A Novel Path Planning Algorithm for Multi-Agent Collaboration in Finite Space

Yihan Xu*
Manchester Metropolitan Joint Institute, Hubei University
Wuhan, China
Yihan_Xu@stu.hubu.edu.cn

Tian Cao*
School of Artificial Intelligence HuBei University
Wuhan, China
ct9201@stu.hubu.edu.cn

Xiaotong Shi+
School of Artificial Intelligence HuBei University
Wuhan, China
0000-0002-0839-7140

2024 8th International Conference on Communication and Information Systems (ICCIS) | 979-8-3315-3117-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICCIS63642.2024.10779383

***Abstract*—Multi-agent collaboration can complete tasks that are difficult for a single agent to handle, making a big difference on the battlefield, in healthcare, and in other domains. Effective path planning is an important factor in ensuring task execution. However, the finite space increases the probability of multi-agent collisions, which poses a challenge to multi-agent path planning. To this end, we propose a novel path planning algorithm by two-module fusion (PLA-TMF). Specifically, the first module is to develop a collision detection model based on discrete point intersection probabilities, which improves the collision detection accuracy between different agents. Then, the second module is to realize the path planning algorithm under the minimum collision probability constraint, which relies on genetic algorithm. Finally, the effectiveness of the proposed algorithm is verified by simulation experiments under specific scenarios.**

Keywords— multi-agent, collision detection, genetic algorithm, path planning

I. Introduction

In recent years, the research of multi-agent is increasingly hot. The real-time battlefield situation recognition technology based on collaborative intelligence is utilized in the battlefield field [1]. In the medical field [2], a general architecture for integrating swarm intelligence into multi-agent healthcare systems is proposed to improve care effectiveness. Due to their adaptability, reliability, and efficiency [3] [4], multi-agent such as unmanned aerial vehicle (UAV) swarms are widely used to perform a variety of complex missions [5].

With the widespread use of drones, the path planning technology that determines the flight path of each drone is becoming increasingly critical to ensuring the successful completion of drone missions [6]. Simultaneously, as the volume of tasks increases, ensuring the minimum distance while accomplishing path planning for multiple UAVs has become a prominent research challenge [7]. Although there are many papers focusing on the multi-UAV path planning problem, multi-UAV path planning in finite space is more difficult to deal with, since finite space has higher requirements such as collision detection accuracy [8].

*Co-first authors.
+This is the corresponding author of the work.

All authors are also with Key Laboratory of Intelligent Sensing System and Security (Hubei University), Ministry of Education.

Specifically, in [9], a decentralized, importance-based multi-UAV path planning algorithm is proposed, and the design, implementation, and use of simulations to evaluate its performance are described. In [10], the traditional sparse reward function is used for the multi-agent deep deterministic policy gradient (MADDPG) algorithm, which leads to slow convergence, and the trained path planning strategy is difficult to adapt to complex scenarios. In order to solve the above problems, an improved MADDPG algorithm of potential field intensive reward function is proposed for multi-UAV trajectory planning in complex unknown environment. By introducing the attraction and repulsion mechanism of potential field, the learning efficiency and the optimality of path planning strategy are improved. In [11], a path planning method based on an improved ant colony system (IACS) algorithm is proposed for the dense target group model. In the process of target selection, IACS algorithm adopts a new target exploration scheme bidirectional simplified search strategy, which improves the efficiency of target detection and minimizes the total execution time of UAVs.

To improve the effectiveness of path planning for multi-agent collaboration in finite space, propose a novel path planning algorithm by two-module fusion (PLA-TMF). The key insights of the proposed algorithm are based on the idea of mathematical-physical analysis and iterative optimization. To be specific, in the first module, the motion characteristics of multiple UAV echelons in finite space are analyzed. Then, the concept of discretization is introduced, the motion coordinates of UAV are equivalent to discrete points, and the collision detection model is established to reduce the collision probability between different UAVs in the process of motion. In the second module, aiming at the path planning under the minimum collision probability constraint, genetic algorithm is introduced to optimize the path under the constraint condition. By coupling the above two modules, a novel path planning algorithm is formed [12] [13].

