Route inspection optimization based on improved ant colony Optimization

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Abstract

Aiming at the problems of slow convergence speed, unstable convergence performance, lowly search efficiency and easy to fall into local optimum of traditional ant colony Optimization in path planning, in this paper, an improved ant colony Optimization is proposed. First, according to the requirements of different systems for accuracy and rapidity, choose different security thresholds; secondly, according to the selected threshold, update pheromones selectively and accelerate the speed of convergence; last, to further accelerate the iteration speed, in the process of route generation, the route beyond the security threshold is stopped. Comparing with other Optimizations through experimental simulation, the feasibility, effectiveness and superiority of the improved Optimization are verified.

Keywords: Security domain values; Patrol system, Eliminate a path; route optimization; Ant Colony Optimization

I. Introduction

Path planning for UAV patrol inspection is a hotspot in various research fields, and it is also the control basis of UAV in engineering application. The UAV is required to be based on certain criteria (e.g. the shortest time, the shortest distance, the lowest energy consumption, etc.). It can search an optimal or near optimal security path in a given working environment. Ant colony Optimization has been proved to have the characteristics of distributed computing, positive feedback of information, strong global optimization ability, easy integration with other bionic Optimizations and so on. However, there are still some problems in the patrol optimization problem, such as slow convergence speed, unstable convergence performance, low search efficiency and easy to fall into local optimum. In order to solve the above problems, this study starts with the principles of ant path selection and pheromone updating, and the basic ant colony Optimization is improved as follows.

In order to reduce the initial time consumption, speed up the search and expand the global search ability, a new comparison principle is designed and improved based on the comprehensive consideration of the length relationship of each path. To preserve the information advantage of the optimal path for each cycle, increase the speed of path selection and improve the convergence performance of the Optimization, the ant route selection is improved by introducing a renewal strategy combining local and global security domain values and pheromones. Through the above improvements, the time of each iteration can be increased without local optimal solution, thus accelerating the convergence speed, and finding the optimal path quickly on the basis of ensuring accuracy.

II. Ant colony Optimization analysis

2.1 Basic Principles of Ant Colony Optimizations

Ant colony Optimization simulates the foraging behavior of ants. It releases pheromones in the search for food, at the same time, it can sense the pheromone concentration left by the front ants in the path to guide its movement. As a result, a positive feedback phenomenon is gradually formed: the shorter the

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path, the higher the residual pheromone concentration; the shorter the path , the higher the residual pheromone concentration; the more ants pass through the path , the higher the pheromone concentration on the path, the more likely the latter ants will choose this path. Ants find food in this way of communication. Two key parts of ant colony Optimization are path selection probability and pheromone updating, and they determine the speed and quality of the solution of ant colony Optimization.

2.1.1 Transition probability

At the beginning of the Optimization, place m ants randomly in n cities. At the same time, the first element of each ant's taboo table is set to the current city in which it is located. At the initial moment, the pheromones on each path are equal. Let C be a smaller constant.

$$\tau_{ij}(0) = c \tag{1}$$

Then each ant chooses the next city independently according to the pheromone quantity and heuristic information (the distance between the two cities) on each path. The state transition rules used in ant systems are called stochastic proportional rules. At time t, the transition probability of ant K choosing City J in city I is as follows:

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

$$allowed_k = \{1, 2\ldots\ldots \text{ n}\} —— tabu_k$$

This means that the ants are allowed to choose the next city. The list records the cities that Ant K is currently traveling through. When all n cities join in, ant K completes a tour. In formula (2) η_{ij} usually takes the reciprocal of the distance between city I and city J. Alpha and beta represent the relative importance of pheromones and heuristic factors respectively.

2.1.2 Theromone updates

When all ants complete a tour, the pheromones on each path are updated according to the following formula.

$$\tau_{ij}(t+n) = \rho\ \tau_{ij}(t) + \Delta\tau_{ij}\Delta\tau_{ij} = \sum_{k=1}^{m}\Delta\tau_{ij}^{k} \tag{3}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{4}$$

Among them, (0 < ρ < l) denotes the information residue coefficient and 1-ρ denotes the Volatilization Coefficient of pheromone.

