OBSTACLE AVOIDANCE FOR MULTI-UAV SYSTEM WITH OPTIMIZED ARTIFICIAL POTENTIAL FIELD ALGORITHM

Yuehao Yan,[*,***] Zhiying Lv,[**,****] Jinbiao Yuan,[***] and Shufeng Zhang[*****]

Abstract

Unmanned aerial vehicles (UAVs) have incomparable advantages and gradually form multi-UAV systems, in which many UAVs work together to accomplish tasks through cooperation. In the case of flying in an unknown environment and the very close distance between them, it is essential to have a useful collision avoidance system to avoid the collision between obstacles and UAVs and between inter-UAVs. In this paper, a comprehensive optimal obstacle avoidant mechanism of UAV path planning is constructed. The flight environment of UAVs is described, and the warning ranges and danger ranges of UAV and obstacles are given fully considering the execution time and flight platform of UAV. Then, a reliable artificial potential field (APF) model for path planning of multi-UAV systems in a complex environment is presented, in which a method to save UAV's energy and the solution for UAV Local minimization problem are proposed. Finally, the applicability of the improved algorithm is verified by simulation experiments.

Key Words

Path planning, UAV, artificial potential field (APF), energy-efficient, collision avoidance, local minimum

1. Introduction

Unmanned aerial vehicles (UAVs) have been widely used in military and civilian fields such as environment monitoring, border patrol, reconnaissance, surveillance, and rescue [1], [2]. Due to the increasing diversity of missions and the limited capabilities of single aircraft, multi-UAV joint missions have become a popular choice in many fields. UAV cluster behaviour means that the members have the same goal, and it is crucial that individuals must coordinate their actions to carry out missions. In addition to the ability of multiple UAVs to perform complex tasks, the collaborative flight performance can also save energy. Collaborative applications of UAVs have attracted the attention of many scholars [3]. Modern advanced flight technology is undertaking more and more essential tasks and is developing towards the unmanned and autonomous trend. This trend inevitably requires UAVs to plan reasonable flight path according to the information of mission objectives and situation constraints, to deal with the uncertainty caused by sudden threat situation changes in real-time during mission execution, and then to re-plan autonomously. At present, the research of the mission path planning method mainly focuses on obstacle avoidance and other fields. A collision with obstacles or other UAVs may be very dangerous and even cause a mission to fail. The obstacle avoidance path planning for UAV refers to the process, in which the UAV can find the path from the beginning to the desired goal and avoid all threats along the way [4]. In this process, the UAV should also evaluate the environment of the planning space according to the mission requirements [5].

UAV mission planning has been a research hotspot in recent years. Many methods have been studied such as genetic algorithm [6], bionic algorithm [7], Voronoi diagram search method [8], Markov decision progress, A* searching algorithm [9], and real-time path planning schemes [10]. Another method is to connect a sequence of waypoints and smooth the path [11]. The Voronoi algorithm is a trajectory planning method based on the graph. However, these methods have not proved the optimal solution. The genetic algorithm obtains the optimal path through a random search, but the convergence rate may become slow after approaching the optimal solution. The A* algorithm is a classic optimal heuristic search algorithm but requires a long time of convergence and ample memory space. These algorithms require much computation, especially in large searching spaces and complex environments. The artificial potential field (APF) algorithm based on the magnetic field is widely used in UAV path planning [12]–[17]. This algorithm meets the real-time control and safety requirements of trajectory generation. The structure

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of this algorithm is simple, and the planning time is short. The central concept of the APF is to regard the motion of UAV in the planned space as a force moving in the virtual force field. UAVs can move to the target point under the combination of gravity and repulsive force. Even if the path given by the APF algorithm is not necessarily the shortest, it is smoother and safer than those obtained by other algorithms. Despite there are many methods, few papers consider energy loss in the process of blocking, which is the sum of the angular variations and the flight distances. In addition, the repulsion force between UAV and obstacles and other UAVs should fully consider the performance of UAV and the execution time of the mission.

