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UAV Path Planning Based on an Improved Ant Colony Algorithm

Hui Song[1], Minghan Jia[2], Yihang Lian[1], Yijing Fan[1], Keshan Liang[2]*

[1]College of Military Basic Education, National University of Defense Technology, Changsha 410000, Hunan Province, China

[2]College of Intelligence Science and Technology, National University of Defense Technology, Changsha 410073, Hunan Province, China

Corresponding author: Keshan Liang, liangkeshan@nudt.edu.cn

Abstract: Reviews and experimental verification have found that existing solution methods can be used to solve UAV path planning problems, but each approximate solution has its own advantages and disadvantages. For example, ant colony algorithm easily falls into the local optimum in the process of realizing path planning. In order to prevent too low pheromones on the longer path and too high pheromones in the shorter path, the upper and lower limits of pheromones as well as their volatile factors are set to avoid falling into the local optimum. Secondly, multi-heuristic factors are introduced, and the overall length of the path serves as an adaptive heuristic function factor that determines the probability of state transition, which affects the probability of ants choosing the corresponding path. The experimental results show that the path length planned by the improved algorithm is 93.6% of the original algorithm, and the optimal path length variance is only 14.22% of the original algorithm. The improved ant colony algorithm shortens the optimal path length and solves the UAV path planning problem in terms of local optima. At the same time, multiple enlightening factors are introduced to increase the suitability of UAV for complex environments and improve the performance of UAV.

Keywords: UAV; Path planning; Ant colony algorithm

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1. Introduction

With the advancement of modern science and technology, the tasks that UAV can perform are continually increasing [1]. For example, UAV can undertake the task of transporting emergency materials, such as medical rescue kits. In order to better apply UAV to practice, scholars have done a lot of research on UAV path planning and have proposed numerous algorithms to increase the efficiency of path planning. The algorithms include artificial potential field method [2], A* algorithm [3], ant colony algorithm [4], genetic algorithm [5], particle swarm algorithm [6], bat algorithm [7], simulated annealing algorithm [8], fast expanding random tree algorithm [9], D* algorithm [10], artificial fish swarm algorithm [11], locust algorithm [12], firefly algorithm, and so on [13]. Genetic algorithm uses codes to represent the solution of the problem. Following the operation of the codes such as selection, crossover, mutation, and so on, the fitness and function values are used as the evolutionary assessment basis, and finally the optimal population, that is the solution to the problems [14], is obtained. Ant colony algorithm and genetic algorithm operate similarly when selecting the optimal solution. The ant colony algorithm seeks the optimal solution through iteration, but it has no crossover and mutation operations when searching for the optimal solution; therefore, the solution is simpler.

Ant colony algorithm is a heuristic search algorithm, which was proposed by DRIGO in the early 1990s by simulating the foraging behavior of ants in the environment [15]. The characteristics of ant colony algorithm include positive feedback, parallel computing, good robustness, and so on [16]. Many scholars have applied the ant colony algorithm to path planning and have achieved successful results. The ant colony algorithm can be used to solve discrete optimization problems since it has a wide search range and a fast convergence speed [17]. However, due to the positive feedback characteristics of the algorithm, pheromones may accumulate on local paths, thus leading to problems, such as falling into the local optimum [18,19]. The ant colony algorithm takes the distance between the current position and the next position as heuristic information. When faced with obstacles, there are still several problems in avoiding them in advance [16]. Hence, many scholars have been working to improve the flaws in the algorithm. With the deepening of research and the characteristics of path planning, the focus is on how to improve the search efficiency of the algorithm [20].

Path smoothing can reduce the flight risk of UAV. Huang and other researchers have introduced the degree smoothing method to generate a smooth path [21]. As the distance between the current node and several neighboring nodes is equal, inspiration cannot play a role in the selection of the next node, so it has been proposed that the shortest distance between the starting point and the target point should be taken as the guide for path search [22]; by calculating the reciprocal of the weighted sum of the distance between the current node and the next node to be left as well as the vertical distance from the next node to the shortest path, the search of the algorithm can be accelerated. Sun Gongwu and others have designed an adaptive heuristic function that takes into account the distance between the current grid and the grid to be walked as well as the distance between the grid to be walked and the target grid to select better nodes, but the adaptive heuristic function only considers the current grid as well as the distance between the grid to be walked and the target grid [23]. Based on the concept of multi-scale path search, Huang Xin and others have proposed an improved guidance factor, which takes into account the distance from the node to the target point and the distance from the node to the starting point; in addition, the flight of the UAV is determined by the height of the terrain but only partially considers the guidance function of the heuristic function [24]. In regard to path smoothing, Li Li and others have introduced the number of turns into the heuristic function, which influenced the improved heuristic function; they also improved the pheromone updating mechanism and the path smoothness, providing good convergence and global searching ability; however, the transition probability is only affected by pheromone and heuristic function, and the iteration times are large, which makes it easy to fall into the local optimum [25].

