Dynamic Path Planning of UAV Based on Pheromone Diffusion Ant Colony Algorithm

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ABSTRACT

Due to the dynamic uncertainty factors in a complex environment, such as flight conditions, movable obstacles and other sudden threats. It is a challenge to realize the real-time path planning of Unmanned Aerial Vehicles (UAV). In this paper, the method is proposed with a model of the dynamic environment and a method of pheromone diffusion ant colony optimization (PDACO) to solve the real-time path planning of UAV in a dynamic environment. The translational obstacle method and the random obstacle method can efficiently simulate the dynamic environment. PDACO takes advantage of pheromone diffusion characteristics in an ant colony, and diffuses the pheromones to adjacent paths after each iteration, thus expanding the guidance range of pheromones. When the environment changes, the pheromone diffusion method can quickly plan new paths and accelerate the convergence of the algorithm. Simulation results show that the dynamic environment model accords with the actual situation. Compared with four algorithms, PDACO ensures that the UAV can optimize a new path with shorter path length and computing time when environment changes. The proposed method is feasible and effective.

CCS CONCEPTS

• **Applied computing**; • **Operations research**; • **Decision analysis**; • **Multi-criterion optimization and decision-making**;

KEYWORDS

UAV, ACO, Dynamic Path Planning, Pheromone Diffusion

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1 INTRODUCTION

With the rapid development of science and technology, the UAV is widely used in the military, civil fields and various specific industries [1]-[3]. Compared with manned aircraft, the UAV has the advantage of low cost, high maneuverability and simple operation. Therefore, the UAV has broad prospects for development in tasks in high altitude, large scale and dangerous environment. With the implementation of complicated tasks, the path planning of UAV has been given considerable attention.

Some recent studies have explained the importance of UAV path planning in a dynamic environment. Wen, N et al. [4] proposed expressing the uncertainties in static threats (ST) based on intuitionistic fuzzy set (IFS) and predict the threat of DT based on the rapidly-exploring random tree (RRT). The receding horizon (RH) was introduced to solve the online path planning problem in a dynamic and partially unknown environment. A local path planner was constructed by improving the dynamic domain rapidly-exploring random tree (DDRRT) to deal with complex obstacles. Fu, Y et al. [5] presented a hybrid differential evolution (DE) with quantum-behaved particle swarm optimization (QPSO) for the UAV path planning on the sea. The DEQPSO algorithm was designed to generate a safe and flexible path in the presence of different threat environments. Bo, Z et al. [6] proposed predator-prey pigeon-inspired optimization (PPPIO) to solve the UCAV three-dimension path planning problem in a dynamic environment. They used the map and compass operation model and the landmark operation model to search for the best result and adopted the concept of prey-predator to improve the global optimal characteristics and speed up the convergence.

This paper proposes a path planning method for UAV in a dynamic environment. The main contributions are as following. Firstly, a model of the UAV dynamic environment is established using the grid method based on the translational obstacle method and the random obstacle method. The established model can efficiently simulate the actual dynamic environment. Then, a dynamic path planning method PDACO is proposed. With the increase of iteration time, the proposed PDACO can enhance the guidance of surrounding pheromones to plan the path after the environment changes. Finally, the dynamic diffusion factor is designed. As the factor increases, the path can be further optimized. The experimental results show that the proposed algorithm can serve as an effective path planning method for practical application in a dynamic environment.

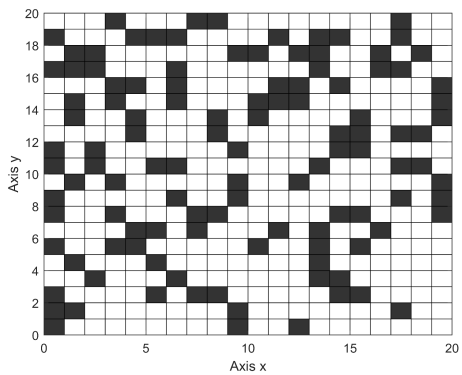

Figure 1: Environment model is constructed by the grid method.

2 DYNAMIC ENVIRONMENT MODEL

This paper mainly studies the path planning of UAV in a dynamic environment with moving and potential threats, such as battlefield [7]. Specifically, it is assumed that the vehicular radar can detect the UAV in a certain range, and the missiles can influence the survival of UAV in killing range. Threats of vehicular radar will suddenly appear, and the threats of missiles will constantly move, which can be regarded as dynamic obstacles. The number and the location of threats are unknown before the assignment of tasks. Thus, the UAV must formulate adaptation policies to deal with the dynamic environment.