In formula(5) “in” means “if antkpassesbyedgeijinthiscycle”:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{d_{ij}}, in \\ 0, else \end{cases} \tag{5}$$

In the ant-quantity system model:

$$\Delta\tau_{ij}^{k} = \begin{cases} Q, in \\ 0, else \end{cases} \tag{6}$$

In the ant-cycle system model:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, \quad in \\ 0, else \end{cases} \tag{7}$$

2.2 Improvement of Ant Colony Optimization

In order to reduce the initial time consumption of path search, speed up the search and expand the global search capability, considering the length relationship of each path synthetically, a new comparison principle is designed and improved on this basis. To preserve the information advantage of the optimal pathforeach cycle, increase the speed of path selection and improve the convergence performance of the Optimization. The ant route selection is improved by introducing a renewal strategy combining local and global security domain values and pheromones.

(1) Find a larger value that is unlikely to be the optimal path. Select a finite number of destinations at random from all destinations, find

the sum of the roundtrip length from each destination to all other destinations, and take the average value as $L_{\max}$.

(2) Set different suit values (1/2 as the benchmark suit 1,1/4 as the benchmark suit 2, and 1/6 as the benchmark suit3). There are different suit values for the same system.

(3)In the process of the ant's search, when the length of the route that the ant has visited reaches the base value of suit, but has not visited all the destinations, the ant will not continue to visit other destinations. (The length has reached the baseline value of suit, but not all cities have been visited.) The pheromone on the "phase-out path" is not updated at the end of each iteration when the pheromone is updated, which is included in the selection of the average length and the optimal path.

Through the above improvements, the time of each iteration can be reduced without local optimal solution. Thus, the convergence speed can be accelerated, and the optimal path can be found quickly on the basis of ensuring accuracy. The flow chart is shown in figure 1.

III. Case study

3.1 Brief Introduction of Examples

Unmanned aerial vehicle inspection technology has many applications such as multi-angle observation of high-voltage transmission lines at close range in the air, and multi-angle image video data captured by hovering. It can detect and check the defects of transmission lines and hidden dangers of channels intuitively, comprehensively and accurately，and can obtain the best field information under complex terrain and bad weather conditions. It can effectively make up for the shortcomings of traditional patrol, such as blind corners, real-time monitoring and not taking into account all terrain, thus improving the work efficiency of the front-line patrol personnel.

However, how can we quickly select the best path, achieve safe obstacle avoidance and complete the task? This involves UAV patrol path planning. This problem has the characteristics of high complexity, large searching space for feasible solutions and non-unique search results. There are still great challenges in solving this problem effectively. But Ant colony Optimization has been proved to have the characteristics of distributed computing, positive information feedback, strong global optimization ability and easy integration with other bionic Optimizations. In this case, the routes to be inspected are expressed in three-dimensional coordinates，and Ant colony Optimization is simulated in three-dimensional coordinate system.

3.2 Comparison and Analysis of Example Results

Taking 31 cities and 50 ants as examples, the basic ant colony Optimization and the improved ant colony Optimization are simulated in Matlab, and the results are compared.

3.2.1Comparison of Basic and Improved Optimizations

In terms of convergence results, By comparing the original Optimization with the improved ant colony Optimization after a certain number of iterations, it is found that after the same number of iterations.Iteration route results are shown in figure 2 and figure 3.A shorter route is obtained. Compared with the original results, the shortest distance between suit1, suit1 is shortened by 14.12%. Route length comparison results are shown in table 2.The city order of the best path is shown in table 1.