Huang and other researchers introduced the K-degree smoothing method to the path smoothing problem [21], while Li Li and other researchers did not only consider the smoothing problem in the heuristic function, but also the number of turns of the path in the heuristic function [25]. Tao and others improved the transition probability to enhance the convergence speed of the algorithm, thus improving the performance of the algorithm; however, the obtained path length is not the shortest [22]. An adaptive heuristic function has been designed in a study [23] according to the distance between the current grid and the target grid, but it only considered the path length, whereas the heuristic function of in the study conducted by Li Li [25] considered many heuristic factors. In another study [24], the leading factor of nodes was introduced into the transition probability; however, it did not improve the inspiring factor. Li Li and other researchers considered the number of turns and the smoothness of the path while making the path as short as possible, and they proposed a multi-heuristic ant colony algorithm that takes the distance correction function, safety function, and smoothness function into account [25]. When ants look for the best path, the path is chosen based on multiple heuristic factors.

In a study [25], the path factor only considers the distance from each adjacent grid of the current grid to the target grid but does not consider the integrity of the path. In this study, under the influence of multiple heuristic factors and considering the integrity of the path, the guiding factor mentioned in the study [24] conducted by Huang Xin is introduced into the transition probability, and the heuristic function, pheromone, and pheromone volatilization factor are processed to increase the accuracy of the algorithm. The results reveal that this method improves the efficiency of path search, reduces the number of iterations, and optimizes the path length.

2. Environmental modeling

In this study, a two-dimensional grid method [26] is used to model the path environment. Taking into account the safety of drones, the distance between the drone's path and the grid obstacles is set to be half of the grid length. Each grid has eight adjacent grids [27] that can be walked, as shown in **Figure 1**. $dis(i,j)$ represents the distance from the current grid i to its j-th adjacent grid.

$$dis(i,j) = \begin{cases} 1, & When\ ants\ go\ 2,4,6,8, \\ \sqrt{2}, & \text{When ants go } 1,3,5,7. \end{cases} \tag{1}$$

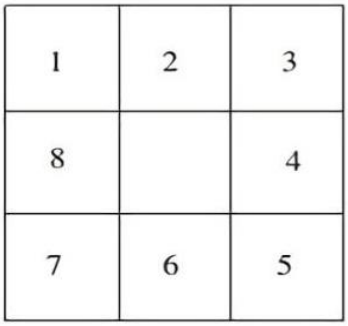

Figure 1. Eight adjacent grids, with the middle grid as the current grid

The process of ants selecting the next grid is discussed below.

(1) **Step 1**: Determine whether there is an obstacle in grid 1. If there is an obstacle, as shown in **Figure 2**, then $dis(i,j) = \infty$; otherwise, proceed to **Step 2**.

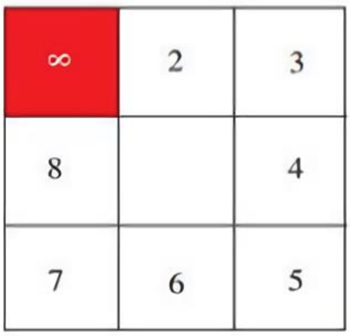

Figure 2. Grid 1 is an obstacle and the distance from the current grid to grid 1 is infinite in this situation

(2) **Step 2:** Determine whether the adjacent grid 1 is out of bounds; that is, beyond the range of the terrain. If it is out of bounds, as shown in **Figure 3**, grids 1, 2, 3, 7, and 8 are out of bounds; otherwise, $dis(i,j) = \infty$, proceed to **Step 3**.

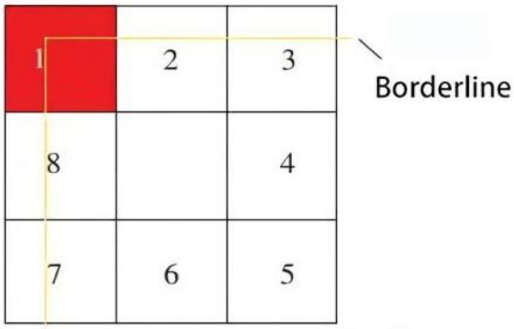

Figure 3. Part of the grids on the boundary

(3) **Step 3:** Determine whether the adjacent grid 1 is a grid in an even direction or in an odd direction. If it is in an even direction, $dis(i,j) = 1$; otherwise, proceed to **Step 4**.
(4) **Step 4:** Determine whether one or both of the two even-numbered grids adjacent to the odd-numbered direction grid are obstacle grids. If yes, $dis(i,j) = \infty$; otherwise, $dis(i,j) = \sqrt{2}$.

3. Multiple heuristics

According to Li Li and others [25], based on the path planning requiring a short path length, only a few turns, a smooth path, and the adaptability to the environment, three factors should be considered: distance correction function, safety function, and smoothness function. The distance correction function increases the distance difference between the adjacent grids of the current grid and the target grid. When selecting the next grid to be walked on, increasing the path length is an inspiration to the ants. The safety function has a certain guiding effect on the turning of the UAV in flight. When the current direction of the UAV is the same as that of the previous moment, the safety function value of this direction will be larger. The smoothness function will inspire the drone to choose a gentle path.

3.1. Distance correction function

$$\varphi(i,j) = \frac{\text{dis }(i)_{max} - \text{dis}(i,j))}{\text{dis }(i)_{max} - \text{dis }(i)_{min} + 0.001} \times \gamma_1 \times g_1 \quad (2)$$

$\text{dis}(i)_{max}$is the maximum distance between the adjacent grids of the i-th grid and the center of the target grid; $\text{dis}(i)_{min}$ is the adjacent grids of the i-th grid the minimum distance between the center of the grid and the target grid; $\varphi(i,j)$ is the corrected distance between the center of the j-th grid and the center of the target grid in the adjacent grids of the i-th grid; γ and g are the correction parameters.