The establishment of environment models includes the viewable method, the free space method, the modeling method, and the grid method, etc. The grid method was proposed by Howden in 1968 and has been most widely used in path planning[8]. The grid method simplifies the actual complex environment, which is conducive to the establishment of an environmental model and convenient for the calculation and deduction of the algorithm. Moreover, the detailed division of the environment into different sizes by the grid method increases the information of the environment and the accuracy of the algorithm.

2.1 Basic Environment Model

In this paper, it is assumed that the flight environment of UAV is a two-dimensional space. Free grid is no obstacle in the grid (white grid), represented by"0"; obstacle grid is an obstacle (black grid), represented by"1" (see Fig.1). If there are obstacles in a grid but not filled with grids, the grid will be regarded as an obstacle grid. This definition makes a certain distance between the planned path and the actual obstacles, which can ensure the safety of UAV. The UAV can fly at a certain altitude and encounter relatively sparse obstacles. Thus, there is always a path from the starting point to the target point in the environment model constructed by the grid method.

The UAV is regarded as a particle in the environment model and can move in 8 directions without obstacles (see Fig.2). It means that the UAV can move from its current position to a free grid but cannot move to the obstacle grid, as showed by the blue and red arrows in Fig.2, respectively.

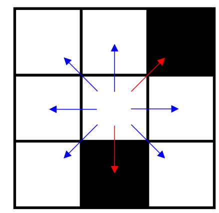

Figure 2: Directions of UAV movement.

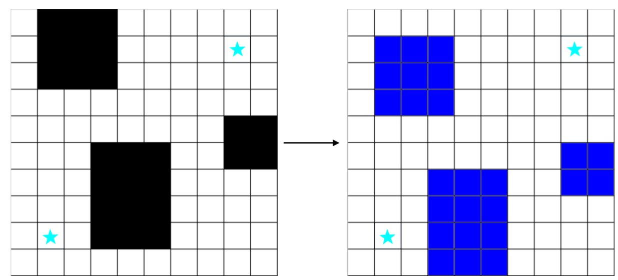

Figure 3: Translational obstacle method.

2.2 Dynamic Obstacles Methods

In the research of dynamic path planning, many articles prefer that most obstacles are static and only a few dynamic obstacles (usually have a certain trajectory). However, these dynamic changes can be avoided immediately by the UAV sensors, which have little impact on the path planning of UAV. The flight environment of UAV is very complex. (1) UAV and obstacle are in relative motion, so the UAV needs to adjust the relative position between itself and the obstacles in the process of planning. (2) In the process of planning, new obstacles appear or some obstacles disappear around the path suddenly, so it is particularly important to optimize path in a short time. In order to reflect the dynamic environment of UAV, two dynamic obstacles methods are proposed in this paper: translational obstacle method and random obstacle method.

The translational obstacle method (see Fig.3) simulates the relative movement of environmental obstacles along with UAV. Within grids of the environment model, whole obstacles randomly move up, down, left or right directions, simulating the relative movement of obstacles along with the UAV. Once the environment is changed, the obstacles may block the previously planned path or generate a better path.

The random obstacle method (see Fig.4) simulates the UAV encountering new barriers or new paths after the environment changes. A small amount of free grid (or obstacle grid) will randomly become the obstacle grid (or free grid), which increases the complexity and suddenness of the environmental changes.

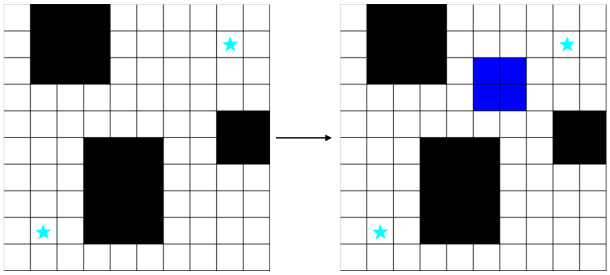

Figure 4: Random obstacle method.