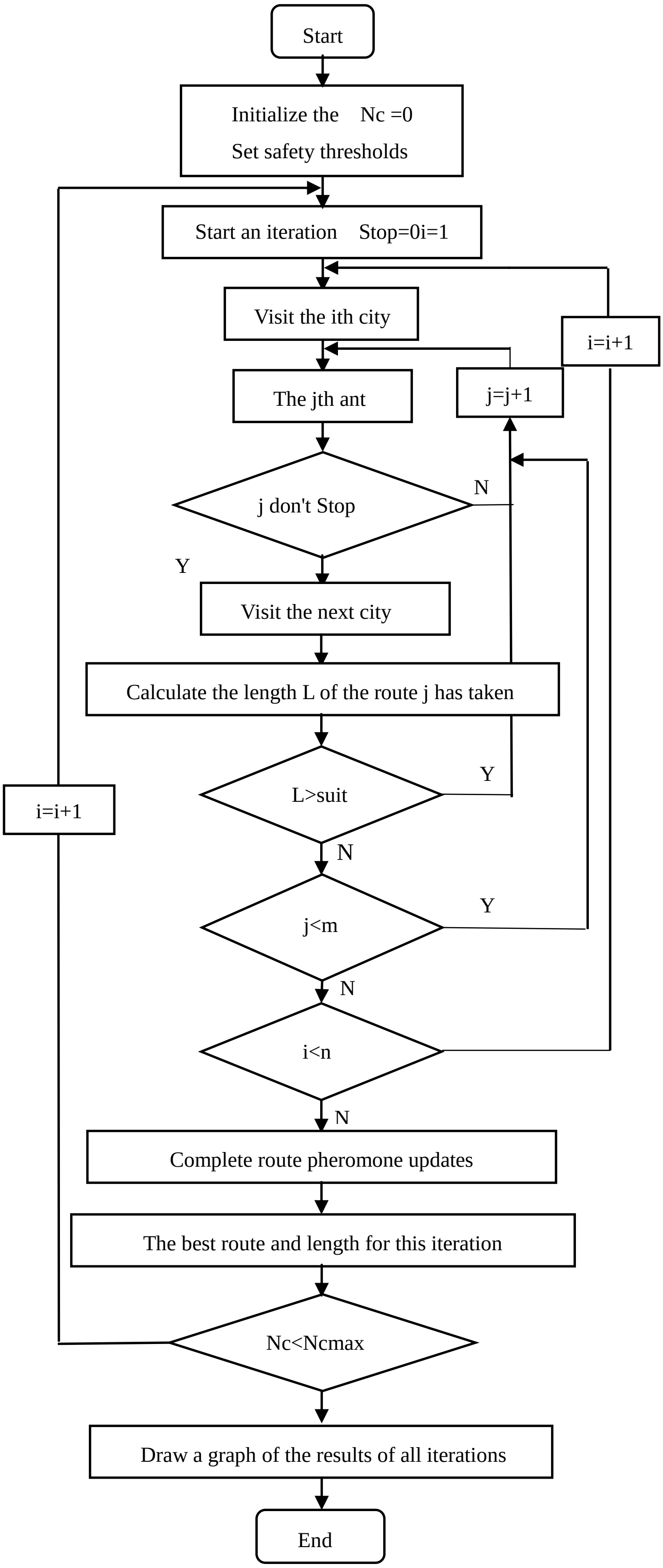

Figure 1 flow chart of improved ant colony algorithm

Table 1 optimal path

The simulation test	Patrol destination order				
The original results	1	31	29	13	7
	6	5	16	23	2
	9	10	4	3	26
	27	30	20	21	19
	17	18	22	28	11
	24	8	12	14	15
Optimization results suit1	9	10	2	5	6
	7	13	23	16	4
	3	26	31	29	1
	15	14	12	30	27
	21	25	19	8	17
	18	22	24	28	11

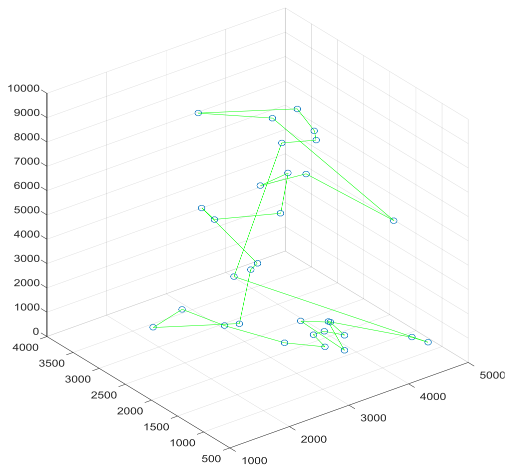

Figure 2 original best route of circuit inspection

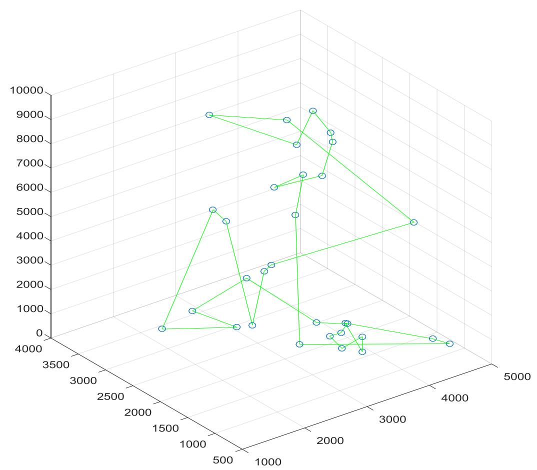

Figure 3 best route for route inspection (suit1)

Table 2 the shortest distance

The simulation test	The shortest distance/km
The original results	3.54E+04
Optimization results suit1	3.04E+04

In terms of iteration time, when the safety threshold is increased, the route generation timedecreases. Since only pheromones on non-obsolete paths need to be updated, the convergence speed is greatly accelerated. It can be seen that under the same number of iterations, the selection of safety threshold is proportional to the iteration time.Iteration rates are shown in figures 4 and 5.