In this paper, the concept of simulating human behaviour to avoid the collision is introduced in an uncertain experiment. To realize the cooperative trajectory planning and collision avoidance of multi-UAVs, we develop an optimization algorithm based on the APF. It not only solves the local minimum problem but also takes into account energy savings for UAVs. Then, simulations on MATLAB prove the validity of the proposed obstacle avoidance mechanism.

The layout of this paper is as follows. The flying environment of the UAV cluster is described in Section 2. Section 3 gives the APF algorithm of the path planning for multi-UAVs, in which the methods of saving energy of UAVs and dealing with local minimization are given. Section 4 presents the simulation models on MATLAB for testing the given methods. Finally, the conclusion and the prospect of future research work are given in Section 5.

2. Unmanned Aerial Vehicles Flying Environment

In formation flight, each UAV in the cluster has its target point. The UAVs will likely collide in the course of the flight, so the distances between UAVs and obstacles and among UAVs should be monitored. Both the UAVs and obstacles have the danger ranges and warning ranges of possible collisions. To simplify the problem, the warning areas of UAVs and obstacles are assumed as circular areas in two-dimensional space. These areas can be determined by the execution time and the flight platform of UAVs. Hence, these ranges may differ for a different performance of UAV. What is more, when a UAV cannot detect the target point, it is necessary to find a sub-target point defined as the virtual target point in one visual space, which can guide a UAV ultimately to the original target. Based on the above discussion, we can build the flight environment of the UAV cluster as follows.

We consider that the UAV cluster is composed of n UAVs ($n \geq 2$), which is denoted as $U = \{u_1, u_2, \ldots, u_n\}$. The position of moving u_i is $P_i^u(x_i^u, y_i^u)$, and the distance between u_i and u_j is $d(P_i^u, P_j^u)$, $(i, j = 1, 2, \ldots, n)$. The flying speed of u_i is v_i, the flight acceleration of u_i is a_i, and the maximum rotation angle of u_i is φ_i. Let r_i^u be the radius of the collision danger area of UAV, and the annular region of $r_i^u < r < r_i^u + s$ be the warning area, in which s is the warning parameter of UAVs. The target set of UAV is $G = \{G_1, G_2, \ldots, G_n\}$, in which G_i is the goal point of u_i, which is denoted by $P_i^g(x_i^g, y_i^g)$, r_i^g is the influence range

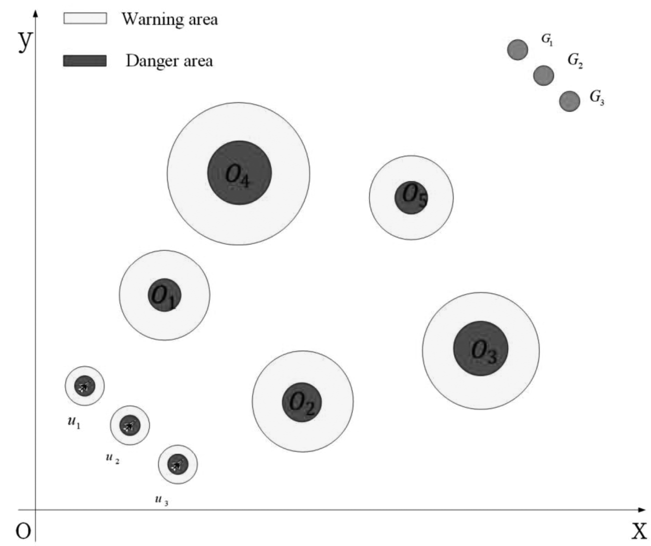

Figure 1. The flying environment of the UAV cluster.

of the target point G_i. Let $O = \{o_1, o_2, \cdots, o_m\}$ be the obstacle set ($m \geq 0$) in the environment, and the position of o_k be $P_k^o(x_k^o, y_k^o)$. The distance between o_i and o_j is $d(P_i^o, P_j^o)$, $(i, j = 1, 2, \cdots, m)$, and the distance between u_i and o_k is $d(P_i^u, P_k^o)$. Suppose that the radius of the collision danger area of o_k is r_k^o, and the warning area of o_k is an annular region of $r_k^o < r < r_k^o + t$, in which t is the warning parameter of obstacles. s and t are decided by the execution time and flight platform of UAVs. The flying environment of the UAV cluster is shown in Fig. 1.