3 TRADITIONAL ANT COLONY ALGORITHM

Ant colony optimization is an algorithm that simulates the ants searching for food in the biological environment. Dorigo, Maniezzo [9] first proposed the ACO in the 1990s. The study found that the behaviour of an individual ant in an ant colony is relatively simple, but the entire ant colony can embody some intelligent behaviors. Each ant will leave a chemical substance as a pheromone in its path, and other ants in a certain range can sense pheromone and tend to move in the direction with high pheromone concentration. Each ant will produce "pheromone" again to deepen the information concentration on this path, thus forming a positive feedback mechanism. As time goes by, more ants gather on the path to follow "pheromones", and the pheromone concentration becomes higher. Finally, ants can approach the optimal path.

3.1 State Transition Probability

The ant m (m = 1, 2, 3· · ·M) moves to the grid according to the pheromone concentration of next position j and the distance from the current position i. The next position is selected by the roulette algorithm and the state transition probability is calculated as $p_{ij}^{m}(t)$.

$$p_{ij}^{m}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{j\in allowed}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}} & j \in allowed \\ 0 & j \notin allowed \end{cases} \tag{1}$$

Where, $\tau_{ij}(t)$ is the pheromone concentration on the path(i, j), $\eta_{ij}(t)$ is the heuristic function between the two points(i, j) and is defined as $\eta_{ij}(t) = 1/d_{ij}$, while d_{ij} is the linear distance between the two points (i, j). This definition is useful to solve the TSP problem. However, in a grid environment, the heuristic effect between the two adjacent points (i, j) is not good. Therefore, $\eta_{iE}(t) = 1/d_{iE}$ is used as the heuristic function, in which d_{iE} is the linear distance between point j and the target point. α is the inspiration factor of pheromone, the greater the value, the greater the influence of pheromone on the ant to find food. β is the distance heuristic factor, representing the importance of distance to path selection. *Allowed* represents the next set of paths that the ant m can choose.

3.2 Pheromone Update Strategy

The pheromone updating strategy includes local updating and global updating. Although the local updating can approach the optimal solution, the algorithm has strong randomness and slow convergence speed in the initial stage. Considering that the path planning of UAV in a dynamic environment needs faster computing speed, the global updating strategy is more suitable than the local updating. The global updating is to update all pheromones on the path according to the current remaining pheromones and the number of pheromones added by each ant after all ants have finished searching once.

$$\tau_{ij}(t+1) = (1-\rho)\,\tau_{ij}(t) + \sum_{m=1}^{M} \Delta\tau_{ij}^{m} \tag{2}$$

Where, ρ is the pheromone volatility factor, usually $\rho \in [0, 1]$, M represents the number of ant colonies, while $\Delta\tau_{ij}^{m}$ represents the residual pheromones by the mth ant during the search and is defined as:

$$\Delta\tau_{ij}^{m} = \begin{cases} \frac{Q}{L_m} & the\ mth\ ant\ goes\ form\ i\ to\ j \\ 0 & others \end{cases} \tag{3}$$

where, Q is a constant, representing the total pheromones that can be released during a single search of ant pheromone and L_m represents the total length of the ant's path.

4 PHEROMONE DIFFUSION ANT COLONY OPTIMIZATION (PDACO)

In the traditional ACO, the ants choose the path according to the pheromone concentration. The higher the pheromone concentration, the easier to choose the path. However, in the global updating strategy, the ACO has faster convergence speed and more repeated paths, resulting in fewer pheromone update paths. When the environment changes, the obstacle may block the path with high pheromone concentration. In the next iteration, a node with a blank pheromone should be selected and the following paths should be replanned. Therefore, it is impossible to plan an effective path for a limited time in an environment of rapid dynamic changes. Inspiration for the ACO comes from the process of ants searching for food, and the information transmission is realized by pheromones. Considering the actual situation, it is not difficult to think that if the pheromone diffuses around when the ant deviates from the current optimal path, it can return to a better path by sensing the diffusing pheromone concentration. This paper proposes dynamic path planning of UAV with PDACO. The purpose of the proposed method is to speed up the planning of the optimal path through the concentration of pheromone diffusion when the obstacles in the dynamic environment block the planned path, thus significantly improving the speed of path optimization in a dynamic environment (see Fig.5).