3.2. Safety function

If the projected course rotates more during the flight, it will not only increase the distance of the flight path, but also the degree of hazard. Therefore, it is necessary to reduce the number of turns as much as possible in path planning.

$$r_{ij}(t) = \begin{cases} \dfrac{u}{J(\text{allowed}_i)}, i = \text{visited}_i, \\ \theta u, dr_{zi}(t) = dr_{ij}(t), \\ \dfrac{(1-\theta)u}{J(\text{allowed}_i)}, dr_{vi}(t) \neq dr_{ij}(t) \end{cases} \quad (3)$$

In the formula, $J(\text{allowed}_\text{i})$; $r_{ij}(t)$ is the safety function; u is the heuristic constant; θ represents the importance of safety; visited_i is the t-th iteration, the k-th ant goes to the current set of grid numbers that have been passed in grid i; ν is the label of the previous grid of the current i-th grid, $\nu = \text{visited}_i(\text{end} - 1)$; $\text{J}(\text{allowed}_i)$ represents the number of feasible adjacent grids of the current grid; $dr_{\nu j}(t)$ represents the direction from the ν-th to the i-th grid at the t-th iteration; $dr_{ij}(t)$ represents the t-th iteration, the direction from the i-th grid to the j-th grid is turned. By comparing $dr_{\nu j}(t)$ and $dr_{ij}(t)$, if the two are the same, it will increase the possibility of continuing in the same direction in the following step, allowing the path to retain a straight line.

3.3. Smoothness function

$$h(i,j) = \frac{h_{max} - |h(i) - h(j)|}{h_{max} - h_{min} + 0.001} \times \gamma_2 + g_2 \tag{4}$$

h_{max} is the maximum value of the difference between the height of the current i-th grid and the height of its adjacent grid; h_{min} is the minimum value of the difference between the height of the current i-th grid and the height of its adjacent grid; $h(i)$Is the height of the grid.

4. Improved ant colony algorithm

The ant colony is required to select the next grid from the eight adjacent grids based on pheromone, heuristic function, and transition probability as well as to determine the nearest path from the starting point to the destination point. Before the ant colony begins to find a path, the pheromone of each grid is the same. The ant selects the next grid to walk according to the transition probability. The pheromone of the path will be left, and the pheromone of the path that has not been walked will be continuously reduced in the iteration. Ants on the shorter path locate food quickly, while ants on the longer path take a longer time to locate food. Therefore, the sum of pheromones left by ants on the shorter path is more, thus attracting more ants to take this path. The shortest path can then be found.

4.1. Transition probability

The transition probability of the ant colony algorithm is affected by two factors: the heuristic function and the pheromone left by ants. There are obstacles in the real environment. The multi-heuristic function enables ants to avoid obstacles, choosing a shorter path and reducing the number of turns. The path with more pheromones will attract ants to choose the path. When a large number of ants walk from the same path and fail to find the optimal path, the current path is considered as the global optimum; in that case, the ants fall into the local optimum.

4.1.1. Adaptive heuristic function factor

In order to improve the search efficiency of an optimal path and jump out of the local optimum, an adaptive heuristic function factor is introduced into the transition probability, as shown in equation (5). The adaptive heuristic function factor is the weighted reciprocal of the sum of the distance from the current grid to the starting grid as well as the distance from the current grid to the destination grid. Based on the distance between the grid to be walked and the target grid, add the distance from the grid to the starting grid; that is, when considering whether the grid to be walked is the best, the adaptive heuristic function factor is taken as one of the influencing factors of the transition probability to increase the overall consideration of the environment.

$$\mu_{ij} = \frac{1}{a(d_{jE})} + \frac{1}{b(d_{Aj} + d_{jE})} \tag{5}$$

μ_{ij} is the adaptive heuristic function factor; d_{Aj} represents the distance between the starting point and the grid to walk in; A is the starting point; j is the label of the grid to walk in; d_{jE} is the distance between the grid to walk in and the destination point; E is the destination point; a and b are the weight coefficients. The smaller the distance between the grid to walk in and the starting point as well as that between the grid to walk in and the destination point, the larger the adaptive heuristic function factor and the transition probability. In that case, a shorter path can be better selected.

By drawing an adaptive heuristic function factor into the transition probability, the ants can select the shortest path and speed up the efficiency of searching the optimal path.

4.1.2. Improved transition probability

The transition probability has been improved as follows:

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}\mu_{ij}}{\sum_{s \in \text{allowedk}} [\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}\mu_{is}}, j \in \text{ allowed }_{k}, \\ 0, j \notin \text{ allowed }_{k}, \end{cases} \tag{6}$$

k is the label of ants; i is the current grid number; j is the following grid number; t is the current number of iterations; τ represents the pheromone strength; η represents the heuristic function; α represents the degree factor of pheromone; $\beta$is the heuristic factor; allowed_k is the grid that can be selected next. The ants at the back will be guided according to the pheromones left by the ants in front. The shorter the path is, the more pheromones will be left, but pheromones will evaporate at the same time. The updated pheromone is determined as follows:

$$S_k(t) = XL_k(t) + YF_k(t) + ZT_k(t) \tag{7}$$

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{Q}{S_k(t)}, i, j \in \text{ visited }_{tq} \\ \quad 0, \text{otherwise}, \end{cases} \tag{8}$$

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{M} \Delta\tau_{ij}(t) \tag{9}$$

$S_k(t)$ is the path comprehensive indicator in the *t*-th iterative of the *k*-th ant; the smaller the $S_k(t)$ is, the better the route; $L_k(t)$ is the path length; $F_k(t)$ is the mean square deviation of the grid height the ant has walked in; $T_k(t)$ is the number of turns of the path when the ant is walking; X, Y, and Z are the adjustment coefficients of the above three factors; M is the total number of ants; ρ represents the pheromone volatilization factor; Q represents the pheromone constant; visited_{tq} is an ordered collection of grid labels passed of the *k*-th ant from the *t*-th iteration to the *q*-th grid.