3. Artificial Potential Field

The artificial potential field (APF) has undergone several decades of development and different modifications. The APF consists of an attractive potential field and a repulsive potential field, attracting UAVs to the target positions and keeping them away from obstacles and other UAVs. In this section, the path planning of the APF method is developed. For each UAV in the cluster, the influence of target points, obstacles, and other UAVs on it must be fully considered.

The clustered-control of multi-UAVs is mainly based on the APF method, in which the total potential field U_i of u_i is given as follows:

$$U_i = U_{ai} + \sum_{j \neq i, j=1}^{n} U_{ri}^{u_j} + \sum_{k=1}^{m} U_{ri}^{o_k} \tag{1}$$

Then, the total force f_i of u_i is given as follows:

$$f_i = f_{ai} + \sum_{j \neq i, j=1}^{n} f_{ri}^{u_j} + \sum_{k=1}^{m} f_{ri}^{o_k} \tag{2}$$

3.1 Attractive Potential Field

The gradient descent method is used to attract the UAV to the target with the help of the attraction field. The guide relies only on real-time status. The attracting potential field descends from the starting point of the UAV to the target position. Then, gravity directs the UAV to its target wherever it goes.

The attractive potential U_{ai} of u_i is given by the following equation:

$$U_{ai} = \frac{1}{2} k_a d(P_i^u, P_i^g)^2 \tag{3}$$

The attractive force f_{ai} is produced by the gradient ∇ of the attractive potential. Thus, the attractive force on u_i is

$$f_{ai} = -\nabla U_{ai} = \begin{cases} k_a d(P_i^u, P_i^g) & if \quad d(P_i^u, P_i^g) \leq r_i^g \\ k_a r_i^g & if \quad d(P_i^u, P_i^g) > r_i^g \end{cases} \tag{4}$$

where k_a is the coefficient of attraction.

The attraction potential of the UAV is depended on the distance between the UAV and the target point, which is proportional to the distance to the goal within r_i^g and is set to be a fixed value $k_a r_i^g$ outside the range r_i^g.

3.2 Repulsive Potential Field for Inter-unmanned Aerial Vehicles

Communication is the basis of the collaboration framework, and UAVs can only exchange information between each other within the range of communication. Necessary information such as current position, flight distance, and target position can exchange between UAVs. However, if two UAVs get too close, they may collide with each other. In this case, the UAVs can be seen as dynamic obstacles blocking each other. Therefore, they should keep a safe distance from each other at all times.

The collision avoidance between u_i and u_j is solved by the repulsive potential field, which is defined as follows:

$$U_{ri}^{u_j} = \begin{cases} k_r \left(\frac{(r_i^u+s)^2-(r_i^u)^2}{(d(P_i^u,P_j^u))^2-(r_i^u+s)^2} \right)^2 & if \quad r_i^u < d(P_i^u, P_j^u) \leq r_i^u + s \\ 0 & if \quad otherwise \end{cases} \tag{5}$$

