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Research on Intelligent Path Planning for Unmanned Aerial Vehicles in Complex Environments

Peiye Sun *

International Education College, Changchun University of Technology, Changchun, Jilin, 130012, China

*** Corresponding author Email:** spyqwertyuiop@yeah.net

Abstract: Aiming at the problems of insufficient real-time performance and safety in path planning for unmanned aerial vehicles (UAVs) in dynamic and complex environments, this study proposes a collaborative path planning method that integrates binocular vision environmental perception, ant colony algorithm for global optimization, and artificial potential field method for local dynamic obstacle avoidance, with the goal of improving the accuracy and robustness of autonomous navigation. This method precisely captures dynamic environmental information through binocular vision, optimizes the global path search using the ant colony algorithm, and combines the artificial potential field method to achieve real-time local obstacle avoidance. It not only enables rapid identification and response to complex environments but also significantly enhances the accuracy and robustness of UAV autonomous navigation.

Keywords: Obstacle Avoidance for Unmanned Aerial Vehicles; Path Planning; Algorithm Fusion.

1. Introduction

In recent years, unmanned aerial vehicle (UAV) technology has been widely applied in both military and civilian fields. Among them, multi-rotor UAVs have become a research and application hotspot due to their small size, low cost, and easy operation. In military and civilian areas, such as disaster prevention and control, agricultural and forestry protection, power line inspection, and logistics transportation, the operation of UAVs can effectively improve efficiency and operational capabilities, and can adapt to different environmental and task requirements. The UAV system mainly includes global path planning and local obstacle avoidance, optimizing path selection and updates in dynamic environments, and ensuring flight safety during mission execution. In the field of global path planning, traditional search-based planning algorithms often show low search and planning efficiency when dealing with large-scale maps, and have limited re-planning capabilities in dynamic environments. In the field of local obstacle avoidance, there is often an unbalanced contradiction between the computational efficiency of the algorithm and the quality of obstacle avoidance decisions. To address these existing deficiencies, this study takes the quadrotor UAV as the research object and conducts in-depth research on global planning and local obstacle avoidance methods in the UAV operation environment. By improving the re-planning ability of the planning algorithm, the planning problem is solved, and by optimizing the process of obstacle avoidance and control, the obstacle avoidance problem of UAVs is addressed.

2. Literature Review

The application of unmanned aerial vehicles (UAVs) in power inspection, forest fire prevention, and urban logistics has demonstrated the complex path planning problems that need to be addressed for autonomous operation of UAVs in such complex environments. How to solve the technical challenges in path planning that require simultaneous consideration of multiple adjacent objects in these complex environments is a key research direction both domestically and internationally at present, including but not limited to research in areas such as visual perception, intelligent algorithm optimization, and multi-strategy integration, which have achieved some progress and formed different technical routes. However, there are still many issues awaiting exploration.

Environmental perception is the foundation of path planning, and its accuracy directly affects the planning outcome. Existing studies mostly adopt visual perception schemes to enhance the ability of environmental modeling. Jayakant Kumar et al. proposed a narrow channel navigation method based on monocular vision and PID control, extracting channel features through edge detection and homography technology, and achieving collision-free flight of micro UAVs[1]. This study verified the effectiveness of visual perception in structured environments, but did not involve precise modeling of three-dimensional dynamic environments. Research shows that visual perception technology has the advantages of low cost and high adaptability, but the real-time performance of a single visual or traditional sensor fusion scheme still needs to be improved. Dual vision's three-dimensional perception capability provides an effective solution to this problem.

Taking advantage of the three-dimensional environmental information brought by binocular vision technology has become one of the important technologies for unmanned aerial vehicle (UAV) autonomous navigation. Zhang Xin et al. proposed a method for UAV power line detection and obstacle avoidance based on binocular vision. The distance of obstacles is obtained by the disparity of feature points in the left and right camera images. Based on the RRT algorithm, the path is re-planned, and this method is applied to power line inspection, effectively preventing the problem of low-altitude flight collisions. It uses binocular vision to obtain accurate depth information of obstacles, but there are issues such as poor stability in matching feature points under weak lighting conditions and the difficulty of obtaining the global optimal solution and local obstacle avoidance solution when using a single algorithm for path planning [2]. Hou Yonghong et al. designed an autonomous navigation system for UAV based on binocular vision using the ORB SLAM2 algorithm to obtain pose information. The improved SAD algorithm and "push-scan" perception were used to obtain the point cloud of ground targets, and a local octree map was established based on the obtained point cloud to guide real-time path planning. Through experimental verification, binocular vision has the ability to construct a certain level of accuracy map in an unknown environment with less mapping time[3]. However, in large-scale and complex scenarios, how to seek a balance between map construction and path planning and improve the prediction ability for dynamic obstacles are still problems to be solved.

