UAV Path Planning Method Based on Ant Colony Optimization

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Abstract: A new UAV path planning method based on ant colony optimization (ACO) is presented. The target position is considered as the food source which the ants are going to find. The enemy defense region is considered as the searching area of the ants and is divided into equally spaced grids. The ants move to the destination node through several nodes on the grid region. The visibility function of ACO algorithm considers the enemy threats intensity on the paths and the distance to the destination node. The weighted sums of the flight path length, the threat cost and the maximum restriction of the yaw angle are considered as the evaluation function of ACO algorithm. The pheromone amounts on the paths are updated according to the evaluation function values. Therefore, the UAV optimal flight path is expressed by a group of node number, which is obtained by the ants finding the optimal route to the food source. The ACO algorithm based UAV path planning method is characterized as simple coding and good optimization guidance, and the simulation results also show its effectiveness.

Key Words: Unmanned Aerial Vehicle, Path Planning, Ant Colony Optimization, Swarm Intelligence.

1 INTRODUCTION

Path planning is a key part of UAV assignment planning system. It is aiming at generating optimal or appropriate optimal flight path, so as to safely finish the task when breaking through the enemy threats area. The key techniques of the path planning include the information acquisition and processing of the terrain and the enemy, the establishment of the threats model, the design of the planning algorithm and the path tracking control.

Based on the different task requirements and battlefield environment, several different planning methods have been put forwarded, such as optimized control, Singular perturbation method, and artificial potential field method and so on. Recently, some intelligent optimization technology based planning methods are proposed, such as genetic algorithm [1], ant colony optimization (ACO) [2], particle swarm optimization [3] etc. Other evolutionary algorithms and strong real-time methods for flight path planning have also been studied [4-5].

ACO is one of swarm intelligent method proposed in the 1990s, which is based on natural behavior of ants looking for food collectively [6]. ACO is originally utilized to solve the discrete optimization problems, and also can solve the continuous optimization problems [7]. If regarding a UAV entering certain point in enemy defensive area as a starting point and the battle and tactical target as a destination point, the mesh diagram connecting the starting point and the destination point is formed, by dividing the planning space, then the UAV path planning problem is transformed to be a route optimization problem, which is a discrete optimization problem.

Therefore, in this paper a UAV path planning method based on ACO algorithm is brought forward. Firstly, the UAV flight area is divided into grids, and the shortest distance between the radar and the flight path segment is taken as the threat intensity. Then, ACO algorithm is used to optimize the path between the starting point and the destination point.

2 UAV PATH PLANNING MODELING

Flying region's threaten modeling is the base of UAV path planning. The main factors include the terminal threats and non-terminal threats which help the terminal threats to be most effective. Pellet guns, guided missiles and high-energy radiations are the terminal threats, while the target surveillance, early radar warning, tracking and firepower control belong to the non-terminal one. In order to survive and complete the tasks safely, UAV must have certain capability to avoid terminal and non- terminal threats. Sensitivity concept is used to measure this capability, which means the probability of being hit by the man-made environmental threats.

In this paper, radar threat intensity is deemed as the distance between radar position and flying path. The shorter the distance is, the greater the radar threaten is and the more dangerous the flying path is. Traditionally, flying path is divided into several segments, threat intensities between the threat point and the segments are calculated, sum of which is considered as the whole threat intensity of the flying path, shown as

$$W_T = \sum_{i=1}^{L} w_i = \sum_{i=1}^{L}\sum_{j=1}^{N} w_{ij} = \sum_{i=1}^{L}\sum_{j=1}^{N}\left(\sum_{k=1}^{D}\frac{1}{d_{ijk}{}^4}\right) \tag{1}$$

where w_i is i-th threat point, D is segments number for i-th path, N is radar threaten amounts, d_{ijk} is the threat intensity of k-th segment of i-th path from the j-th threat point, L is the total number of path segments.

Fig. 1 shows the schematic diagram of the threat intensity, in which the dot line represents a flying path, T_1 and T_2 are threats points, A and B are flying through points. For example, for flying segment OA, it is traditionally divided into several segments, and calculates threat intensities between the threat and each segment, and the sum is the threat intensity of segment OA. Large calculation is the main shortcoming for the above mentioned traditional method. In this paper, only the shortest route from the threat to the flying path is considered to measure the threat intensity. In fig. 1, point A is the nearest point from threat T_1 to the segment OA, and point H is the nearest point from threat point T_2 to the segment OA. The nearest point on the segment is the worst threaten case so it can reflect the threat intensity and the safety level of flying path OA. Therefore, the distance between the threat and the nearest segment endpoint on flight path segment from the threat will be used to express the threat intensity when the pedal is out of the line segment.