And the repulsive force is given by the gradient of the potential field $f_{ri}^{u_j}$ as follows:

$$f_{ri}^{u_j} = \begin{cases} k_r \frac{(r_i^u+s)^2-(r_i^u)^2}{(d(P_i^u,P_j^u))^3-(r_i^u+s)^3} & if \quad r_i^u < d(P_i^u, P_j^u) \leq r_i^u + s \\ 0 & if \quad otherwise \end{cases} \tag{6}$$

where k_r is the coefficient of repulsion. When u_i enters the warning area of u_j, it will be repelled by the force $f_{ri}^{u_j}$. As the distance $d(P_i^u, P_j^u)$ decreases, the repulse will increase rapidly, in which u_i must keep a safe distance from the forbidden area of u_j. If $d(P_i^u, P_j^u) > r_i^u + s$, the repulsive force is no longer needed. When u_j enters the alarm area of u_i, u_i also enters the alarm area of u_j. So, if there is a repulsive force that u_j is going to exert on u_i, then there is a repulsive force that u_i will exert on u_j at the same time. In this way, both UAVs will have an additional repulsion force, which increases the computation. If both UAVs change their original paths to avoid a collision, it will consume more energy because it increases the total distances and angles of the flight trajectory. To solve this problem, we suggest changing only one UAV's flight path to maintain a safe distance to avoid a collision. In contrast, the other UAV keeps its original trajectory. In this way, it can reduce the total energy consumption of the system. In this paper, we assume that the energy consumption of the UAV cluster system depends on the total distance flown by UAVs and the changes of turning angles in UAV flight paths. Therefore, to reduce the total energy of the system, we suggest choosing the UAV with a small flight distance and changing its flight trajectory to avoid the collision when a collision between two UAVs is detected. Based on the above assumptions, the UAV flying short distance consumes less energy than the UAV flying long distance. By selecting the UAV with less energy consumption for collision avoidance, the total energy consumption of the system will be reduced.

Now, we present a method to calculate $f_{ri}^{u_j}$ that is the repulsive force u_j on u_i and to choose which UAV should change its path. Suppose that s_i and s_j are the distances the u_i and u_j have travelled from the start point, respectively. Let $f_{ri}^{u_j}$ be the repulsive force on u_i caused by u_j in the swarm. Now, to calculate the repulsive force, an algorithm is given as follows:

Algorithm 1

Input: $P_i^u(x_i^u, y_i^u)$,$P_j^u(x_j^u, y_j^u)$,$r_i^u + s$
Output: $f_{ri}^{u_j}$
Step 1: Set up $f_{ri}^{u_j} = 0$.
Step 2: For u_i, if $d(P_i^u, P_j^u) < r_i^u + s$, then calculate s_i and s_j.
Step 3: If $s_i < s_j$, calculate $f_{ri}^{u_j}$ based on (6), else $f_{ri}^{u_j} = 0$.

Algorithm 1 is implemented on all UAVs. The algorithm is used to check the potential collision probability of each UAV and calculate its repulsive force. As only the selected UAV is likely to change its path to avoid the collision, the total energy consumption will reduce.

3.3 Repulsive Potential Field for Obstacles

A UAV may encounter obstacles and some enemy threats. To ensure the safety of the UAVs, the UAV needs to avoid the threat areas. The other vital part of the APF is the repulsive potential field with obstacles, driving the UAV away from the obstacles and threats by applying a repulsive force. The repulsive potential and force based on obstacle o_k are given by the following equations:

$$U_{ri}^{o_k} = \begin{cases} \frac{1}{2} k_r \left(\frac{1}{d(P_i^u, P_k^o)} - \frac{1}{r_k^o + t} \right)^2 & if \quad d(P_i^u, P_k^o) \leq r_k^o + t \\ 0 & if \quad d(P_i^u, P_k^o) > r_k^o + t \end{cases} \tag{7}$$

$$f_{ri}^{o_k} = -\nabla U_{ri}^{o_k} = \begin{cases} k_r \frac{1}{d(P_i^u, P_k^o)^3}\left(\frac{1}{d(P_i^u, P_k^o)} - \frac{1}{r_k^o + t}\right) & if \quad d(P_i^u, P_k^o) \le r_k^o + t \\ 0 & if \quad d(P_i^u, P_k^o) > r_k^o + t \end{cases} \tag{8}$$