The artificial potential field method is a method that uses gravitational and repulsive fields to achieve obstacle avoidance path planning. It has advantages in path optimization in three-dimensional space. Yu Shunjin et al. improved the artificial potential field method and established a three-dimensional grid model based on forest fire prevention. The gravitational field and repulsive field functions were optimized to enable collision-avoiding target points to form in areas that the original artificial potential field method could not reach, successfully solving the problems of unreachability of target points and local minimum values in traditional methods, and enabling the avoidance of dynamic obstacles. This path planning method is suitable for more complex situations[4]. However, in cases where multiple obstacles are densely distributed, the parameters of the potential field function are difficult to optimize, and the entire global path cannot be reasonably selected as the optimal solution based on the initial potential field model, which cannot fully meet the adaptive requirements of actual situations.

The ant colony algorithm is a method based on group intelligent search. It is widely used in global path optimization. Yan Jing et al. used the ant colony algorithm to provide path planning solutions for UAV-assisted wireless communication networks during flight. The optimal flight route was obtained by using the accumulation and update of pheromones. This method can reduce the overall energy consumption of the UAV[5]. However, the ant colony algorithm still has certain limitations when facing multi-objective problems. When dealing with complex three-dimensional environments, it may have problems such as slow operation speed and insufficient smoothness of the path, and cannot effectively make more effective adjustments in dynamic environments. Therefore, in the aspect of global planning algorithms, Hui Song et al. targeted the problem that the traditional ant colony algorithm is prone to fall into local optima, by setting upper and lower limits of pheromones and introducing multiple heuristic factors, improved the global optimality and smoothness of the path[6].But its local obstacle avoidance ability still needs to be supplemented by additional mechanisms. However, in the local obstacle avoidance algorithm, Farid Bounini et al. proposed an improved artificial potential field method by dynamically adding repulsive fields to solve the problem of local minimum values, ensuring the safety of obstacle avoidance[7]. Firdos N. Irzoqe et al. combined the artificial potential field method with Q networks to optimize the convergence speed of path search[8]. However, the local precision of the ant colony algorithm and the global planning defect of the artificial potential field method lead to the fact that a single algorithm cannot meet the comprehensive requirements of complex environments.

In order to enhance adaptability to complex environments, Xiang Jin et al. proposed the Chaotic Parent Particle Swarm Optimization Algorithm (CCCPPSO), which utilizes chaotic mapping and the diversity mechanism of parent feedback to achieve obstacle-free collision-free path planning in a three-dimensional urban environment[9]. For static complex environments, this method has a good effect. However, for dynamically distributed obstacle distributions, the CCPPO algorithm cannot make corresponding real-time adjustments. Zhu Yifan et al. proposed the Nonlinear Normal Differential Sparrow Search Algorithm (NLN-DSSA), which uses the improved initial population position and differential mutation strategy of NSGA-III. Compared with NSGA-III, the NLN-DSSA algorithm can significantly accelerate the convergence rate and search accuracy of the algorithm. At the same time, this method provides a new intelligent algorithm optimization scheme[10]. However, how to combine environmental perception information with the dynamic reduction of the algorithm's search space remains a problem to be solved.

In conclusion, in view of the current research's poor adaptability to complex environments and the inability to well integrate multiple technologies, based on the advantages of binocular vision, artificial potential field method and ant colony algorithm, the above algorithms are deeply integrated, and a method for integrating unmanned aerial vehicle path planning algorithms for intelligent path planning in complex environments is proposed.

3. Algorithm Structure Overview

3.1. Binocular Vision Perception

The core function of this is to accurately obtain the three-dimensional information of the complex environment. By inputting the binocular image pairs, after several simple steps such as image noise reduction, feature point matching, disparity calculation, and coordinate transformation, the three-dimensional coordinates of the obstacles in the environment under the world coordinate system can be obtained, which can be used for subsequent path planning.

3.2. Ant Colony Algorithm Global Planning

This method is to search for the global optimal path from the starting point to the destination. The module converts the obstacle coordinates sensed by the system into a grid map, simulates the mechanism of pheromone accumulation and evaporation of ants for foraging, combines distance heuristic guidance, and finds the shortest path to avoid obstacles in the global range, outputting the initial sequence of path nodes.

