An improved ant colony optimization algorithm with negative feedback

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Abstract. To improve the ability for solving complex problems, an improved ant colony optimization algorithm with negative feedback strategy was proposed. Based on an inspired matrix, the new negative feedback strategy was designed to change the basic ant colony algorithm pheromone matrix to the opposite damper matrix. That was, even more dampers occurred on the shorter path found by the colony, reducing the probability that each section on the path was selected in the next time. Because of the enlightening matrix, the probability of more short circuit segments on the path was still greater in the process of optimization again, while the probability of longer path selected was decreased which was not easy to be selected in the next process. It was suitable to do further optimize. Through the experiment of TSP, it showed that the ant colony algorithm with combining the damper matrix and the original pheromone matrix can improve the searching ability obviously.

Keywords: Algorithm, ant colony optimization, negative feedback.

1. Introduction
Ant colony optimization (ACO) algorithm [1] proposed in 1992 is inspired by the process of ants searching for food and have been applied to solve complex problems [3,4]. Some research find that ants are unable to obtain information about their surroundings through their eyes, which release a special hormone in their body while search for food, and other ants can detect the chosen path by sensing the hormone. The route that ants searching for food is random. Due to the different length of the route, ants spend a shorter time on the shorter path, and the number of foods is more correspondingly. So, they can leave more hormones on the shorter path. The longer path is just the opposite. Other ants in the process of choosing path will get a greater probability to choose the path with higher hormone concentration. After a period, the hormone concentration of the shorter path will increase which make most ants select this path. Such a group search way makes the whole ant group can find a better route. The key to the ant colony algorithm optimization lies in the determination of the probability transfer formula. Assuming that the position of the ant is now at point i, the probability that the ant moves from point i to j is $p_{ij}$. 

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In formula 1, $m$ is the inspired matrix. Different optimization problems need to set different enlightening matrices. $n$ is pheromone matrix. The updated formula for the pheromone matrix is formula 2. $w$ is pheromone volatile factor. Too small volatile coefficient and too much have a great influence on the optimization process of ACO. $\Delta n_{ij}(t)$ indicates the increase of pheromones between $i$ and $j$ at the $t$-th iteration. $a$ is enlightening factor. The value of $a$ illustrates the extent to which the inspired matrix dominates in the optimization process. $b$ is pheromone factor. The size of the $b$ illustrates the extent to which the pheromone matrix dominates in the optimization process. A larger $b$ indicates that the pheromone matrix shows a larger dominant during optimization. $c_1$ is the collection of sites where ants have not yet reached.

2. The Proposed algorithm

2.1. The thought of a negative feedback strategy with damping

Ant colony optimization algorithms are very robust, with good search performance and are easy to be integrated with other heuristic algorithms. However, there are also some shortcomings: it has a complex calculation process; its convergence speed is slow and easy to fall into the local optimal solution. XUE [4] proposes a super-inspired ACO with negative feedback applied to AGV planning. Based on the generation of the positive feedback pheromone matrix of ACO, the path with the smallest fitness in each iteration is added a punishment, while the path with the largest fitness value is added a motivation, then a new pheromone matrix jointly. The above pheromone update mechanism can accelerate the convergence. Bai [5] provides a maximum and minimum negative feedback ant colony optimization algorithm applied to the robot path search, which makes full use of the optimal worst path of the colony. It takes the optimal solution to produce a pheromone matrix with positive feedback and uses the worst solution to build a pheromone matrix with negative feedback. Using the above pheromone update strategy, the application of two pheromone matrixes can expand the population search range and avoid falling into local optimal solutions partly.

In the related study, the negative feedback strategies are to utilize the worst solution in the ant colony and propose improvement methods. The basic ACO algorithm pheromone updating is to produce the corresponding positive feedback pheromones according to the fitness. In this process, the possible unfavorable sections in the optimal solution path are ignored, which are retained during the next iteration due to the greater probability of pheromone generation with positive feedback.

Based on this consideration, we propose a more thorough negative feedback strategy that it generates a damper matrix, produces more damper for the solution with a better fitness, and reduces the probability of being selected in the next iteration of the optimal solution segments properly.

Due to the role of enlightening matrix, the better section in optimal solution will still be selected with high probability. Therefore, the unfavorable section in optimal solution will further reduce the probability of being selected.

2.2. The updating model design

Update the damper matrix for applying the new negative feedback strategy as formula (3):

$$n_{ij}(t+1) = (1-w) \times n_{ij}(t) - \Delta n_{ij}(t)$$  \hspace{1cm} (3)
The meaning of each symbol in the formula is the same as formula 2. To fully reflect the role of the new negative feedback strategy, two improved models based on the basic ant colony optimization algorithms are designed:

(1) The ant colony optimization algorithm with only the damper matrix (DACO). That is, the original pheromone matrix is replaced by a damper matrix. Other parameters and iterative mode are unchanged.

(2) Built a dual population structure. It divides the ants into two groups during searching. The first group is adjusted by the pheromone matrix in basic ant colony algorithm and another group is according to the damper matrix. The optimal solutions of the two populations are evaluated and integrated, taking a part of the preferred path involved in the update of the pheromone and damper matrices. This improved algorithm is named ant colony optimization algorithm with dual matrix groups (ACODMG).