The main contributions are as follows:

- This paper proposes a novel path planning algorithm, which is based on the ideas of mathematical analysis and iterative optimization.
- To improve the accuracy of multi-agent collision detection in finite space, a collision detection model

based on discrete point intersection probability is developed.
- Genetic algorithm-based path planning scheme under minimum collision probability constraints is implemented.

The remainder of this paper is organized as follows. The system model is introduced in Section II. The details of the first module in PLA-TMF, collision detection model based on discrete point intersection probabilities, is presented in Section III. Then, the second module in PLA-TMF, path planning under the minimum collision probability constraint, is presented in Section IV. Simulation results is presented in Section V. Finally, conclusion and future work are presented in Section VI.

II. Dynamic Motion Model

A. Describe the route and area of movement

The entire UAV echelon consists of a directorial UAV and several subordinate UAVs, in which the directorial UAV is responsible for directing and the subordinate UAV is responsible for following. The whole group of UAVs collaborates, starting from point P, and coils clockwise along the isometric spiral with the same pitch, and both ends of each fuselage are located on the spiral, as shown in Fig. 1.

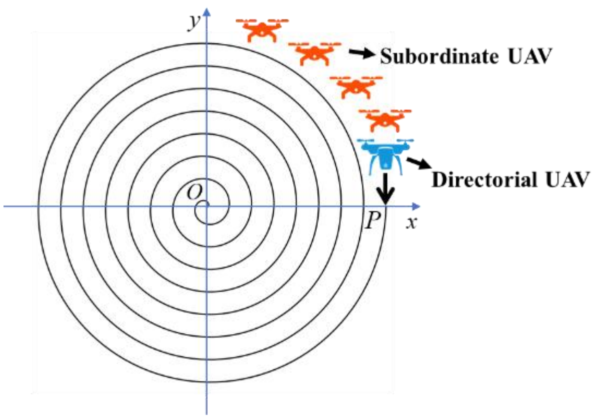

Fig. 1. A diagram of a drone flying into a spiral line

B. Establishment of the Dynamic Motion Model

1) Establish the Spiral Line Equation

In the polar coordinates, the equation for a spiral line is:

$$r(\theta) = r_0 + \frac{p}{2\pi}\theta, \tag{1}$$

where $r(\theta)$ is the radius, θ is the pole angle, r_0 is the initial radius, and p is the pitch. Since the pitch is the same, the parameter equation of the spiral line is:

$$x(\theta) = r(\theta)\cdot\cos(\theta), y(\theta) = r(\theta)\cdot\sin(\theta). \tag{2}$$

Through iterative calculations, the initial position is constantly updated, and the polar angle changes within $[-2k\pi, 2k\pi], k \in Z$, establishing the spiral line equation.

2) Calculate the Position of UAV in second

Because the UAV moves along a spiral line at a constant velocity, its angular velocity needs to be calculated. The displacement $s(t)$ of the UAV at time t is:

$$s(t) = v \cdot t. \tag{3}$$

For each dt period, the length ds along the spiral line can be expressed as:

$$ds = \sqrt{(dx)^2 + (dy)^2}. \tag{4}$$

The length s is the length of the path along the helix, which takes into account the parameter equation of the helix:

$$ds = \sqrt{\left(\frac{d}{d\theta}\left[r(\theta)\cdot\cos(\theta)\right]\right)^2 + \left(\frac{d}{d\theta}\left[r(\theta)\cdot\sin(\theta)\right]\right)^2}. \tag{5}$$

With the help of the relation on θ, use the numerical method to solve $\theta(t)$, so as to obtain the specific location of the UAV every second.