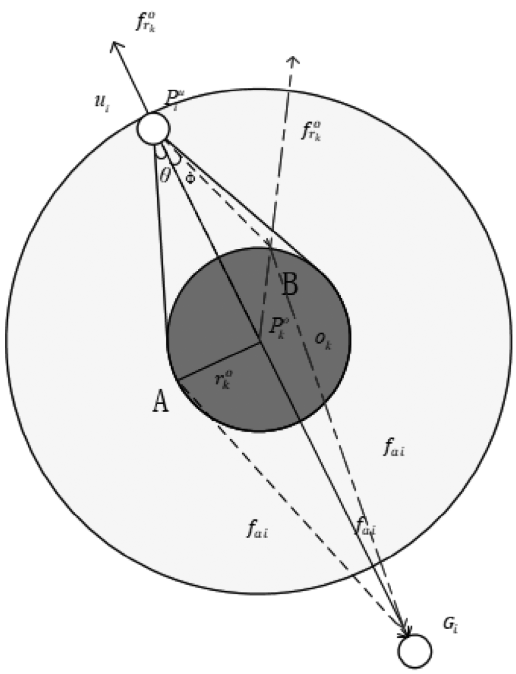

Figure 2. Local minimum problem.

where k_r is a positive constant. When u_i enters the warning area of o_k, it will be repelled by force $f_{ri}^{o_k}$. As $d(P_i^u, P_k^o)$ decreases, the repulse will increase rapidly, which can keep a safe distance from the forbidden area. If $d(P_i^u, P_k^o) > r_k^o + t$, the repulsive force is no longer needed.

3.4 The Treatment of Local Minimization Problem

If there is an obstacle on the path close to the target position, then the UAV is within the affected scope of obstacles whose repulsion is rapidly increasing while attraction is reducing. When the UAV, obstacle and target are on the same straight line, at a certain point, the gravitational force of the UAV subjected to the target position and the repulsive force of the obstacle are equal. As their directions are opposite, the resultant force will be zero, thus causing a kind of local minimum phenomenon. This will happen in a UAV environment when the UAV faces away from an obstacle and the target is behind the obstacle. This phenomenon is shown in Fig. 2.

To deal with this problem, u_i should rotate at an angle ω to avoid obstacle o_k and gradually flew to its target point G_i. Then the resultant force f_i of u_i can be obtained by Algorithm 2, which is presented as follows.

Algorithm 2

Input: P_i^g, P_k^o, r_k^o, P_i^u, G_i, φ
Output: f_i
Step 1. Compute $d(P_i^u, P_k^o)$ and $\theta = \arcsin(r_k^o / d(P_i^u, P_k^o))$.
Step 2. If $\theta \le \varphi$, then $\omega = \theta$, calculate the attractive force f_{ai} at point A based on (4), in this case, $f_i = f_{ai}$.
Step 3. If $\theta > \varphi$, then $\omega = \varphi$, calculate the attractive force f_{ai} and the repulsive force f_{rk}^o at B based on (4) and (8), so $f_i = f_{ai} + f_{rk}^o$.

Then at the next moment, due to the change of UAV's direction, the resultant force and the attraction force are no longer collinear and then continue to achieve the obstacle avoidance effect according to the previous artificial potential field principle.

3.5 Flow of Artificial Potential Field Path Planning

The obstacle avoidance mechanism presented in this paper can be represented by a flow chart, which is shown in Fig. 3. If two UAVs enter the warning range of each other during the flight, then Algorithm 1 is used to determine which UAV needs to change the path. When the UAV enters the warning range of the obstacle, the APF is used to re-plan the path according to the path parameters, the location of the obstacles, and the target points. If there is a local minimal problem, then Algorithm 2 is used to deal with it.

4. Simulations Evaluation

The simulations are performed within one measurable range of UAVs. The UAVs in the swarm have the same type and performance, and these optimized methods are run in the environment of high UAV platforms and low consume time. The general movement parameters are used in all of the following experiments, which are illustrated in Table 1. The operating system is Window 10, and the code is written and implemented using MATLAB 2016. UAV trajectories in different flying environments are presented in Figs. 4–6.