In this study, the initial pheromone adopts a fixed value and sets the range of pheromone to prevent ants from falling into the local optimum when searching for the optimal path.

$$\tau_{ij}(t) \geqslant \tau_{ij}(t)_{min} \tag{10}$$

$$\tau_{ij}(t) < \tau_{ij}(t)_{max} \tag{11}$$

At the same time, a bounded setting is formed for the pheromone volatilization factor, $i\sigma\rho > \rho_{min}$, then $\sigma\rho > \rho$; otherwise, $\rho = \rho_{min}$.

4.2. Heuristic function

The Euclidean distance from the current grid to its adjacent grid is added to the heuristic function as one of the factors affecting the heuristic function. Through the distance correction function, an adjacent grid closest to the target grid is selected from the adjacent grids of the current grid. The distance from the current grid to its adjacent grid is not exactly the same. In order to more accurately consider the influence of the path length on the ant colony's selection of the following grid, the Euclidean distance $d(i,j)$ from the current grid to its adjacent grid is added to the heuristic function. When the distance $d(i,j)$ increases, the value $\frac{1}{d(i,j)}$ will decrease, making multiple heuristic function values $\eta_{ij}(t)$ decrease; the value of the transition probability is then influenced to form a closed-loop feedback. The heuristic function is shown in equation (12).

$$\eta_{ij}(t) = \frac{1}{d(i,j)} + \varphi(i,j) + h(i,j) + r(i,j) \tag{12}$$

$d(i,j)$ is the Euclidean distance between the *i*-th grid center and the *j*-th grid center; $\varphi(i,j)$ is distance correction function; $r(i,j)$ is a security function; $h(i,j)$ is the smoothness function.

5. Algorithm simulation

5.1. Algorithm flow

(1) **Step 1:** Build the grid map and set the coordinates of the starting point A and destination point E.
(2) **Step 2:** Initialize parameters, place all the ants on the starting point, and build a tabu table.
(3) **Step 3:** Calculate the heuristic function and transition probability according to equations (12) and (6), respectively, to determine the next grid that the ant will walk in; fill in the number of the grid that has been passed by the ant in the tabu table; when the ant reaches the destination, it completes a search and records the optimal path of this iteration.
(4) **Step 4:** Update the pheromone according to equation (9).
(5) **Step 5:** Compare the optimal path of each iteration to determine the current optimal path.
(6) **Step 6:** Judge whether the number of iterations reaches the maximum; if it reaches the maximum, output the result; otherwise, continue the iteration.

According to the above steps, the pseudocode of the improved ant colony algorithm is given as follows:

Algorithm: Improved Ant Colony

Tabu = [ ]
Tabu ← Start grid numter;
while $t \leqslant t_{max}$
for each ant do
$\eta_{ij}(t)$ ← each ant;
$P_{ij}^{\kappa}(t)$ ← each ant;
$j \leftarrow \eta_{ij}(t)$, $P_{ij}^{\kappa}(t)$;
Tabu ← j ;
stpath ← path ;
update τ ;
end
bestpath ← ChooseBestPath(stpath) ;
end

The algorithm flow chart is shown in **Figure 4**.