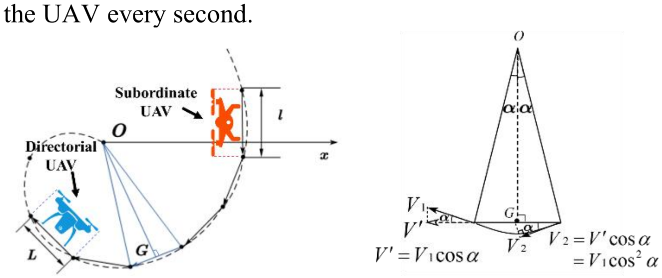

Fig. 2. Velocity vector diagram of UAV in motion

3) Recursive Algorithm to Solve the UAV Position

Through the initial two steps, the spiral motion trajectory of the UAV can be established, allowing for the calculation of the head's movement speed on a second-by-second basis, as shown in Fig. 2. Consequently, the position of the head in polar coordinates can also be determined at each second. The position of the UAV in section n is (x_n, y_n), then section $n+1$ UAV shall meet:

$$d_1 = \sqrt{(x_{n+1} - x_n)^2 + (y_{n+1} - y_n)^2}. \tag{6}$$

In the formula, d_1 represents the location between the centers of the two UAVs.

4) Solve for the Speed of each UAV

By using the position change rate to approximate the velocity of the UAV, the instantaneous velocity is solved by considering the position change in a very short time interval.

The formula of position change rate is:

$$v(t) = \lim_{\Delta t \to 0}\frac{|\Delta r|}{\Delta t} = \lim_{\Delta t \to 0}\frac{\Delta s}{\Delta t} = \frac{ds}{dt}, \tag{7}$$

where s represents the distance traveled by the UAV, and t represents the time during which the UAV moves. By taking the derivative of distance with respect to time, the instantaneous speed at that moment can be calculated.

Since the motion helix equation of the directorial UAV has been determined, the motion helix equation of each point of the UAV has also been determined. Therefore, the velocity of the UAV in section n can be calculated as:

$$v_n(t) = \frac{d}{dt}\sqrt{x_n(t)^2 + y_n(t)^2}. \tag{8}$$

III. COLLISION DETECTION MODEL

A. Analysis of the Collision Detection Model

In the process of calculating the UAV fleet collision problem, this paper adopts a simplified model. In a two-dimensional plane, each UAV is represented as a line segment, as shown in Fig. 3, distributed around this segment within a rectangular area that defines the value range. We extract a subset of scatter points to form a set of discrete points and subsequently evaluate whether there is an intersection between the discrete point sets generated by any two UAV line segments.

By introducing vector analysis, each UAV is approximated as a line segment. Based on the specific characteristics of the two vacancies at each segment position, we calculate the position vector of each arbitrary UAV.

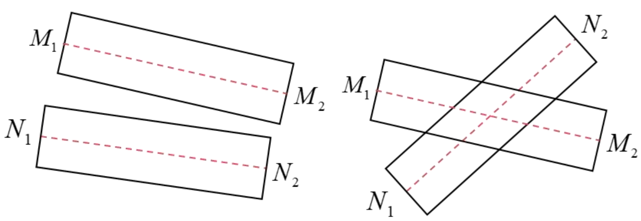

Fig. 3. The UAV is represented by the line segments

B. Establishment of the Collision Detection Model

1) Establish Collision Coordinates

If the two UAVs are not parallel, the normal vector is not point multiplied by 1, and then the new center O' of the collision coordinate system is determined, as shown in Fig. 4.

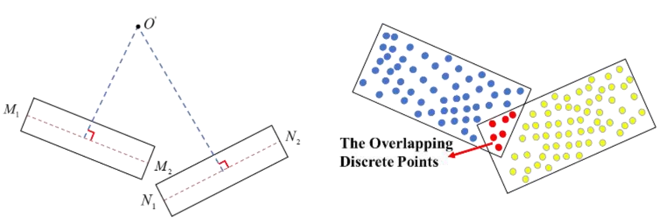

Fig. 4. A diagram of the distribution of discrete points in the case of collision

The diagram represents the coincidence of discrete points. Around the UAV line, the discrete points set in the rectangular range is generated by calculation. The first set of discrete points is rotated by the rotation matrix T, aligning the two coordinate systems.

The expression for the rotation matrix is:

$$R = \begin{bmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \end{bmatrix}. \tag{9}$$

Using the unit four-element method, the rotation matrix is constructed with four algebraic parameters:

$$\begin{bmatrix} q_0^2 + q_1^2 - q_2^2 + q_3^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\ 2(q_1q_2 + q_0q_3) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\ 2(q_1q_3 - q_0q_2) & 2(q_2q_3 - q_0q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix}. \tag{10}$$

The set of two discrete points is transformed into a unified coordinate system, which is then used to determine whether an intersection exists.