In Fig. 4, at first, the resultant force is collinear to the gravitational force from the target point and is in the same direction of motion. Then, u_1 enters the warning area of obstacle. Because the repulsion force is very small, it will continue to move in the direction of the resultant force until the repulsion force is greater than the attraction from the target point. Hence, it will slow down. But its flying direction remains unchanged, so it is easy to collide with

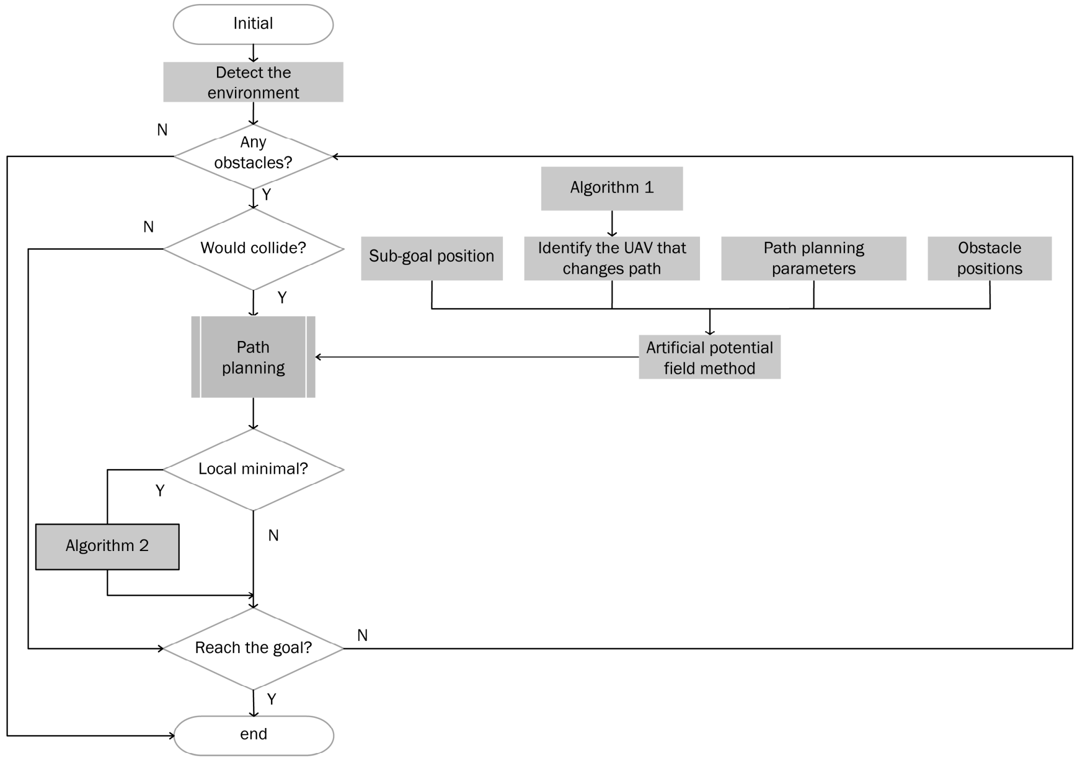

Figure 3. The flowchart of the APF path planning process.

Table 1
Parameter List

Name	Value	Unit
u_i	15	m
s	100	m
v_i	[5,10]	m/s
a_i	3	m/s^2
s	100	m
t	50	m
φ_i	30	degree

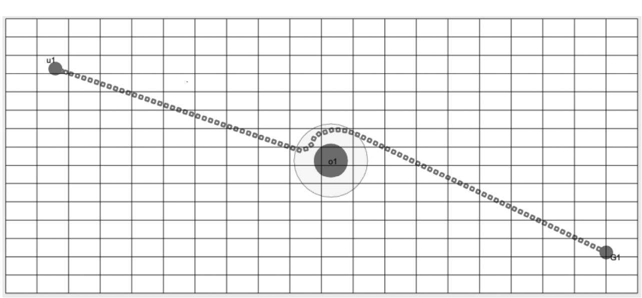

Figure 4. The local minimal problem.

obstacle. By changing the direction of the path based on Algorithm 2, the resultant force and the attractive force are no longer collinear at the next moment.

