\text{RS}}$ a method which adds the random selection from the beginning to ASwide and ASrank. ASwide_{λ} and ASrank_{λ} which adds random selection only after it satisfies the convergence inequality by λ-branching factor to ASwide and ASrank. To determine the best random selection rate for the 4 methods we did a sensitivity experiment. Since it is impossible the determine the "best" random selection rate we prepared 14 random selection rates to compare, 0.1 to 1.0 at intervals of 0.1 and 1.0 to 5.0 at intervals of 1.0. All the parameters used in this simulation are same as the computer experiment in Section 3 and the parameter λ was set to 0.001. Also to check the best threshold value we changed the threshold value Λ from 2.2 to 4.0 at intervals of 0.2 and used the best value for our comparison.

Table 3. Comparison between the 4 Methods

	$\text{ASrank}_{\text{RS}}$	$\text{ASwide}_{\text{RS}}$	ASrank_{λ}	ASwide_{λ}
Random Selection Rate	0.8	0.6	0.7	0.7
Λ	-	-	3.4	3.8
Best Solution	9649	**9501**	9585	**9495**
Relative Error	3.08	**1.57**	2.49	**1.51**
Average	9797.8	**9724.8**	9843.7	**9822.7**
STDEV	141.36	**138.61**	117.51	**107.09**

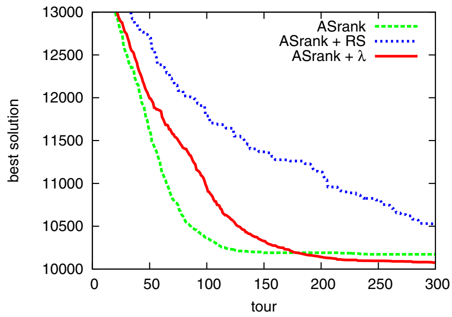

Fig. 1. Best solution found using ASrank

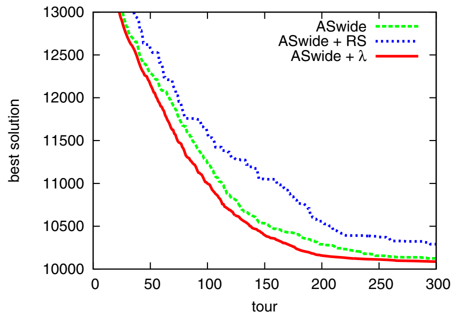

Fig. 2. Best solution found using ASwide

The experiment results for the 4 methods $\text{ASwide}_{\text{RS}}$, $\text{ASrank}_{\text{RS}}$, ASwide_{λ} and ASrank_{λ} using the best paramaters from the sensitivity experiment with 10000 tours is shown in Table 3. The computer experiments results were results by doing 30 simulations using qa194.tsp.

From Table 3 we confirmed that ASwide outperforms other methods not only focusing on intensification by weight control but also with maintaining diversification using random selection. In addition, compared from the results in Section 3 introducing random selection to maintain diversification improves the result of not only ASwide but also ASrank. Also from the same Table we can see that ASwide_{λ} and ASrank_{λ} both has 0.7% as the best average with 3.8 and 3.4 for the threshold of Λ. From the best solution, relative error and average we can confirm that ASwide_{λ} and ASrank_{λ} has better results than $\text{ASwide}_{\text{RS}}$ and $\text{ASrank}_{\text{RS}}$ from Table 3.

Fig. 1 and Fig. 2 shows the result until 300 tours which had the best average and also with the original ASwide and ASrank's average. From the two figures we can confirm that random selection introduced using λ-branching factor converges faster than introducing it at the beginning of the search. From the previous experiment we had confirmed that ASwide_{λ} and ASrank_{λ} had better results. Therefore, we conclude that the timing of random selection using λ-branching factor is an attractive method which intensifies at the beginning at the search and diversifies after it converges, making the system to maximizing the quality of the solution in any period of the search.

In addition we also did the same experiments with eil51.tsp and all 4 methods were able to output the best known solution 426. In other experiments we were able to get the mostly the same property as the experiments using qa194.tsp.

5 Conclusion

In this paper we proposed a method called ASwide which adds the ratio of the maximum pheromone value that a single ant agent can secrete and the ant agents tour length to the pheromone calculation formula. From the computer experiments using TSP we confirmed that ASwide was able to give an appropriate reward to the system. In addition we confirmed ASwide outputs better solutions in large numbers of cities.

In Section 4 we proposed a new way of introducing random selection using λ-branching factor. From the results of ASwide$_\lambda$ and ASrank$_\lambda$ which adds random selection by using λ-branching factor, over half of the results were able to output a solution that has a relative error less than 3.0% and confirmed that it could outperform the Nakamichi's method. In addition we also confirmed that by introducing λ-branching factor it could maximize the quality of the solution in any period of the search.

In the future we would like to introduce random selection using λ-branching factor in other ACO based algorithms such as $\mathcal{MAX}-\mathcal{MIN}$ Ant System [17] and Ant Colony System [7], and reducing some parameters for the system. In addition we would also like to introduce random selection dynamically according to the value of Λ, and use the system to a TSP in a larger number of cities.

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