4.1 Pheromone Diffusion Model

When an ant is at point i, there are eight directions to move in if no obstacles are around. Thus, pheromones can also spread in eight directions. The diffusion of the pheromone can be divided into local diffusion and global diffusion. Global diffusion means a strategy for the pheromone of each ant on the path to spread, although this is beneficial to improve the diversity of route choice in the beginning. The biggest problem is that the local spread needs to consider whole ants' pheromone and moving direction, requiring a large amount of calculation and resulting in a less obvious effect. Therefore, the local diffusion method is adopted to update the pheromones on the

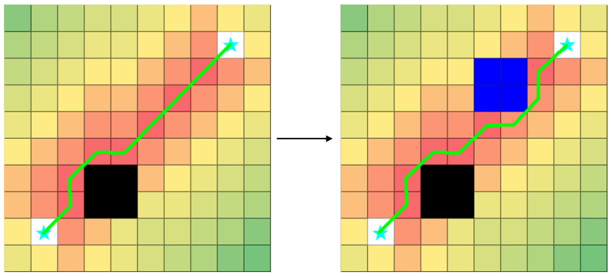

Figure 5: On the right, the new obstacle (blue) blocks the planned path. (Red and green represent high and low pheromone concentrations, respectively)

current optimal path of this iteration after all ants complete the search process each time. Pheromones on the updating path are diffused in two adjacent directions x and y. The calculation formula of pheromone diffusion incremental update is as following:

$$\tau_{ix}\left(t+1\right)=\tau_{iy}\left(t+1\right)=\sigma * best\tau_{ij}(t) \tag{4}$$

where σ is the pheromone diffusion factor. The greater the value, the greater probability of choosing the diffusion path. $\sigma = 0$ is the traditional ACO.

4.2 Dynamic diffusion factor

The pheromone diffusion factor $\sigma \in (0, 1)$ has an important influence on the global searching ability and the convergence speed of the algorithm. If σ is too small, the global searching ability will be reduced. If σ is too large, the search range will expand, which is more conducive to finding the global optimum, but the convergence speed will be slow. The pheromone diffusion factor needs to be small enough in the initial iteration of ensure to plan an acceptable path in a complete iteration. Then the diffusion of pheromone can provide a better guide effect after the environment changes. A method of dynamic diffusion factor is proposed to solve the above problems:

$$\sigma=\frac{C}{(T-t+1)^2} \qquad t \in (0, T) \tag{5}$$

where C is the diffusion factor constant, T is the average number of iterations in the cycle of environmental change and t is the current number of iterations in the cycle.

4.3 PDACO for Path Planning

5 SIMULATION AND RESULTS

5.1 Experimental Methods

In order to verify the effectiveness and robustness of the proposed algorithm, the performances of five algorithms are compared, namely PDACO, ACO[10], PSO[11], Q-learning[12] and RRT[13]. In a 20*20-grid environment, the obstacle density is 25%, the start position of the UAV is (1, 1), and the target position of the UAV is (20, 20).

5.2 Path Planning in the Static Environment

Firstly, the advantages and disadvantages of various algorithms in the static environment are analyzed. This paper mainly analyzes two characteristics of algorithms: convergence speed and computing time.

The PSO initializes the path through the Dijkstra algorithm. Hence, it is not difficult to find that the path planned at the beginning is relatively good. The RRT algorithm is based on random sampling and needs to generate multiple paths to select the best path in every iteration, so the convergence situation is unstable. The Q-learning needs to interact with the environment, so it is impossible to plan the optimal path quickly. The performance of the Q-learning algorithm is unsatisfactory. Because of the heuristic function, the ACO can plan the path well, and the convergence speed is fast. The proposed PDACO algorithm has pheromone diffusion, so it can expand its exploration scope in the early stage while ensuring a reasonable route. At the same time, the dynamic diffusion factor will increase with the increase of iteration time. Thus avoiding falling into the local optimal solution. Therefore, it can be seen from Fig.7 that after 5 iterations the PDACO still have a further optimized path.

