An Improved Ant Colony Algorithm Based on Dynamic Weight of Pheromone Updating

Guiqing Liu
School of Association of Southeast Asian Nations
Guangxi University for Nationalities
Nanning, China

Dengxu He
School of Science
Guangxi University for Nationalities
Nanning, China

Abstract—To effectively overcome the defects of local and global pheromone updating for the basic Ant Colony Algorithm, this paper has proposed a new improved Ant Colony Algorithm based on the dynamic adaptive weight in the pheromone updating strategy. The proposed algorithm can update pheromone dynamically and adaptively according to the pheromone density and the quality of iteration-best solutions. By the simulation of several typical Traveling Salesman Problems(TSP), the proposed algorithm is clearly better than several other typically Ant Colony Algorithms in the solution quality and convergence speed. The simulation reflects its effectiveness and feasibility to some extent.

Keywords- basic Ant Colony Algorithm; dynamic weight; pheromone updating; TSP

I. INTRODUCTION

The Ant Colony Algorithm is a novel swarm intelligent algorithm by imitating the behavior of natural ants looking for food. Its main characteristics are positive feedback, parallelism and being easy to combine with other algorithms [1,2].It attracts close attention of the scholars at home and abroad in terms of the transfer rules and pheromone updating. M. Dorigo proposed the Ant Colony System (ACS) [3] in 1997, which made improvement in transfer rules and pheromone updating in order to avoid effectively the local optimum, but ACS was single in the pheromone updating. To reduce the misleading role of poor paths by enhancing the optimal paths and weakening the worst paths respectively, the ants can better focus on the optimal paths around. Cordon proposed the Best-Worst Ant System (BWAS) in 2000, however, the global updating only occurs in the optimal and worst paths. It doesn't consider the role of other good paths. Wang Ying etc. proposed an Ant Colony Algorithm [5] which can adaptively change the evaporation parameter of the pheromone in 2002. This algorithm guarantees the convergence rate and also improves the global searching capability. Qingbao Zhu etc. proposed an Ant Colony Algorithm [6] based on the variable and dynamic pheromone updating in 2004. This algorithm uses an unique dynamic local updating strategy to ensure that all ants contribute to the searching paths, but the global updating only occurs in the optimal paths. Peng Zhang proposed an Ant Colony Algorithm [7] based on the path similarity. Non-optimal solution elements of sub-optimal paths which satisfy the given similarity are globally updated besides the basic updating. This algorithm performs better than other basic Ant Colony Algorithms by experiments. The pheromone updating is crucial for Ant Colony Algorithms [8, 9]. All Ant Colony Algorithms above have been improved from different aspects, however, these improved algorithms are not considered the impact of iterative optimal solutions in the pheromone updating. By the analysis above, this paper has proposed a new updating strategy based on the dynamic adaptive weight in the local and global pheromone updating. The aim is speeding up the searching speed in the condition of ensuring the solution quality.

II. THE BASIC IDEA OF THE ANT COLONY ALGORITHM

Let n mean the city amount, m mean the ant amount, d_{ij} mean the distance between the city i and city j, $\eta_{ij}(t)=1/d_{ij}$ mean the expectancy degree when ants will transfer from the city i to city j at time t, α and β mean the importance of pheromone strength τ and heuristic information η respectively when ants will select their paths. At the initial moment of the algorithm, put m ants to n cities randomly. Set the initial pheromone amount of every path ($\tau_{ij}(0)=c$). Each ant will select the next city according to the transferring rules at time t.

In order to improve the performance of the Ant System (AS) [4], M. Dorigo etc. proposed ACS which made three major improvements compared with AS. ACS is the typical Ant Colony Algorithm and its basic idea is shown from the following three aspects.

A. *The Pseudo-random Rate Rule*

To achieve better balance between using prior knowledge and exploring new paths, this rule is selected when the ant k chooses next city j from city i, specifically according to the formula (1) and (2),

$$j=\begin{cases}\arg\max\limits_{s\in allowed_k}\{[\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}\} & if \quad q\le q_0\\ J & else\end{cases} \tag{1}$$

$$p_{ij}^k(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{s\in allowed_k}\tau_{is}^{\alpha}(t)\eta_{is}^{\beta}(t)}, & if \quad j\in allowed_k \\ 0 & else\end{cases} \tag{2}$$

where J is determined by the formula (2), $q\in[0,1]$ is a random number. $q_0\in[0,1]$ is a parameter whether ants choose next city j according to the formula (1). This parameter reflects the relative importance between exploring the new paths and using the effective information.