3.3. Artificial Potential Field Method

To better optimize the path, the route output by the global path planning is used as the basic data source, and on this basis, a potential field with "attractive force" close to the destination and a potential field with "repulsive force" away from obstacles are constructed. The resultant force direction is calculated, and the current path position is shifted a certain distance in this direction to correct the local collision hazards, making the path more in line with the requirements of the unmanned aerial vehicle.

4. Dual Vision - Artificial Potential Field - Ant Colony Fusion Path Planning Algorithm Design

4.1. Construction of Environmental Perception Model Based on Dual Vision

The dual vision system uses two cameras, each 50mm apart, to simultaneously capture scene images, one on the left and one on the right. The key of the dual vision model lies in calculating the distance of obstacles from the unmanned aerial vehicle through disparity calculation. Its basic principle is triangulation. When a certain point in the same scene is imaged by the left and right images, there is a certain pixel coordinate difference value, namely the disparity value, on the imaging planes of the two images. By calculating the disparity value, the three-dimensional spatial coordinates of the target can be obtained, and finally, the depth information can be obtained.

Here, Z represents the vertical distance from the target point to the bottom (unit: mm), f is the camera focal length (unit: pixel), B is the baseline length of the dual vision camera (unit: mm), and d is the disparity between the matching points of the left and right images (unit: pixel). This formula gives a quantitative correspondence relationship between pixel displacement and physical distance, providing geometric constraints for environmental perception.

$$Z=\frac{f\cdot B}{d} \tag{1}$$

Based on the results of the depth information calculation, the system converts the three-dimensional point cloud information into a two-dimensional raster map. Firstly, a bilateral filter is used to eliminate the noise in the depth image while retaining the boundary information; then, based on the elevation value of a certain point as the judgment condition, threshold segmentation is performed to obtain all elevation areas above 0.5 meters as the obstacle areas; subsequently, the environment is discretized into grid units with a resolution of 0.1 × 0.1 meters, and the occupied grid cells are labeled as 1, while the idle space grid cells are labeled as 0. Through this rasterization method, the obtained map can quantitatively express key information such as the gaps between buildings and the positions of dynamic obstacles, providing a structured environmental input for the path planning algorithm. The entire process takes approximately 150ms, which can meet the real-time requirements.

4.2. Fusion Strategy of Artificial Potential Field and Ant Colony Algorithm

To address the issues of the traditional ant colony algorithm being prone to getting stuck in local optima and having a slow convergence speed, the physical guiding mechanism from the artificial potential field method is introduced into the probabilistic search process of the ant colony algorithm. By leveraging the advantages of the artificial potential field method, the probability search framework of the ant colony algorithm is improved to achieve an ant colony algorithm based on the artificial potential field method. On the basis of the restructured ant colony algorithm, the gravitational and repulsive components of the artificial potential field are further introduced; the gravitational component is driven by the target point, and its force magnitude is inversely proportional to the Euclidean distance between the drone and the target point; the repulsive component is driven by the distance to the obstacle, and when the distance between the drone and the obstacle is less than 1.5m, the force magnitude of the repulsive field will increase exponentially as the distance decreases. The heuristic function is defined as:

Among them, η_ij (t) denotes the heuristic information value from node i to node j (dimensionless), d_ij is the Euclidean distance of path segment ij (unit: m), X ⃗_j is the spatial coordinate vector of node j (unit: m), X ⃗_g is the coordinate vector of the target point (unit: m), X ⃗_(obs,k) is the center coordinate vector of the k-th obstacle (unit: m), α and β are the attraction and repulsion coefficients respectively (dimensionless), and N_obs is the total number of obstacles. This function enables ant colony individuals to have both shortest distance orientation and active obstacle avoidance capability when selecting paths.

$$\eta_{ij}(t)=\frac{1}{d_{ij}}+\alpha\cdot\frac{1}{|\ |\vec{X}_j-\vec{X}_g|\ |^2}-\beta\cdot\sum_{k=1}^{N_{obs}}\frac{1}{|\ |\vec{X}_j-\vec{X}_{obs,k}|\ |^2} \tag{2}$$