2) Collision Determination Conditions

Preliminary test criteria: For sections i and j UAV, test whether the distance between them is less than the length of the UAV.

Distance is expressed as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{11}$$

Collision was considered to occur if the distance d_{ij} was less than the minimum safe distance. Then determine whether there is an intersection between the discrete point set range, and to further determine whether a collision will occur.

IV. PATH FINDING ALGORITHM DESIGN

A. Motion path description

We study the motion trajectory of UAV echelon under specific circumstances. The turning motion of UAV echelon is carried out in the circular turning area with the radius of $4.5m$ and the center of O as the spiral circle, as shown in Fig. 5. The turning path is an S-shaped curve formed by the tangent connection of two arcs, the radius of the former arc is twice that of the latter, and it is tangent to the incoming and outgoing spirals.

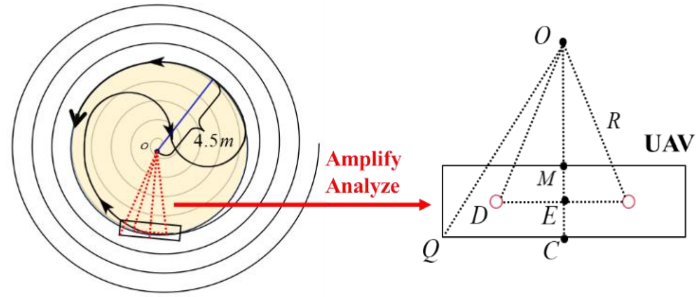

Fig. 5. Analysis of the instantaneous position of UAV in turning space

B. Circular arc path analysis

To ensure that the spiral movement in and out of the center is symmetrical, two parallel lines are selected to define the circular range, as shown in Fig. 6. Through mathematical and geometric analysis, the positional relationship between the first arc and the second arc is established as follows:

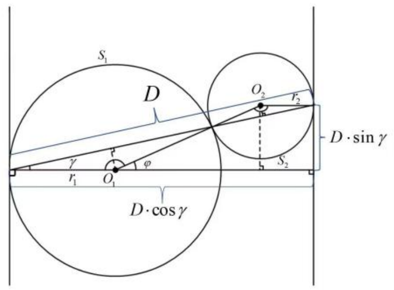

Fig. 6. The relation between two circular arcs

The total length S of the turning curve obtained from the graph analysis is:

$$S=(r_1+r_2)(\pi-\arcsin\frac{D\sin\gamma}{r_1+r_2}). \tag{12}$$

From the vertical path theorem:

$$D=2(r_1+r_2)\cos\gamma. \tag{13}$$

Since both disc entry and disc exit points are tangent to the spiral, and the disc entry spiral and disc exit spiral are symmetric about the center, it can be proved that the two tangent points are symmetric about the center of the origin. The whole turning process of launching the UAV echelon is actually composed of two inferior arcs, and the centers of the two inferior arcs are also center-symmetric.

C. Analysis of different motion states

The movement of the UAV on the turn-around path is mainly divided into the following four situations, as shown in Fig. 7. We mainly analyse situation 3, the remaining three situations have similar computational ideas.

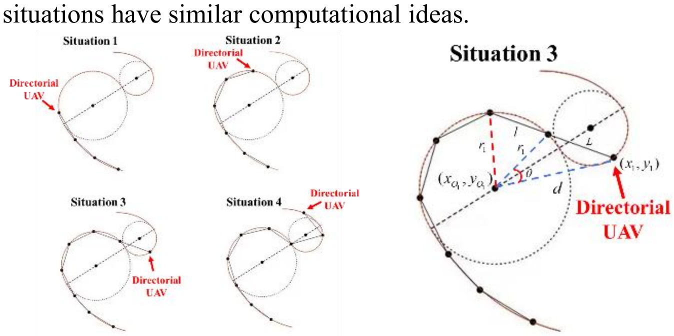

Fig. 7. Four situations in the whole process of UAV turn

For situation 3, firstly, calculate the known directorial UAV position (x_1, y_1), the center coordinate of the great circle (x_0, y_0). Having known the radius r_1 of the big circle, the angle θ can be solved, and then the position coordinates of the second section UAV can be obtained.

$$\begin{cases} d=\sqrt{(x_1-x_{O_1})^2+(y_1-y_{O_1})^2} \\ \cos\theta=\dfrac{r_1^2+d^2-L^2}{2r_1d} \end{cases}. \tag{14}$$

Through recursive calculation, the position coordinates of all UAVs can be obtained.