B. Global Pheromone Updating

When all ants finish their laps, only the globally optimal path is updated in ACS, specifically according to the formula (3),

$$\tau_{ij}(t+n)=(1-\rho)\tau_{ij}(t)+\rho\Delta\tau_{ij}^{gb}, \quad \rho\in(0,\ 1) \tag{3}$$

C. Local Pheromone Updating

In the solving process, only the passed edges are updated online, specifically according to the formula (4),

$$\tau_{ij}(t+1)=\varepsilon\tau_{ij}(t)+\tau_0 \tag{4}$$

where $\varepsilon\in(0,1)$ is a residual factor of local pheromone, τ_0 is a constant.

III. THE MAIN IDEA OF DWACS

On the basis of mainly analyzing of the ACS algorithm, this paper has proposed an improved Ant Colony Algorithm (DWACS) based on the dynamic adaptive weight in the local and global pheromone updating.

A. Dynamical Local Updating of Pheromone

The experiment results show that ACS gets into local optimum easily because of large differences of the pheromone density. To effectively solve this problem, we have corrected the formula (4) of local pheromone updating by dynamical adjusting the residual factor (marked $\varepsilon_{ij}(\mu)$). The new updating strategy can ensure the denser pheromone there is on the paths, the smaller residual factor the paths have, vice versa. The new local updating strategy is shown according to the formula (5),

$$\tau_{ij}(t+1)=\varepsilon_{ij}(\mu)\tau_{ij}(t)+\tau_0 \tag{5}$$

$$\varepsilon_{ij}(\mu)=\begin{cases}0 & \tau_{ij}=0 \\ \varepsilon_{ij}\left(\dfrac{\tau_{i-\min}}{\tau_{ij}}\right)^{\varphi}, & \tau_{ij}>0\end{cases} \tag{6}$$

in the formula (6), $\varphi\in(0,\ 1)$ is an adjustable parameter, $\tau_{i-\min}$ represents the least pheromone density of the optional paths from the city i.

B. Dynamical Gobal Updating of Pheromone

In the AS, all ants are updated globally at the end of a cycle which can't reflect the differences between the good and the bad paths. This updating method could not well guide ants towards the global optimal path, on the contrary, it prevents ants from further searching for better solutions. The positive feedback mechanism isn't well used. Only the best path is updated globally for ACS compared with AS when all ants complete their cycles. Because the difference of pheromone on the ant paths is increasing, it is easy to fall into the local optimum and produce stagnation in ACS. Based on the analysis above, strengthening the positive feedback mechanism can speed up the convergence of the current optimal solution, but easily lead to the premature phenomenon. In this paper, to balance this contradiction, we firstly compare the iteration-best (marked L_{ib}) with the global-best (marked L_{gb}^*) and classify secondly according to the strengths and weaknesses for the L_{ib}. The dynamically adaptive global updating is shown according to the formula (7) and (8),

$$\tau_{ij}(t+n)=(1-\rho)\tau_{ij}(t)+\rho\Delta\tau_{ij} \tag{7}$$

$$\Delta\tau_{ij}=\sum_{k=1}^{x}\omega_k Q/L_k \tag{8}$$

$$\omega_k=\begin{cases}2-(L_k/L_{gb}^*)^p & , if(L_{ib}<L_{gb}^*)and(L_k<L_{gb}^*) \\ (\overline{L}-L_k)/\overline{L}-2 & , if(L_k=L_{ib}=L_{gb}^*)and(\mathrm{T}_{gb}^{same}\geq num) \\ 1-(L_k/\overline{L}) & , if(L_k=L_{ib}=L_{gb}^*)and(\mathrm{T}_{gb}^{same}<num) \\ 0 & , else\end{cases} \tag{9}$$

where x is the path number satisfying the global updating in this cycle. L_k is the path length of ant k. $\overline{L}$ is the average path length of this cycle. L_{ib} is the iteration-best. L_{gb}^* is the global-best until the last iteration. T_{gb}^{same} is the number of the same global-best. num and p are two parameters which are determined respectively by the scale of the problem and the total iteration number. ω_k is the global pheromone updating weight of ant k which is explained from the following two aspects.