In terms of computing time (see Table 1), the algorithms are quite different. The PSO combined with the Dijkstra algorithm can obtain a better path. However, the Dijkstra algorithm needs to traverse the nearest neighbor nodes, which have not been visited from the starting point until it extends to the end. The computing time of planning in high-dimensional map increases exponentially. The PSO is not suitable for real-time planning. The computing time of Q-learning and RRT is relatively short. But each has serious shortcomings. Compared with other algorithms, the path generated by the Q-learning algorithm after 80 iterations still cannot reach the ideal length. In the following dynamic environment experiment, a

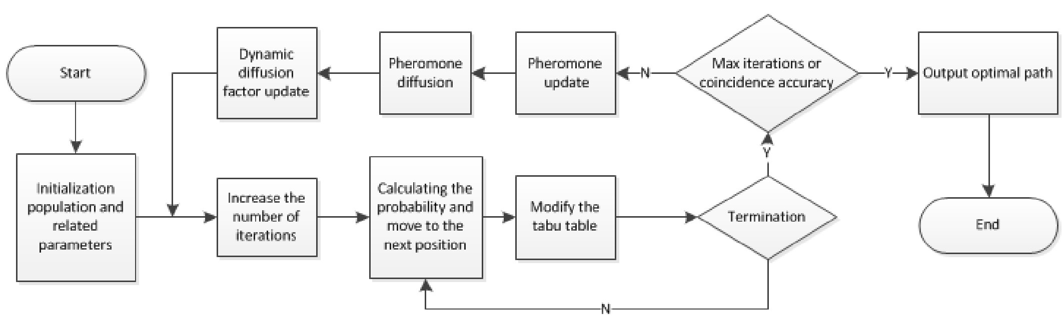

Figure 6: Flow chart of PDACO algorithm.

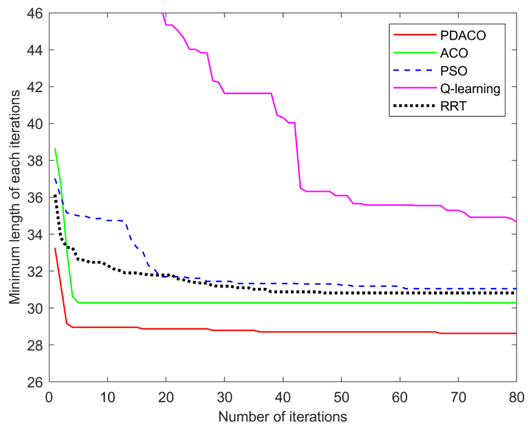

Figure 7: Convergence of different algorithms.

detailed comparison is not described. The RRT has a good advantage in computing time, and the planned path is better. When the space contains a large number of obstacles or narrow channel constraints, it is difficult for the RRT to find a path. Both the PDACO and the ACO have the same computing time, but PDACO is more effective than ACO in path optimization. In terms of computing time, PDACO takes longer than RRT, but PDACO can plan better paths to save flight time by offline planning in static environment.

5.3 Path Planning in the Dynamic Environment

Fig.8 shows the partial changes in the dynamic environment. From 'a' to 'b', the entire environment moves up, resulting in a new obstacle (blue rectangle); From 'b' to 'c', the entire environment moves right, and an obstacle disappears (transparent rectangle); From 'c' to 'd', the entire environment moves up, resulting in a new obstacle (blue rectangle). The PDACO (red, solid) is shown on the left; the ACO (green, solid), PSO (blue, dash) and RRT (black, dots) are shown on the right.

Fig.9 shows the minimum path length in each iteration and in the change period. Whenever the environment changes, the algorithm will perform 30 iterations, which is called a change period. Because dynamic changes are not frequent in the actual scene, we assume that all algorithms can complete 30 iterations in a change period. As we can see from Fig.7, the path lengths of all algorithms have converged after 30 iterations. In other words, the path replanning has completed in a change period.

The figure shows that each algorithm has different convergence characteristics. The path of RRT has strong randomness, so the convergence graph has an obvious periodic change in a change period. Compared with the PDACO, the PSO has a slower convergence speed. It can be seen from the previous two change periods that

Table 1: Computing times of different algorithms per iteration (Time unit: ms)

Algorithm	10*10	20*20	50*50	100*100
PDACO	3.2	24.3	655.2	9192.7
ACO	2.6	18.2	601.3	8237.6
PSO	23.4	130.9	6595.4	174228.5
Q-learning	0.7	1.5	3.3	12.3
RRT	2.3	3.1	12.0	24.4