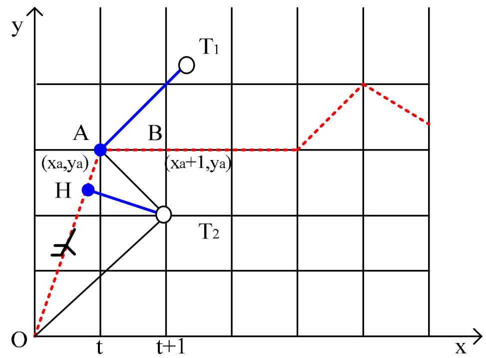

Fig 1. Threat intensity diagram

The proposed method greatly reduces the calculation cost. The radar threat intensity function is expressed by

$$W_T = \sum_{i=1}^{L} w_i = \sum_{i=1}^{L}\sum_{j=1}^{N} \frac{1}{d_{ij,\min}^{\;4}} \tag{2}$$

where $d_{ij,\min}$ is shortest distance between threat point j and path segment i, L is the number of path segments.

Based on UAV physical conditions and tactical use requirements, actual reasonable flying path should consider other factors like shortest flying distance, largest turn angle and largest flying distance. These kinds of factors are not constants. They vary with different tasks and different stages of tasks. Flight path planning aims at generating one relative effective and shorter path that UAV can avoid threats while meeting all the above requirements. Hence the threaten function is given by

$$F = \omega_1 W_T + \omega_2 W_L + \omega_3 W_\psi \tag{3}$$

where W_T is radar total threat, W_L is flying distance that represents the total cost of fuel, W_ψ is the sum of turn angles, $\omega_1 \sim \omega_3$ is the weights which reflect preference between different tasks.

3 ANT COLONY OPTIMIZATION BASED UAV PATH PLANNING METHOD

3.1 Description of Ant Colony Optimization

ACO algorithm key steps are the calculations of transition probability, visibility and pheromone amount. Ants choose their next route or goal point based on pheromone amount and visibility. At time t, the probability for ant k choosing the path from point i to j is calculated by

$$P_{ij}^{(k)}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum\limits_{s \subset \text{allowed}_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta}, & \text{if } j \in \text{allowed}_k \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where the allowed_k is selectable points group that ant k can choose, α and β are the pheromone and expectation factor respectively, $\eta_{ij}(t)$ is visibility, $\tau_{ij}(t)$ is pheromone amount between point i and j. The more pheromone amount on the path is and the higher the visibility is, the bigger probability to choose this path is.

Ant will release pheromone on the passed route. The more ants pass this route, the more pheromone remained. Visibility is related to specific case and specific object's characters. Pheromone on the route from point i to j is calculated by

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{5}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{M} \Delta\tau_{ij}^{(k)}(t) \tag{6}$$

$$\Delta\tau_{ij}^{(k)}(t) = \frac{Q}{L^{(k)}(t)} \tag{7}$$

where M is the ant amount, ρ is the volatilization factor, Q the pheromone intensity and $L^{(k)}$ is evaluation value of the k-th ant after finish the search task.

3.2 ACO Algorithm for Flight Path Planning

ACO is especially suitable to solve this path planning problem because it is a discrete optimization problem. ACO algorithm steps for UAV flight path planning are shown in following:

Step 1: Divide the UAV horizontal flying area into the grids according to certain interval. The threats on ground are mapped to the flying area. The given UAV start point is the origin of Cartesian coordinate system. Of course, as long as the starting point and target point will be placed in the first vertical line and the last vertical line, it is free to establish vertical and horizontal coordinates. The X axis is averagely divided into m parts.

Step 2: Consider the yaw angle constraint. The UAV is not allowed to exceed the allowed maximum yaw angle. Therefore the ants should consider the yaw angle constraint when they choose the next path. Given ant k is at $(x(t), y(t))$ in time t, ψ_0 represents the angle between X coordination axis and the line from the current point to the origin point, ψ_m is the allowed maximum flying yaw angle, then the ant can choose the point meeting this constraint: $y(t+1) \in [y(t) + \tan(\psi_0 - \psi_m), y(t) + \tan(\psi_0 + \psi_m)]$.

Step 3: Calculate the path visibility. Assume the Radar constantly threatens on the path all the time, thus the threat intensity is considered as the visibility for ant, that is $\eta_{t,t+1} = w_i$.