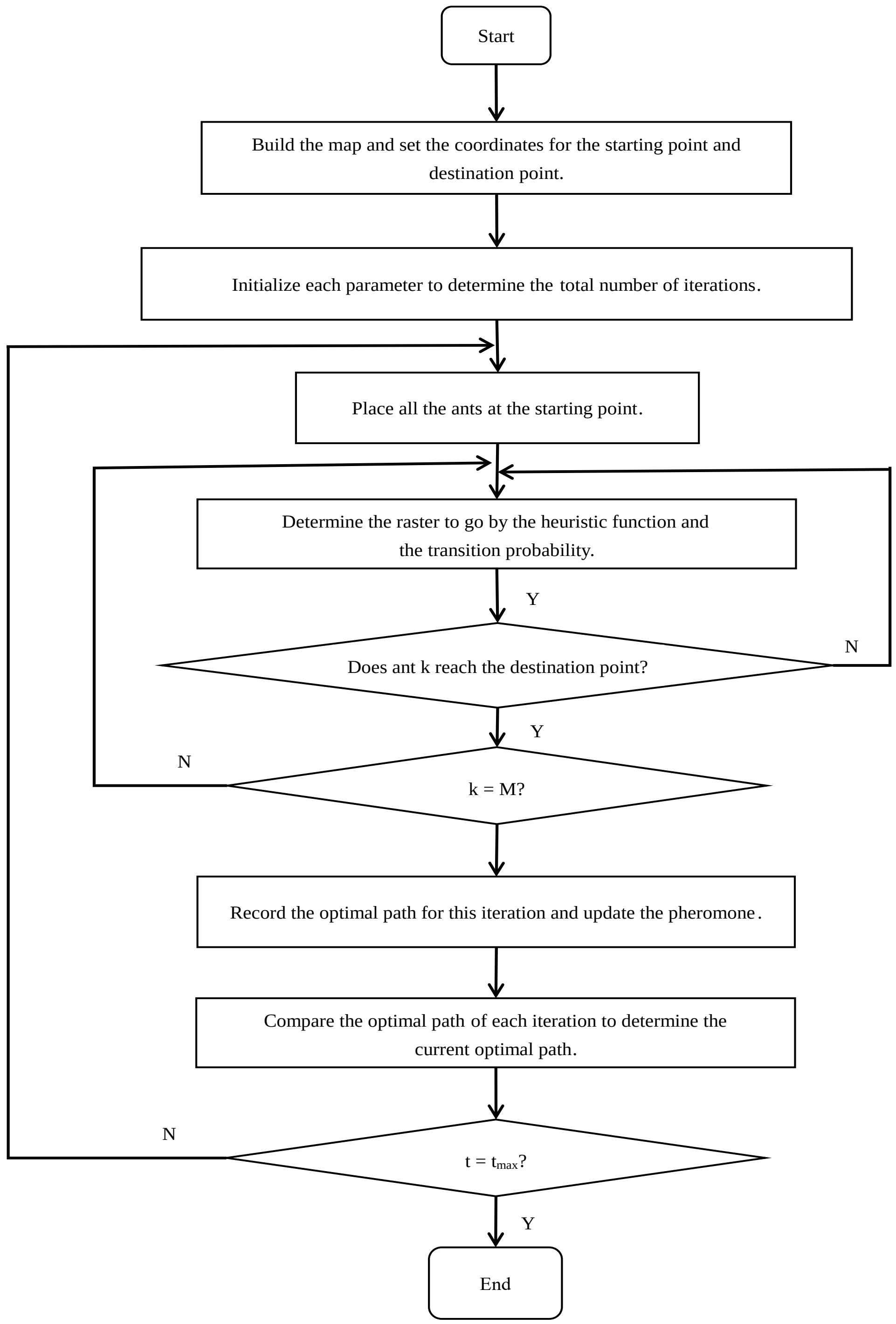

Figure 4. A flow chart of the improved ant colony algorithm

5.2. Parameter setting

In order to better compare the data, the parameters in this study are changed based on the parameters used in the comparison algorithm. Continue to run and debug according to experience to find the appropriate value. **Table 1** shows the initialization parameters.

Table 1. Initialization parameters

Algorithm	l_{max}	M	p	Q	γ_1	g_1	γ_2	g_2	u	θ
Literature [25]	30	50	0.3	100	10	1	10	1	10	0.5
Improved algorithm in this study	30	50	0.3	100	10	1	10	1	10	0.5
Algorithm	$\tau_{ij}(t)_{min}$	$\tau_{ij}(t)_{max}$	ρ_{min}	$\tau_{ij}(o)$	X	Y	Z			
Literature [25]	10	40	0.2	20	1	0.1	0.1			
Improved algorithm in this study	10	40	0.2	20	1	0.1	0.1			

5.3. Simulation comparison

In order to improve the reliability of the transition probability, this study improves the transition probability, introduces the adaptive heuristic function factor, and takes the Euclidean distance from the current grid to its adjacent grid as one of the influencing factors of the heuristic function. As the technique employed in this study is a heuristic random optimization method, this study employs MATLAB to simulate and compare the improved algorithm to a literature [25] – Path Planning Based on Improved Ant Colony Algorithm with Multiple Inspired Factor – for 30 times, in order to evaluate its efficiency. The terrain environment is studied in the 10 × 10 and the 30 × 30 grid obstacle maps.

5.3.1. Simulation in the 10 × 10 grid environment

As shown in **Figure 5**, the dotted line represents the optimal path in the aforementioned literature [25], and the solid line is the optimal path of the improved ant colony algorithm in this study. It can be seen from the figure that most of the paths overlap. However, from the overall effect of the path, the solid line has four turns, while the dotted line has six turns. When the dotted line turns for the fourth time, the solid line continues to move forward in the direction of the original path, which is smooth.

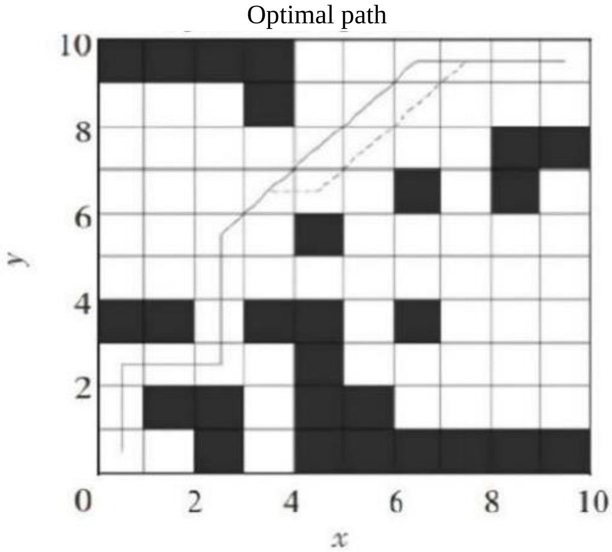

Figure 5. Graph of optimal path comparison in the 10 × 10 grid environment

Figure 6 shows the comparison of the optimal path length at different iterations. Initially, the solid line has a longer path length than the dotted line, but after iteration, the solid line finds a shorter path, whereas the dotted line does not even under the same number of iterations.