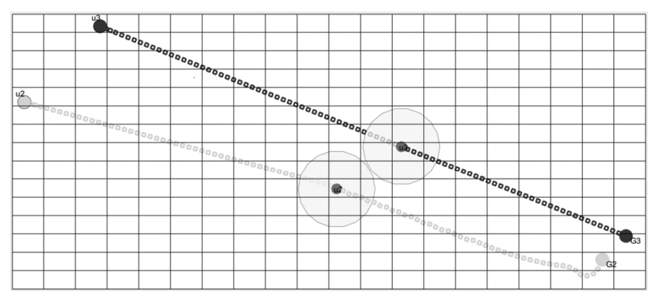

Figure 5. Inter-UAV collision avoidance with the given method.

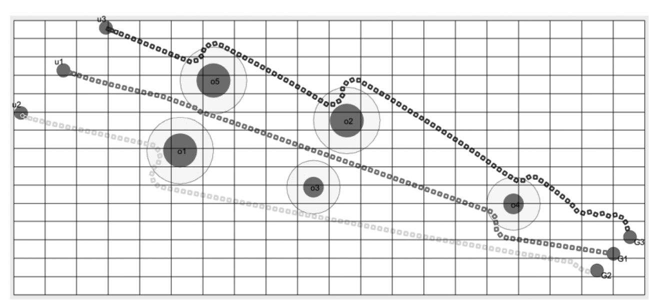

Figure 6. Obstacle avoidance in multiple obstacles' scene.

In Fig. 5, there are two UAVs u_2 and u_3, and their target points are G_2 and G_3, respectively. When they enter each other's threat area, they will repel each other. Therefore, in this case, we calculate the path accumulation of u_2 and u_3 and give priority to the UAV with a small cumulative path value to make changes based on Algorithm 1. It can be seen that only u_3 changes path due to the small cumulative path value, which can avoid collision and save energy.

In Fig. 6, through the simulation program, we can find that three UAVs can successfully avoid obstacles and reach their target points.

5. Conclusion

In this paper, the obstacle avoidance path planning of UAVs is presented based on the APF algorithm in uncertain environments. On this basis, an improved algorithm is proposed, in which only some UAVs are selected to change the paths to avoid the collision between UAVs. The algorithm reduces the total distance and the turns of the system, thus reducing the energy consumption of the whole system. This paper also gives an algorithm to solve the problem of local minimization. Simulation results show that the presented algorithms have excellent performance for the UAV cluster. The path planning method proposed in this paper is easy to apply in 3D space without a significant increase in computational complexity. However, the 3D path planning needs to consider the minimum flight altitude, the maximum climbing angle, and the maximum diving angle. This paper mentioned that the warning range of UAV and obstacle is related to the UAV's flight platform and execution time, which can achieve the accuracy of obstacle avoidance and save energy. Our future work will focus on UAV sense obstacle avoidance based on multiple attribute three-way decision to reduce the problem size and save energy of UAVs. We can calculate the conditional probability, in which the obstacle will produce a threat to the UAV by the fuzzy multiple attribute decision method [2], [18], [19]. Then, based on the three-way decision [20]–[24], we can divide the threat of obstacles into danger, safety, and make a further evaluation to reduce the loss caused by bad decisions.

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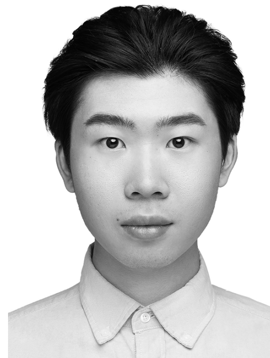

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