If L_{ib} is smaller than L_{gb}^*, this searching effect is better than the last. In order to make full use of current information and search the next solution in the vicinity of L_{ib}, the positive feedback mechanism of better paths are treated differently in this cycle. The pheromone is adaptively globally updated by the weight if the path satisfies the condition of $L_k<L_{gb}^*$. The smaller L_k is the larger ω_k is, on the contrary the smaller. This

updating strategy can make further searching for a better solution around the current optimum solution. Because updated paths are not only the optimal path, this method can effectively prevent the phenomenon from the local optimum.

If L_{ib} and L^*_{gb} are equal, this iteration doesn't change the global-best and this searching effect is bad. If the number of same global-best has reached the given number num, the algorithm is likely to run into the local optimum. We judge the polymerization of ant paths by calculating the differences between L_{ib} and $\overline{L}$. The differences can reflect the overall similarity between ant paths. The greater similarity there is on the paths, the greater polymerization ant paths will be, conversely the smaller. If $T^{same}_{gb} \geq num$, the pheromone on ant paths is cut by the different degrees according to the degree of polymerization. The closer the difference is between the $\overline{L}$ and L_{ib}, the greater polymerization of all ant paths is, vice versa, the smaller. If $T^{same}_{gb} < num$, the pheromone on ant paths is strengthen by different degrees according to the degree of polymerization.

IV. Solving steps for TSP by DWACS

Step1 Initializing parameters. The termination number N_c, the maximum iteration $N_{\max c}$, the adjustable parameter φ, time t, the pheromone increment $\Delta\tau_{ij}(0)$, an adjustable parameter q_0 of the state transition rule, the number of the same global-best T^{same}_{gb} and the parameter num and p. Place m ants on n cities.

Step2 Assign the initial pheromone $\tau_{ij}(0)$ for each path.

Step3 Put the number of the initial city for ant k into the taboo list $tabu_k$ and generate an optional list of cities for each ant.

Step4 If the taboo list isn't full, choose the next city j to visit from the $allowed_k$ according to the formula (1), put the number of city j into the corresponding taboo list , update the local pheromone according to the formula (5), and repeat this step until all ants have finish all cities.

Step5 Calculate the path length of each ant , compare the L_{ib} with L^*_{gb} and update L_{gb} and T^{same}_{gb} if the current L_{ib} is better than the last, otherwise update T^{same}_{gb} .Update the global pheromone according to the formula (7).

Step6 $N_c = N_c + 1$.

Step7 If $N_c = N_{\max c}$, terminate the loop and output the shortest path, otherwise clear all taboo lists and set $t = t + n$, $\Delta\tau_{ij}(t) = 0$, go to Step3.

V. The Example Simulation and Analysis

In order to test the effectiveness and feasibility of DWACS, three typical problems of 20cities, Oliver30 and Eil51 will be selected and simulated from the TSP list. The main parameters are set by experiments, α =1, β =2, ρ =0.1, ε =0.9, c =0.1, q_0 =0.9, Q =100, $m = n$, φ =0.1 , τ_0 =2, num =5, p =2. Programming by Matlab7.0, three algorithms will be run 20 times separately, 200 iterations each time in the case of the same parameters. The comparison results of AS, ACS, reference [11], reference [13] and DWACS are shown in table1. The solution curves are shown respectively in figure 1 and figure 2 by AS, ACS and DWACS for Oliver30 and Eil51. The path graphs of the optimal solution are shown in figure 3 and figure 4 after 12 iterations respectively by DWACS and ACS for Eil51.