3.2.2 Comparison of ImprovedOptimizations

By comparing the optimal route of different suit values of the improved ant colony Optimization after a certain number of iterations, it is found that after the same number of iterations, the suit values are different and the iteration results are different. Suit1 and suit2 reduced the shortest distance by 1.64% over the same number of iterations. Suit1 and suit3 reduced the shortest distance by 1.97% over the same number of iterations. Suit2 and suit3 reduced the shortest distance by 0.33% over the same number of iterations.

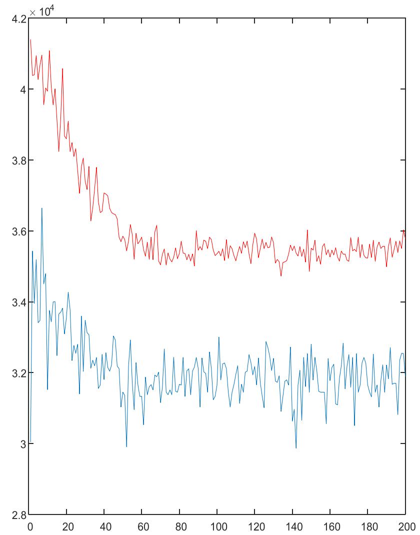

Figure4 improved average distance and minimum distance (suit1)

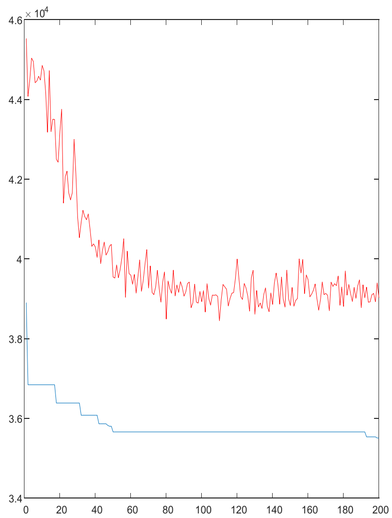

Figure 5 original average distance and shortest distance

Table 3 minimum distance

The simulation test	The shortest distance/km
Line inspection optimization results suit1	3.04E+04
Line inspection original results suit2	2.99E+04
Line inspection original results suit3	2.98E+04

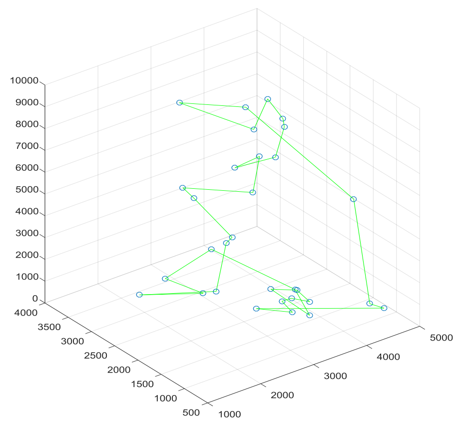

Figure 6 the best route for circuit

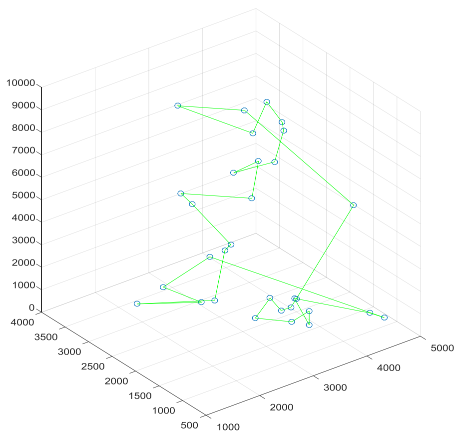

Figure 7 the best route for circuit

Table 4 best path

The simulation test	Patrol destination order				
Optimization results suit1	9	10	2	5	6
	7	13	23	16	4
	3	26	31	29	1
	15	14	12	30	27
	21	25	19	8	17
	18	22	24	28	11
Optimization results suit2	9	10	2	5	6
	7	16	23	28	4
	3	26	31	29	13
	1	15	14	12	30
	27	20	21	25	19
	8	22	18	17	24
Optimization results suit3	13	7	2	5	6
	23	16	9	10	4
	3	26	31	29	1
	15	14	12	30	27
	20	21	25	19	8
	24	17	18	22	28