D. Genetic algorithm optimization

For the long-term prediction of UAV positions on a two-dimensional map, we employ a genetic algorithm to optimize the prediction model.

The procedure is outlined as follows:

1) Vector Definition: A ten-dimensional vector is established to represent the UAV's position at different time points.

2) Population Initialization: A population consisting of 1000 individuals is created, where each individual represents a potential UAV position prediction scenario.

Each individual's elements (latitude and longitude coordinates) are randomly initialized within predefined ranges to ensure diversity.

3) Fitness Evaluation: Considering the objective function value (prediction accuracy) and constraint conditions (such as flight area restrictions and speed limits), a fitness function is defined to evaluate the merit of each individual.

4) Selection: The roulette wheel selection method is utilized to randomly select the next generation of individuals based on their fitness values, aiming to retain superior solutions.

5) Crossover and Mutation: New offspring are generated through crossover operations that combine the genetic information of two individuals.

Mutation operations randomly alter individual elements to enhance population diversity.

6) Elite Selection: The individual with the highest fitness in each generation is selected to ensure that the optimal solution is retained.

7) Iteration: The steps of selection, crossover, mutation, and elite selection are repeated for a predetermined number of iterations.

Ultimately, the best UAV position prediction coordinates are selected from the remaining individuals as the final result. This process is applied separately to both latitude and longitude predictions, achieving notable optimization effects.

V. SIMULATION

To validate the reliability of our collision detection model and genetic algorithm in solving practical problems, we established a formation consisting of 223 drones, with the first unit serving as the directorial UAV and the subsequent 222 as subordinate UAVs. The drones are set to move in an equidistant spiral in a clockwise direction within a defined range, making turning maneuvers while ensuring no collisions occur, and finally exiting in an equidistant spiral in a counterclockwise direction. We used MATLAB to program and simulate the motion paths of the drone formation.

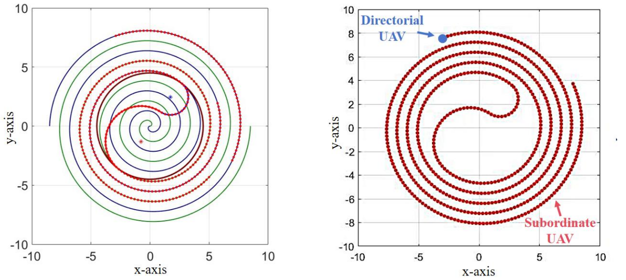

Fig. 8. Computer simulation of the path results

Fig.8 shows the path planning results as the generation goes over. The red line formed by the interconnection of multiple coordinate points represents the optimal path trajectory under the restricted conditions.The simulation results indicate that our model can iteratively find the optimal motion path while ensuring that no collisions occur.

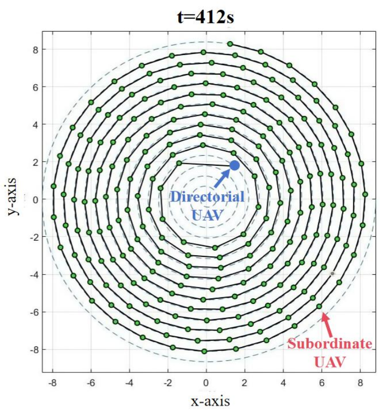

Fig. 9. Position coordinates for the drone echelon

According to the established collision model, the collision time can be predicted and the specific position can be given. Fig.9 shows position coordinates of the UAV after 412 seconds of echelon motion.The simulation results demonstrate that we can adjust the size of the movement range to ultimately identify the time at which collisions occur within the drone formation. This effectively showcases the reliability of the model and provides assurance for predicting drone movement in various scenarios.