TABLE I. THE COMPARISON RESULTS OF DWACS, AS AND ACS FOR SOLVING TSP

TSP	algorithms	the optimal solution	the worst solution	average of the optimal solution	the minimum iteration for the optimal solution
20 cities	AS	24.14	28.03	25.42	59
	ACS	23.82	26.78	24.37	38
	Reference[11]	23.20	26.41	24.28	16
	Reference[13]	23.18	26.10	24.11	15
	DWACS	23.18	26.12	23.92	13
Oliver 30	AS	433.62	458.58	436.56	74
	ACS	426.85	456.73	434.40	56
	Reference[11]	425.22	457.32	434.36	25
	Reference[13]	424.39	456.50	433.09	22
	DWACS	424.20	456.32	432.03	9
Eil51	AS	433.66	482.30	439.58	73
	ACS	429.98	478.89	432.92	58
	Reference[11]	429.32	476.26	430.97	22
	Reference[13]	427.32	478.66	430.60	18
	DWACS	426.68	478.10	429.95	11

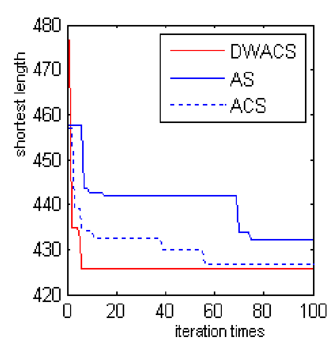

Figure 1. optimal solutions for Oliver30

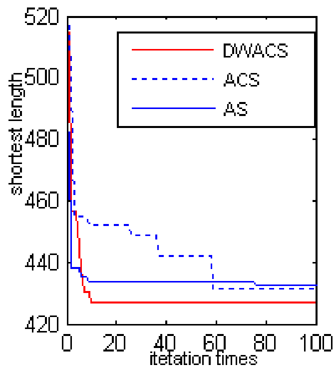

Figure 2. optimal solutions for Eil51

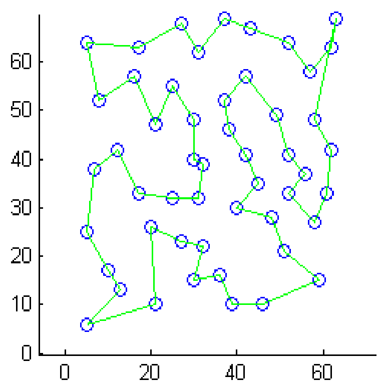

Figure 3. the path of the optimal solution after 12 iterations by DWACS for Eil51

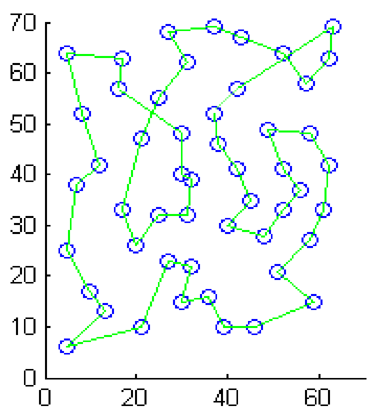

Figure 4. the path of the optimal solution after 12 iterations by ACS for Eil51

VI. CONCLUSION

This paper has introduced a new improved Ant Colony Algorithm for solving TSP based on the dynamic adaptive weight in the pheromone updating strategy [10,12] for the slow convergence and prematurity [14,15]. The simulation results show that the proposed algorithm is clearly better than several other typically Ant Colony Algorithms in the solution quality and convergence speed. From the tabular and graphical illustrations provided in talbe1 above, the optimal solutions by DWACS are 23.18, 424.20 and 426.68, respectively after 13, 9 and 11 iterations for 20cities, Oliver30 and Eil51. Compared with the other four algorithms AS, ACS reference [11] and reference [13], the solution quality and convergence speed has been improved significantly. The path graphs of the optimum solution are shown in figure 3 and figure 4 after 12 iterations respectively by DWACS and ACS for Eil51. The path of figure 3 is the globally optimum solution for Eil51 which can be seen from figure 2. But the path of figure 4 isn't the globally optimum solution because the intersection phenomenon of paths happens. It is likely to fall into the local optimum at present. For ACS, the variant of local pheromone updating is a constant and only the globally optimum path will be updated when all ants have visited all cities. But DWACS can update the pheromone dynamically and adaptively according to the pheromone density and the quality of iteration-best solutions.

The research on the Ant Colony Optimization is still in the theoretical study and simulation steps and our work presented in this paper is also rather preliminary. Much work remains to be done, e.g., how to test further the effectiveness and feasibility of the proposed algorithm by more typical examples, how to determine the relationship between the parameters, how to solve the specific issues by the proposed algorithm, how to compare the performance of the compared algorithms in more fair and reasonable way, etc. These are our future research work.

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