Step 4: Calculate the path probability. The probability of the ant to choose the next flying path is

$$P_{x,x+1}(t)=\frac{[\tau_{x,x+1}(t)]^{\alpha}[\eta_{x,x+1}(t)]^{\beta}}{\sum_{r=ceil(y(t)+\tan(\psi_0-\psi_m))}^{floor(y(t)+\tan(\psi_0+\psi_m))}[\tau_{x,r}(t)]^{\alpha}[\eta_{x,r}(t)]^{\beta}} \quad (8)$$

Step 5: Evaluate the ant searching task. When the ant finds one path from the start point to the destination point, the ant finishes one searching task, and then the evaluation value should be obtained by calculating the function (3). Then we get $\{F^{(k)}(t)\}$.

Step 6: Update the path pheromone. When finishing one searching task, the path pheromone is updated based on evaluation function. The new pheromone is obtained according to (5)-(7), where $F^{(k)}(t)=L^{(k)}(t)$.

4 SIMULATION

UAV flying over the battle field is simulated to verify the effectiveness of the ACO based UAV path planning method. Suppose that the enemy's attack area is 10km×10km, which is averagely divided into small grids with 1km×1km. All the threats strengths are 0.5. The distribution location coordinates of the threats are: (3km, 5km), (5km, 6km), (8km, 2km), (2km, 6km), (6km, 7km), (5km, 2km), (8km, 6km), (3km, 2km). Only one ant is dispatched to search the destination node in an iteration process of the algorithm. Test number is 100. One test has 20 iterations. Other parameters for ACO algorithm are: $\alpha=1$, $\beta=1$, $Q=1$. Fig. 2 shows the average convergence process of ACO algorithm obtained by 100 tests. Fig. 3 shows the final UAV penetration flying path obtained by the ACO algorithm. 100 paths are obtained after 100 tests. The node which the most ants move through is considered as the final node of each segment.

It can be seen from the simulation results that the ACO algorithm based path planning method can generate a reasonable path, flowing which the UAV can safely flying through the defensive area and arrive at the destination point within shorter time. Because one iteration only has one ant, the computation cost of this intelligent planning algorithm is small.

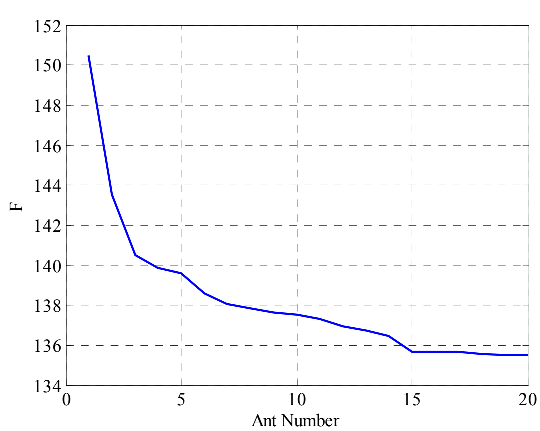

Fig 2. Convergence process of ACO algorithm

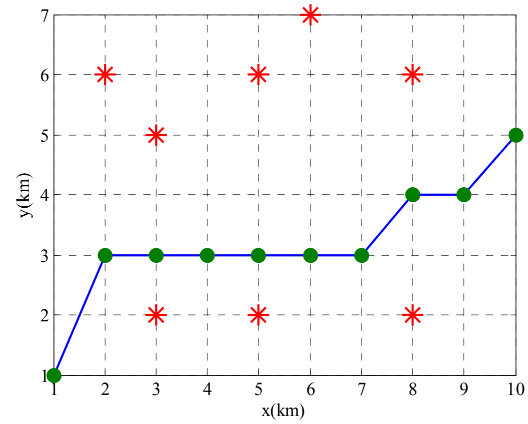

Fig 3. UAV flight path optimized by ACO algorithm

5 CONCLUSION

In this paper, ACO is used for UAV path planning by dividing flying area into grids and optimizing path between grid point and destination point. Because ACO is ants looking for the shortest route of food, it is much more proper for path planning compared with other optimized methods. ACO takes positive feedback mechanism, so its process with strong instructions to get good result. Comparing to the traditional ACO based path planning methods, the calculation of the threat intensity is smaller. Simulation results also prove that ACO can effectively and quickly accomplish UAV path planning. However, because of the path generated by ACO includes a series of connected points, it still need smoothness processing in order to be applied for real UAV flying.

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