In terms of iteration time, the improved ant colony Optimization with different domain values takes different time to reduce route generation due to different domain values. When the pheromone on the non-elimination pathis updated, the convergence rate of different domain values is also different. It can be seen that under the same number of iterations, the selection of safety threshold is proportional to the iteration time. Iteration rates are shown in figures 8 and 9.Route length comparison results are shown in table 3.The city order of the best path is shown in table 4.Iteration route results are shown in figure 6 and figure 7.

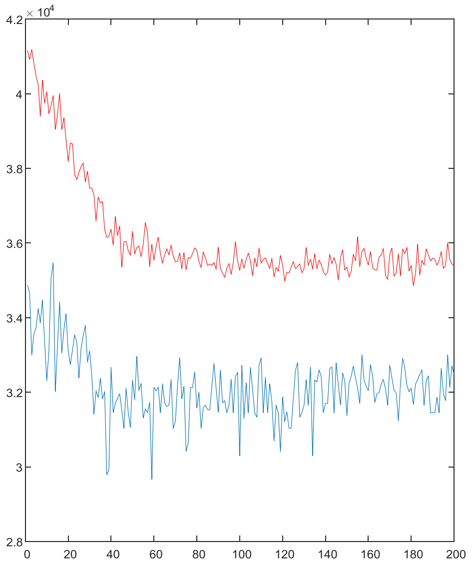

Figure 9 improved average distance and minimum distance (suit3)

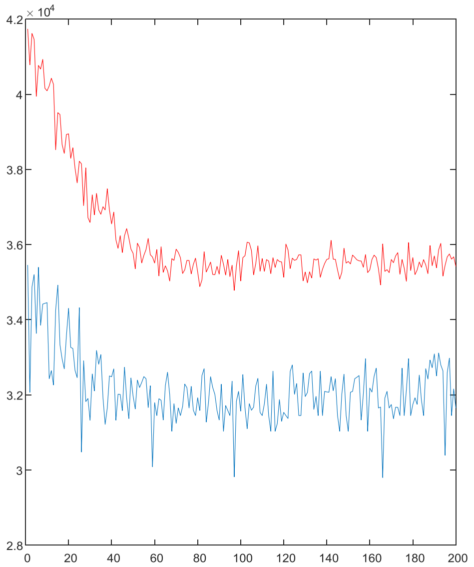

Figure 8 improved average distance and minimum distance (suit2)

IV. Conclusion

In this paper, the ant colony Optimization is improved. The parameters of ant colony Optimization can be set according to different requirements of different systems. As different systems pursue different goals, the appropriate security domain value can be selected according to the actual situation. If the system requires high speed, without affecting the authenticity of the results, it reduces the range of security limits and greatly speeds up the iteration time. If the accuracy of the system is high, the range of security domain values can be increased appropriately. The suit should be selected as a high reference value to improve the accuracy of the search results.

In this way, the improved Optimization can greatly reduce the initial time consumption of UAV patrol path search, accelerate UAV search speed and expand the ability of global optimization. By considering the length relationship of each path synthetically,design new principles of comparison,and on this basis, improvement is made. To preserve the information advantage of the optimal path for each cycle,it increases the speed of path selection and improves the convergence performance of the Optimization. The ant route selection is improved by introducing a renewal strategy combining local and global security domain values and pheromones. Through the above improvements, the time of each iteration can be increased without local optimal solution. In this way, the convergence speed is accelerated. It can quickly find the optimal path on the basis of ensuring accuracy. It greatly improves the efficiency of UAV inspection.

Although the improved ant colony Optimization accelerates the convergence Speed to some extent. However, there is still a problem that the optimal number of iterations cannot be determined when the iteration results have reached the engineering requirements and objectives. So that the improved Optimization cannot accelerate the convergence speed at the same time, by choosing a suitable number of iterations further shortening the solving time. In the future, we will study and learn from this deficiency, further improve and optimize this Optimization and continue to explore and apply it in more fields.

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