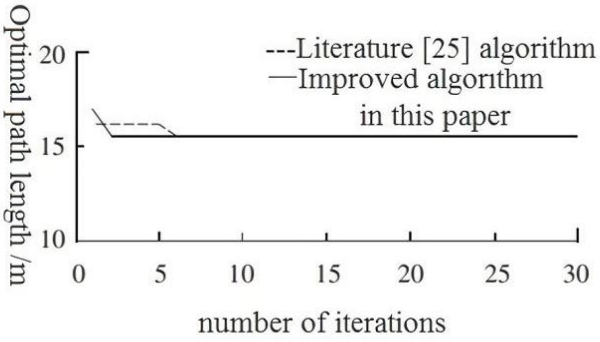

Figure 6. Graph of optimal path length in the 10 × 10 grid environment

Figure 7 compares the mean square error of the optimal path with different iterations. The initial value of the solid line is the same as that of the dotted line. With the increasing number of iterations, it can be seen that the height mean square deviation of the solid line reaches a stable value within five iterations, whereas the dotted line only reaches a stable value with more than five iterations.

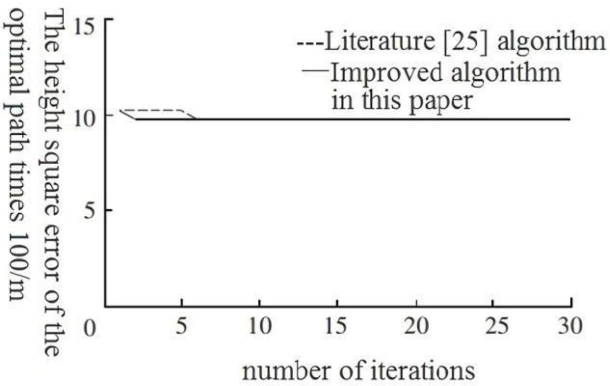

Figure 7. Comparing the mean square deviation of the optimal path height in the 10 × 10 grid environment

Figure 8 is a comparison of the number of turns of the optimal path at different iterations. It can be seen from **Figure 8** that the number of turns of the solid line and the dotted line is the same under the same number of iterations. With the increasing number of iterations, the solid line with the adaptive heuristic function factor is introduced to obtain lesser number of turns, whereas the dotted line maintains the original number of turns, which shows that the improved ant colony algorithm increases the ant colony's overall consideration of the path environment and jumps out of the local optimum.

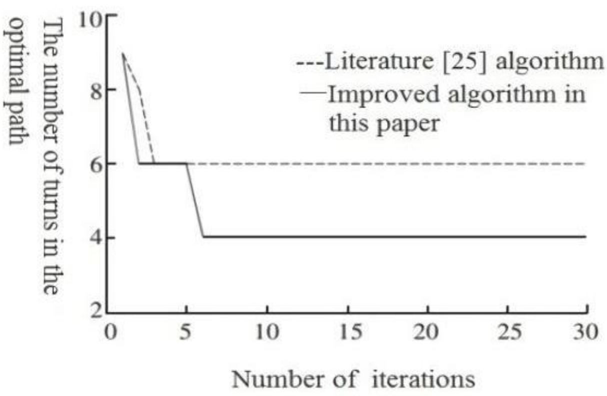

Figure 8. Comparison of number of turns of the optimal path in the 10 × 10 grid environment

Figure 9 shows a comparison of the comprehensive index and average comprehensive index of the optimal path at different iteration times. The comprehensive index is the comprehensive evaluation of the distance correction function, safety function, and smoothness function. The lower the index, the better the algorithm. As can be seen from **Figure 9**, the comprehensive index of the optimal path of the improved algorithm has a large value initially and converges to a stable value with increasing number of iterations.

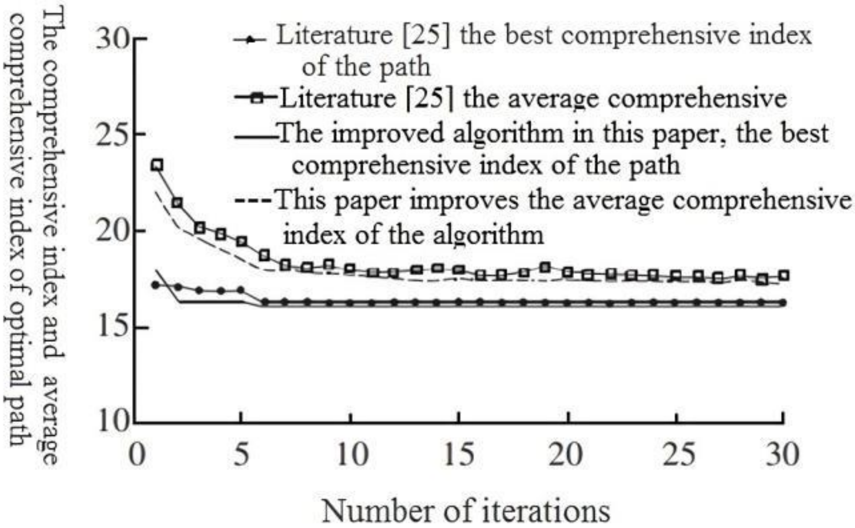

Figure 9. Comparison of the comprehensive indicators of the optimal path in the 10 × 10 grid environment

It can be seen from **Table 2** that the improved algorithm reduces the number of iterations, and the comprehensive index is relatively small. In order to reduce the influence of the randomness of the algorithm on the experimental results, the average value and variance of the optimal solution are calculated under the condition of running 30 times, as shown in the average value and variance of the optimal path length in **Table 2**.