To enhance the global search capability, the state transition probability formula is adjusted. A dynamic adjustment factor is introduced. The larger the number of iterations, the smaller the dynamic adjustment factor. That is, in the early stage of the algorithm, a larger value is taken to strengthen the influence of heuristic information on path selection, and a smaller value is used in the later stage to enhance the guiding role of pheromones on path selection. The improved state transition probability formula is as follows:

pij(k)(t) denotes the probability that the k-th ant moves from node i to node j at time t; τij(t) represents the pheromone concentration left on the path (unit: pheromone unit); δ is the pheromone heuristic factor (dimensionless); and allowedk is the set of feasible nodes available to ant k at present. Therefore, this operation can well balance the exploration and exploitation capabilities of the algorithm while avoiding the problem that the potential field method is prone to falling into local minima.

$$P_{ij}^{k}(t)=\frac{[\tau_{ij}(t)]^{\delta}\cdot[\eta_{ij}(t)]^{\gamma(t)}}{\sum_{s\in allowed_k}[\tau_{is}(t)]^{\delta}\cdot[\eta_{is}(t)]^{\gamma(t)}} \tag{3}$$

4.3. Overall Process Design of the Fusion Algorithm

The dual-camera vision - artificial potential field - ant colony fusion path planning algorithm operates in a three-level progressive manner. The entire workflow is shown in Figure 1. In this process, the first stage is the environment perception layer, where the dual-camera collects images at a frequency of 10Hz with a resolution of 1280×720. After performing disparity calculation to obtain point cloud data, it is rasterized with a resolution of 0.1m to convert it into a recognizable grid map, which is then sent to the output end. Specifically, the already measured set of obstacle coordinates and the set of target point coordinates are structuredly displayed and sent as the final data to the next stage. The first stage takes no more than 150ms. The second stage is the fusion path search layer, which takes the aforementioned grid map as input, initializes the ant colony parameters, and each ant starts from the starting point and selects the next moving node according to the improved state transition probability formula. The key innovation here is to integrate the gravitational field and repulsive field obtained in real time by the artificial potential field in the ant colony, enabling the ant colony to avoid known obstacles in real time during the path search process. When more than 30% of the individuals in the ant colony reach the destination or the ant colony has performed 100 iterations, the path with the highest pheromone concentration in the ant colony at this time is used as the rough solution output; the third stage is the optimization path section, which applies the method of cubic B-spline curve fitting to smooth the rough solution, and draws this curve using each node on the rough solution path as the control point; at the same time, the curvature constraint condition kmax ≤ 1.5 m—1 is added to meet the maximum turning radius requirement of 0.8m; finally, a smooth, continuous, and complete flight trajectory is output and sent back to the environment perception layer for the next cycle of planning.

Oobs Pg Uatt Urep C^2 refers to the following key elements in path planning. Among them, Oobs is the set of obstacle coordinates, Pg is the coordinates of the target point, Uatt represents the attractive field, Urep stands for the repulsive field, and C^2 denotes the flight trajectory.

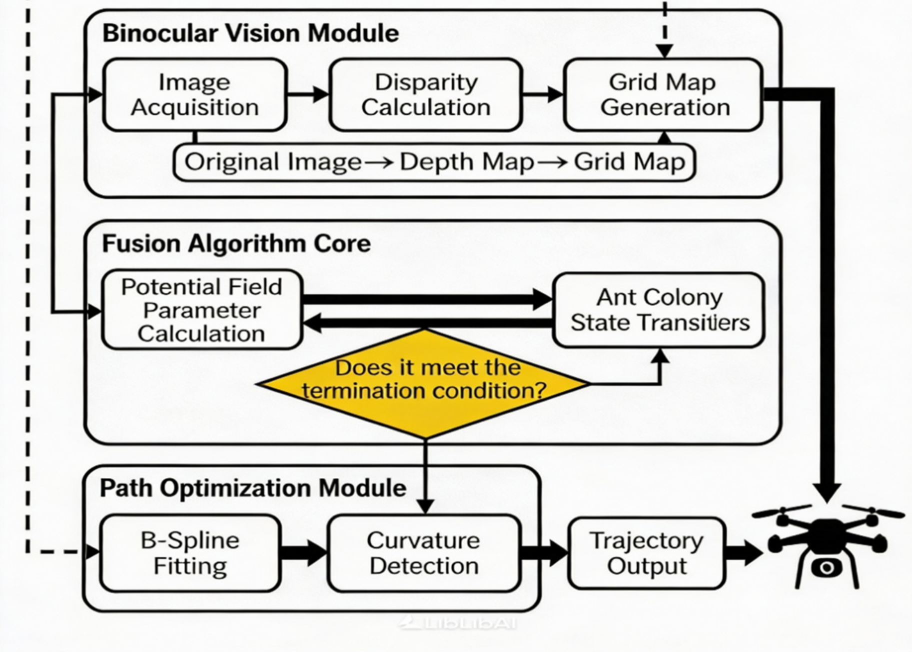

Figure 1. Flowchart of the Dual Vision - Artificial Potential Field - Ant Colony Fusion Path Planning Algorithm