3. Experiment and result
To verify the effectiveness of the improvement, we select five test examples: dantzig42, st70, eil101, bier127 and pr144, which are from the library of the standard test functions TSPLIB. All algorithms are programmed by MATLAB 2018a and run on the i5 CPU 2.50 GHz processor, 4 GB RAM, 64-bit Win10 system platform. In the experiment, each algorithm runs 20 times independently and the results are analysed via the average, optimal, worst, standard deviation (St.d), and improvement rate(P).

3.1. The effect of damper matrix test
In this experiment, the effect of damper matrix is tested from the comparison between ACO and DACO. The results with damper matrix are shown in Table 1. As shown from the average value in Table 1, the ant colony algorithm with the damper matrix outperforms the ACO only on the problem of dantzig42, eil101. The test results of the example st70, bier127, pr144 average are inferior to the basic ant colony algorithm. In general, the ability of DACO algorithm gradually decreases with the increase of the number of cities. As shown from the variance column in Table 1, with the number of cities increases, the DACO has a larger St.d value than the ACO. It is shown that the DACO algorithm is less stable than ACO algorithm for large-scale TSP problem.

Figure 1 shows the convergence of the basic ACO and DACO. It can be seen from the figure that the convergence speed of DACO on the examples dantzig42, eil101, bier127 and pr144 are litter slower than ACO, and the convergence rate of the examples st70 is basically the same. That indicates that DACO is worse than the ACO in small scale problems. In conclusion, the damper matrix strategy is more suitable for local search, and the small-scale problem. With the increase of the problem scale, only the damper matrix will reduce the search ability and stability.

| No.    | Alg. | Best | AVG  | Min  | Max  | St. d | P /% |
|--------|------|------|------|------|------|-------|------|
| dantzig42 | ACO  | 699  | 722.6| 703.4| 745.6| 12.83 |      |
|         | DACO | 712.9| 694.9| 742.8| 14.12| 1.34  |      |
| st70    | ACO  | 675  | 720.3| 703.9| 747  | 13.57 |      |
|         | DACO | 725.2| 710.4| 748.6| 11.68| -0.68 |      |
| eil101  | ACO  | 629  | 698.2| 672  | 709.4| 5.75  |      |
|         | DACO | 696.0| 682.4| 714.5| 8.55 | 0.31  |      |
| bier127 | ACO  | 118282| 125745| 124090| 126830| 782.4 |      |
|         | DACO | 130149| 126822| 133451| 2847 | -3.50 |      |
| pr144   | ACO  | 58537| 59696| 59088| 60183| 345.6 |      |
|         | DACO | 61462| 60172| 63392| 894.5| -2.96 |      |
3.2. Dual colonies with damper matrix and origin matrix test

This experiment is to analyze the effect of the dual colonies with damper matrix and origin matrix to test the searching ability of the ACODMG. The results of ACODMG and ACO test are shown in Table 2. It can be seen from the average, best and worst in Table 2 that ACODMG outperforms ACO in the five test examples. From the St.d in Table 2, the value of ACODMG is less than ACO except eil101, which proves that the searching ability and stability of ACODMG is better than the basic ant colony algorithm.

Figure 1. Convergence results of test 1
Figure 2 shows the convergence of ACODMG and ACO. It can be seen from the curves that the convergence speed of ACODMG is faster than ACO obviously, indicating that the convergence of ACODMG is better than ACO. In summary, the overall performance of ACODMG is better than ACO algorithm and dual colonies with damper matrix and origin matrix strategy can improve the search ability of the ants effectively.

Figure 2. Convergence results of test 2
Table 2. Results of test 2

| No.   | Alg.    | Best  | AVG   | Min   | Max   | St. d | P /%  |
|-------|---------|-------|-------|-------|-------|-------|-------|
| dantzig42 | ACO     | 699   | 722.6 | 703.4 | 745.6 | 12.83 |
|        | ACODMG  | 695.3 | 688.1 | 704.5 | 5.927 | 3.78  |
| st70  | ACO     | 675   | 720.3 | 703.9 | 747.0 | 13.57 |
|        | ACODMG  | 704.3 | 690.5 | 715.4 | 6.697 | 2.22  |
| ceil101 | ACO     | 629   | 698.2 | 672   | 709.4 | 5.75  |
|        | ACODMG  | 680.3 | 667.2 | 689.4 | 9.72  | 2.56  |
| bier127 | ACO     | 118282| 125745| 124090| 126830| 782.4 |
|        | ACODMG  | 123803| 122721| 125660| 752.6 | 1.54  |
| pr144  | ACO     | 58537 | 59696 | 59088 | 60183 | 345.6 |
|        | ACODMG  | 59436 | 59047 | 59727 | 224.6 | 0.44  |

4. Conclusions

Based on the basic ant colony algorithm, a new negative feedback strategy is proposed to improve the searching ability of the swarm. A damper matrix is introduced to the updating model of pheromone. To verify the effect of the negative feedback strategy, five benchmark problems of TSP are selected. From the experiment result, it proves that the damper matrix with negative feedback is more suitable for local search and small-scale problem search in the population search process. The mixed damper matrix and pheromone matrix with dual population can achieve a better search performance.

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