Table 2. Simulation results of the 10 × 10 grid environment

Optimal path index	Literature [25] algorithm	Improved algorithm in this study
Path length / m	15.6	15.6
Height means square error / m	9.815	9.815
Number of turns	6	4
Comprehensive index	16.21	16.01
Number of iterations of path length	6	2
Optimal path length average	15.7000	15.6467
Optimal path length variance	0.050000	0.063156

5.3.2. Simulation in the 30 × 30 grid environment

As shown in **Figure 10**, the dotted line represents the optimal path in the aforementioned literature [25], whereas the solid line represents the optimal path of the improved algorithm in this study. From **Figure 10**, it can be seen that in the second corner, the path of the dotted line is straight, while that of the solid line is diagonal; in addition, the length of the solid line is shorter compared to the dotted line. From the overall effect of the path, the solid line has 19 turns, whereas the dotted line has 16. Considering the integrity of the path, although the number of turns increases, the length of the path decreases.

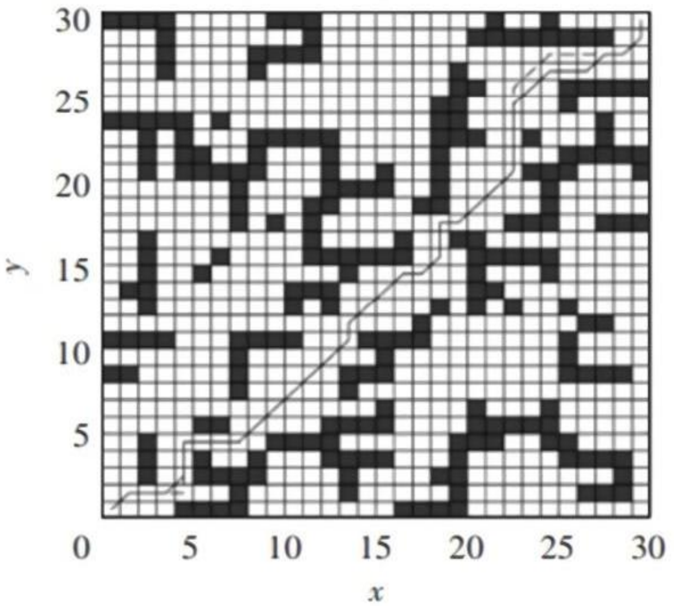

Figure 10. Graph of optimal path comparison in the 30 × 30 grid environment

Figure 11 shows the comparison of the optimal path length at different iterations. As can be seen from the figure, when the adaptive heuristic function factor is introduced, the path length of the improved algorithm is short at the beginning of the iteration. After the iteration, the shorter path is found and reaches a stable value. It can be concluded from the results that this algorithm increases the ability of ants to consider the integrity of the path and improves the efficiency of ants in searching for the optimal path.

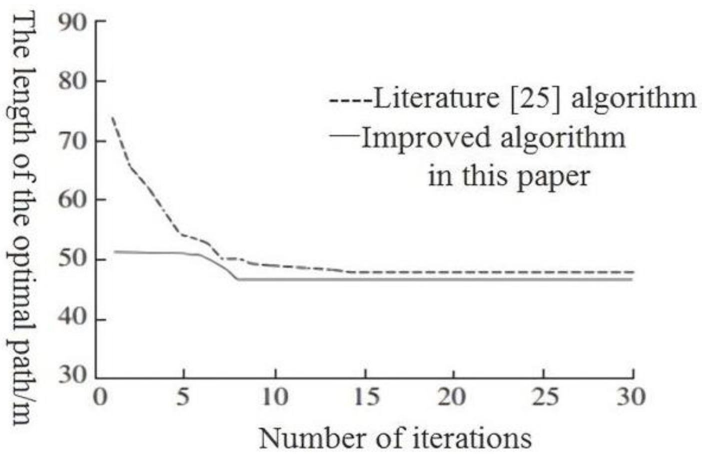

Figure 11. Comparison of optimal path length in the 30 × 30 grid environment

Figure 12 is a comparison of the height mean square deviation of the optimal path at different iterations. The initial value of the solid line is the same as that of the dotted line. With the increasing number of iterations, it can be seen that the height mean square deviation of the solid line reaches a stable value within 10 iterations, whereas the dotted line reaches a stable value only after 10 iterations; thus, it can be concluded that the solid line reaches a stable value at a faster rate. **Figure 13** is a comparison of the number of turns of the optimal path at different iterations.