5. Matlab Simulation Experiment and Result Analysis of the Integrated Algorithm

5.1. Simulation Experiment Setup

Table 1. Parameter Setting Table of the Fusion Algorithm Simulation Experiment

Parameter Category	Symbol	Value	Unit	Physical Meaning
Pheromone Evaporation Coefficient	ρ	0.3	—	Controls the pheromone decay rate
Heuristic Factor	δ	1.5	—	Balances the weight of pheromone and heuristic information
Attractive Force Coefficient	α	2.0	—	Intensity of attraction from the target to ants
Repulsive Force Coefficient	β	3.5	—	Intensity of repulsion from obstacles to ants
Safety Threshold	dsafe	1.5	m	Minimum distance to trigger the repulsive field
Ant Colony Size	Nant	30	—	Number of ants in a single iteration
Maximum Number of Iterations	Tmax	100	—	Upper limit for algorithm termination

A 120 m × 80 m urban building complex scene was set up in Matlab R2023a. The building heights were uniformly distributed between 20 m and 60 m. Static obstacles were represented by a grid with a resolution of 0.1 m and were indicated as obstacle areas. The target point was set at the topmost point in the northeastern part of the scene, and the starting point was located at the southwest corner, with a straight-line distance of 100 m. The algorithm parameters were determined through a pre-experiment to ensure the stability and effectiveness of the fusion algorithm in the simulated complex environment. As shown in Table 1, the key parameters include the pheromone evaporation coefficient ρ, heuristic factor δ, potential field gravitational coefficient α, repulsive coefficient β, safety threshold dsafe, ant colony size Nant, and maximum number of iterations Tmax. Each parameter was calibrated through multiple rounds of pre-simulation to achieve a balance between algorithm convergence speed, path optimization effect, and obstacle avoidance safety. The sampling frequency of the dual-camera simulation was 10 Hz, and the average depth error was 0.05 m. The evaluation indicators were defined as follows: the path length Lp is the cumulative distance of the trajectory's three-dimensional coordinates; the convergence time Tc is the time from when the algorithm is activated until all ants reach the target or reach the maximum iteration number (Tmax = 100 times as shown in Table 1); the obstacle avoidance success rate is the percentage of 100 Monte Carlo runs where the minimum distance between Lp and the obstacles is greater than or equal to 1.2 m, lower than the safety threshold dsafe = 1.5 m in Table 1, reserved for error redundancy; all the above evaluation indicators were obtained on the same hardware platform to ensure consistency.

5.2. Experimental Results and Performance Comparison Analysis

For the 120m×80m urban building complex Matlab scene, the fusion algorithm generated a three-dimensional trajectory that closely followed the building outline, maintaining a 1.5m safety distance, and had 32% fewer path turning points. The curve curvature was continuous and the maximum value did not exceed 1.2m-. This satisfied the requirements for the unmanned aerial vehicle's maneuverability. Compared with the traditional manual potential field method, the fusion algorithm eliminated the oscillation ring caused by the local minimum values of the potential field through global search by the ant colony, reducing the path length by 18%. Compared with the pure ant colony algorithm, when the potential field heuristic factor was added, the ant colony algorithm could conduct search more quickly in the early stage, reducing the convergence time by 24%, and the real-time correction effect of the repulsive field combined with it made the obstacle avoidance success rate reach 100%. Compared with other single-modal methods, due to the potential field achieving rapid local guidance and the ant colony achieving global optimization, the two methods improved the overall performance through interaction and fusion.

6. Conclusion

This paper integrates the precise environmental perception capability of binocular vision, the real-time obstacle avoidance feature of artificial potential field method, and the global path optimization advantage of ant colony algorithm, and proposes a binocular vision-assisted artificial potential field-ant colony fusion path planning method. Through simulation experiments conducted in complex scenarios with multiple types of static obstacles, it is verified that this method outperforms traditional single algorithms or simple combined algorithms in terms of shortening the path length, accelerating the algorithm convergence speed, and ensuring flight safety. Future research will focus on breaking through the real-time processing technology for obstacles with dynamic movement characteristics and the expansion of the three-dimensional space path planning framework, which is of great value for improving the robustness and universality of the algorithm and can also open up new directions for the research on autonomous navigation of intelligent unmanned aircraft.

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