VI. Conclusion and Future Work

This paper proposes a novel path planning algorithm based on two-module fusion, aimed at addressing the challenges faced by multi-robot collaboration in finite spaces where collisions may occur. The study establishes a collision detection model and utilizes a genetic algorithm for path planning under collision probability constraints. Through simulation experiments, the algorithm is demonstrated to possess strong accuracy and stability. This model can be applied in multi-agent collaborative scenarios such as coordinated operations of multiple drones on the battlefield, showcasing significant potential for practical applications.

References

[1] Lee C, Baek J, Do S, et al. Multi-Agent Based Collaborative Agent Architecture for Battlefield Situation Awareness[C]//2024 IEEE International Conference on Big Data and Smart Computing (BigComp). IEEE, 2024: 395-396.

[2] X. Shi, G. Liu, Y. Dai, S. Zhang and T. Jiang, "MDTW Metric: A Signal Matching Yardstick for Accurately Evaluating the Quality of Tactile Internet," in IEEE Transactions on Network Science and Engineering, vol. 11, no. 4, pp. 3824-3837, July-Aug. 2024.

[3] T. Jiang, X. Shi, S. Cheng, Y. Dai and G. Liu, "Human-Cyber-Physical Ubiquitous Intelligent Communication: System Architecture, Key Technologies, and Challenges," in IEEE Communications Magazine, vol. 60, no. 12, pp. 36-42, December 2022.

[4] J. Rückin, F. Magistri, C. Stachniss and M. Popović, "An Informative Path Planning Framework for Active Learning in UAV-Based Semantic Mapping," in IEEE Transactions on Robotics, vol. 39, no. 6, pp. 4279-4296, Dec. 2023.

[5] B. Zhu, E. Bedeer, H. H. Nguyen, R. Barton and Z. Gao, "UAV Trajectory Planning for AoI-Minimal Data Collection in UAV-Aided IoT Networks by Transformer," in IEEE Transactions on Wireless Communications, vol. 22, no. 2, pp. 1343-1358, Feb. 2023.

[6] W. Hu et al., "Multi-UAV Coverage Path Planning: A Distributed Online Cooperation Method," in IEEE Transactions on Vehicular Technology, vol. 72, no. 9, pp. 11727-11740, Sept. 2023.W. He, X. Qi, and L. Liu,"A novel hybrid particle swarm optimization for multi-uav cooperate path planning," Applied Intelligence, vol. 51, pp. 7350-7364, Mar. 2021.

[7] W. He, X. Qi, and L. Liu,"A novel hybrid particle swarm optimization for multi-uav cooperate path planning," Applied Intelligence, vol. 51, pp. 7350-7364, Mar. 2021.

[8] J. Zhao, L. Zhong, H. Li and Z. Hou, "Safe Formation Control and Collision Avoidance for Multi-UAV Systems Using Barrier Lyapunov Function," *2024 43rd Chinese Control Conference (CCC)*, Kunming, China, 2024, pp. 5504-5510, doi: 10.23919/CCC63176.2024.10661886.

[9] Islam S M T, Hu X. A Decentralized Importance-based Multi-UAV Path Planning Algorithm for Wildfire Monitoring[C]//2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2023: 2513-2518.

[10] Z. Zhou, X. Xing, Y. Li and R. Wang, "Multi-UAV Path Planning Based on Potential Field Dense Reward in Unknown Environments with Static and Dynamic Obstacles," 2023 China Automation Congress (CAC), Chongqing, China, 2023, pp. 1289-1294, doi: 10.1109/CAC59555.2023.10450792.

[11] Sun Y, Chen J, Du C. Path planning of UAVs based on improved ant colony system[C]//2020 IEEE International Conference on Progress in Informatics and Computing (PIC). IEEE, 2020: 396-400.

[12] Heracleous C, Kolios P, Panayiotou C G. An integrated UAV system for wildfire evolution monitoring and data acquisition[C]//2022 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE, 2022: 1131-1138.

[13] Kumar S, Kumar S R. Barrier lyapunov-based nonlinear trajectory following for unmanned aerial vehicles with constrained motion[C]//2022 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE, 2022: 1146-1155.