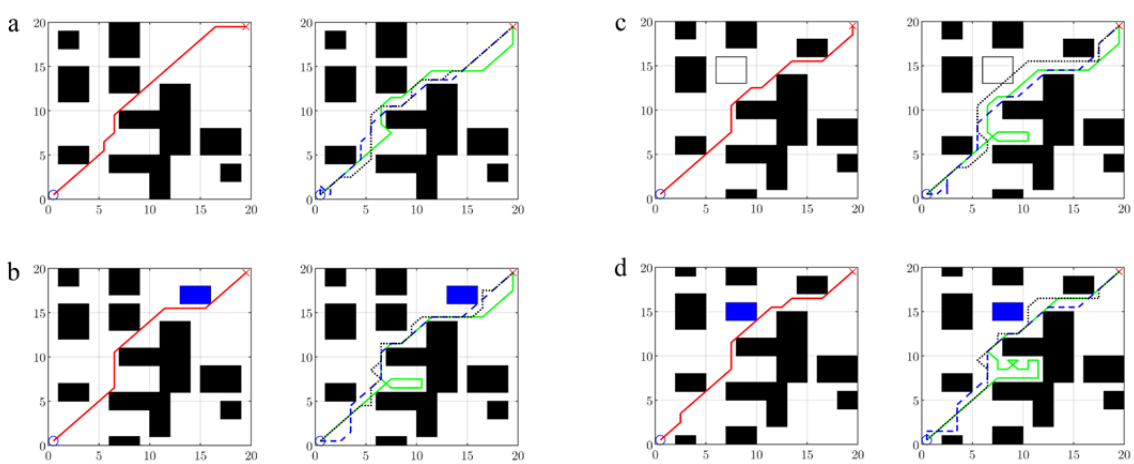

Figure 8: Path planning in the dynamic environment.

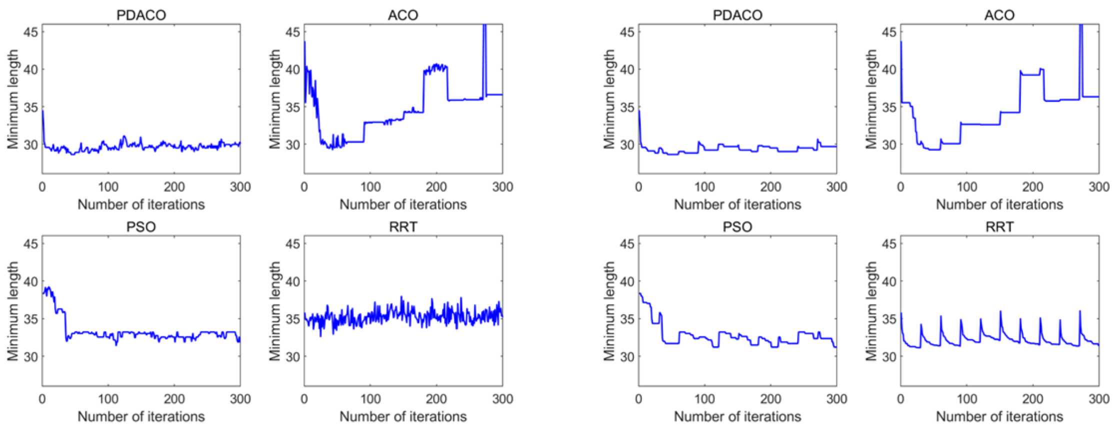

Figure 9: The minimum length path in each iteration and each change period.

there is still a trend of further convergence after the environment changes. However, due to the slow convergence speed, the effect of path optimization is not obvious in the change period. Although the ACO is the original algorithm of the PDACO, its planning effect is seriously affected by the changes in the environment. The more iterations, the worse the pheromone evaporation guidance effect of each path, and the worse the algorithm effect. Compared with the ACO, the proposed PDACO utilizes the advantage of pheromone diffusion, plans a better path quickly, and further optimizes it when the environment changes. Therefore, it can be seen that the path planned by the PDACO converge rapidly at the beginning and have no obvious fluctuation in the latter indicating strong robustness.

6 CONCLUSION

In the paper, dynamic path planning of UAV based on PDACO is proposed. Firstly, two dynamic obstacles methods are proposed to simulate the dynamic environment of UAV. The experimental results demonstrate that in both static and dynamic environments, the PDACO has the advantages of fast convergence speed, short computing time and little influence of environmental changes compared with ACO, PSO, Q-learning and RRT. The PDACO improves the adaptability of ACO to a dynamic environment by pheromone diffusion and enhances the robustness of path planning. The dynamic diffusion factor is used to balance the searching range and convergence speed, which increases the powerful performance of dynamic path planning.

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