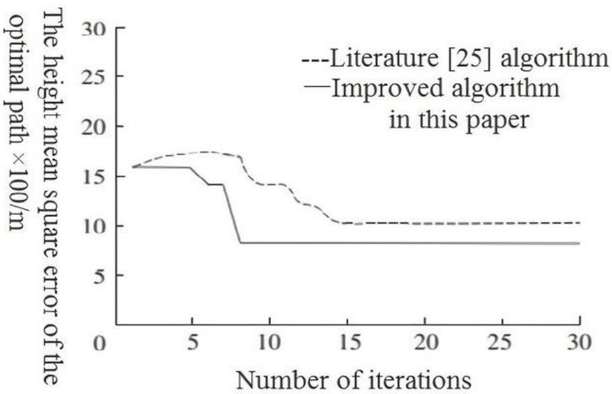

Figure 12. Comparison of mean square deviation of the optimal path height in the 30 × 30 grid environment

As can be seen from **Figure 13**, due to the introduction of the adaptive heuristic function factor, the ants consider the integrity of the path while choosing a path; hence, the solid line is relatively flat, and its does not fluctuate excessively.

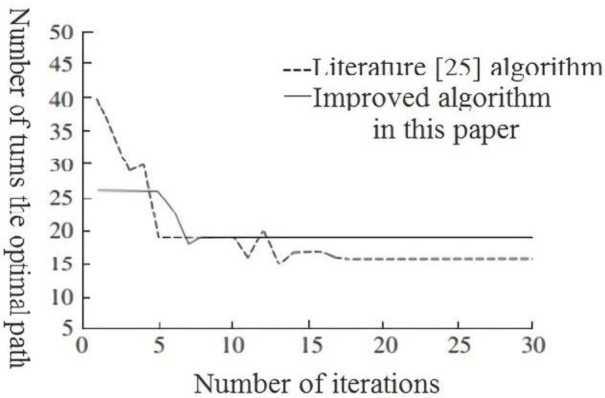

Figure 13. Comparison of the number of turns of the optimal path in the 30 × 30 grid environment

Figure 14 is a comparison of the comprehensive index and average comprehensive index of the optimal path at different iteration times. The lower the index, the better the algorithm. As can be seen from the figure below, the comprehensive index curve of the optimal path of the improved algorithm is relatively flat and tends to a stable value earlier with the increasing number of iterations.

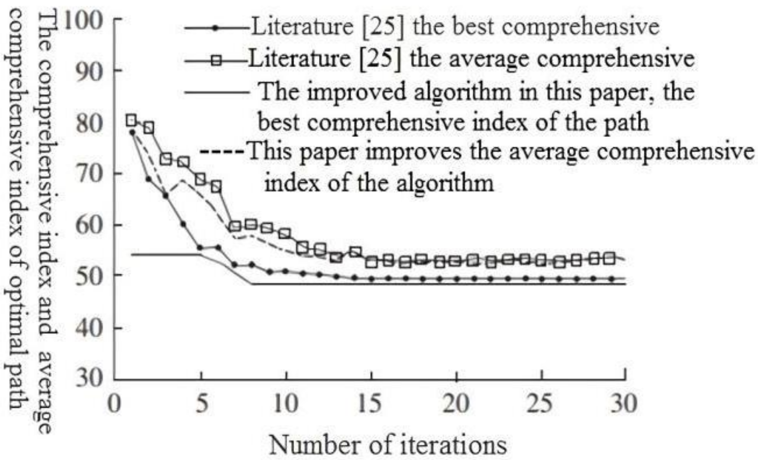

Figure 14. Comparison of the comprehensive indicators of the optimal path in the 30 × 30 grid environment

Based on the results of the path length, height mean square deviation, number of turns, comprehensive index, and iteration times, it can be seen from **Table 3** that the path length found by the improved ant colony algorithm is relatively short, and its iteration times are relatively few in regard to its path length.

Table 3. Simulation results of the 30 × 30 grid environment

Optimal path index	Literature [25] algorithm	Improved algorithm in this study
Path length / m	47.8	46.6
Height means square error / m	10.260	8.225
Number of turns	16	19
Comprehensive index	49.51	48.51
Number of iterations of path length	14	8
Optimal path length average	49.1867	46.0267
Optimal path length variance	40.040774327	5.693385127

6. Conclusion

When ants look for paths in the grid environment, the distance from the current grid to its adjacent grid is not exactly the same. In order to accurately consider the influence of path length on the selection of the following grid by the ant colony, the Euclidean distance from the current grid to its adjacent grid is added to the heuristic function in this study; in addition, this study increases the influencing factors of the heuristic function, forms a closed-loop feedback, and introduces the adaptive heuristic function factor into the transition probability. The distance from the starting point to the grid and finally to the destination point is taken as one of the factors affecting the transition probability of ants in their selection of the next grid, which increases the consideration of the overall environment, improves the pheromone and the pheromone volatilization factor, as well as reduces the impact of excessive or insufficient pheromones in their path selection, thus preventing ants from falling into the local optimum in the search process.

In this study, the improved algorithm enhances the efficiency of search path. From the results, it can be appreciated that the improved algorithm decreases the length of the path, reduces the number of iterations, makes the path smoother, generates a more stable curve, and aids in reaching a stable value more rapidly. Adaptive multi-heuristic ant colony algorithm reduces the comprehensive index and average comprehensive index of UAV path planning.

In this study, the three-dimensional environment of UAV is projected as two-dimensional for research, which simplifies the flight environment. In the future, the complexity of the flight environment needs to be magnified to improve the practical application of the algorithm.

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