Theory and Practice of Science and Technology
2025, VOL. 6, NO. 10, 197-201
DOI: 10.47297/taposatWSP2633-456939.20250610

Research on 3D Intelligent Path Planning Method for Unmanned Aerial Vehicles Based on Dynamic Multi-objective Ant Colony Optimization

Yiming Pei

Wuhan Britain-China School, Wuhan, Hubei, 430000, China

ABSTRACT

Multi-objective path planning in complex three-dimensional environments is a key challenge for improving the application efficiency of unmanned aerial vehicles in rescue, logistics and other fields. This paper proposes a dynamic multi-objective ant colony optimization algorithm to address the problems of traditional ant colony algorithms such as getting stuck in local optimum, slow convergence and difficulty in adapting to dynamic environments. This paper systematically constructs a multi-objective model that integrates path length, height constraints and threat avoidance, and designs a hierarchical pheromone update strategy based on path quality and a hybrid heuristic function for environmental adaptation to balance global exploration and local optimization capabilities. Simulation experiments show that compared with traditional ant colony, particle swarm and other algorithms, this method has significant improvements in path length, smoothness and computational efficiency, especially showing better obstacle avoidance success rate and real-time re-planning ability in high dynamic scenarios. This method effectively enhances the intelligent decision-making level of unmanned aerial vehicles in complex environments and has practical application value for improving the reliability of emergency response and logistics distribution.

KEYWORDS

Unmanned aerial vehicle path planning; Dynamic multi-objective optimization; Ant colony algorithm; Three-dimensional environment

1 Introduction

The use of unmanned aerial vehicles (UAVs) for disaster relief, logistics transportation, military reconnaissance and other activities has broad application prospects [1-2], but at present, UAVs have insufficient intelligent obstacle avoidance and path planning capabilities in complex three-dimensional environments and are vulnerable to changes in environmental factors. In view of the shortcomings of traditional path planning methods at present, such as the difficulty in achieving multi-objective optimization and the inability to dynamically identify obstacles, this paper establishes an intelligent path planning model to achieve obstacle avoidance for unmanned aerial vehicles while improving the level of autonomous decision-making.

1.1 Research Background and Significance

Three-dimensional path planning for unmanned aerial vehicles (UAVs) should meet three requirements: safety, economy, and timeliness. These requirements often conflict with each other and constitute a typical multi-objective optimization problem. In situations such as post-disaster rescue and emergencies, UAVs need to achieve the maximized optimized path to avoid dangerous areas in various complex environments such as buildings and mountains [3]. From the existing research, the main disadvantages of ant colony algorithm in solving 3D path planning are as follows: First, it is vulnerable to the influence of local optimal solutions, resulting in slow convergence of the algorithm; The traditional ant colony algorithm has a relatively short path length, which is not conducive to considering flight altitude and is also difficult to meet the requirements of multi-objective optimization [4]; Third, the update mode of fixed parameters does not meet the requirements of algorithm adaptability in dynamic environments.

1.2 Research Questions and Objectives

In response to the above challenges, this study proposes a three-dimensional path planning method for unmanned aerial vehicles based on dynamic multi-objective ant colony optimization, mainly addressing the following key issues:

(1) Traditional ant colony algorithms have insufficient Pareto frontier search capabilities in multi-objective optimization scenarios;

(2) Static pheromone update mechanisms struggle to adapt to dynamic environmental changes;

(3) The problem of computational complexity in 3D path planning increasing cube-level with spatial dimensions.

The research aims to achieve efficient path planning for unmanned aerial vehicles (UAVs) in complex three-

*** Corresponding Author:** Yiming Pei, 1549822612@qq.com

dimensional environments by improving the ant colony algorithm framework, designing dynamic pheromone update mechanisms and multi-objective optimization models. Specifically, it includes:

(1) Build a multi-objective optimization model that integrates path length, height constraints, and threat avoidance;

(2) Develop an adaptive pheromone update strategy based on environmental feedback;

(3) Propose hybrid heuristic functions to reduce search complexity in three-dimensional space.

2 Relevant Theories and Research Status

2.1 Overview of Drone Path Planning Algorithms

Path planning algorithms can be classified into search-based, sampling-based, and intelligent optimization based on their basic principles, and there are significant differences in their application in three-dimensional environments [1-5]. Search-based algorithms, represented by A and Dijkstra, use heuristic functions to guide the search process and are suitable for efficient computation in known environments; Algorithm A uses the cost function f(n)=g(n)+h(n) to obtain an estimate through the heuristic function h(n), and then combines the real cost g(n) to achieve the best path search [1]. However, this type of algorithm cannot solve the problem of dynamic obstacles in a mobile environment, and for high-dimensional Spaces, there is the problem of excessive node expansion dimension, and the neighborhood expansion dimension in a three-dimensional environment extends from 8 neighborhoods in two dimensions to 26 neighborhoods, which greatly increases the computational load [1].

For sampling-based methods such as Fast Expansion Random Tree (RRT) and Probabilistic Roadmap (PRM), sampling is the core idea. Although RRT and improved versions of RRT have strong search capabilities in dynamic unknown environments and can improve path quality through methods such as relinking, the problem of unstable path quality still exists due to the randomness of sampling. Experimental data show that the RRT algorithm has an excessive variance of path length compared with the A* algorithm in the same three-dimensional scene, reflecting the poor path optimality and robustness of the RRT algorithm [5].

Intelligent optimization algorithms include bionic methods such as ant colony algorithm and particle swarm optimization to achieve global optimization through swarm intelligence. These algorithms have unique advantages in multi-objective optimization scenarios and can balance conflicting objectives such as path length, energy consumption, and safety [6,7]. Ant colony algorithms, in particular, perform well in complex static environments for collaborative search through pheromone positive feedback mechanisms. However, traditional intelligent optimization algorithms have problems such as slow convergence speed and tendency to fall into local optimum, and the cubic growth of node size in three-dimensional path planning significantly reduces computational efficiency [4].

The performance gap among the three types of algorithms in a three-dimensional environment stems from the core principles of different algorithms: search-based algorithms require accurate environmental modeling; Sampling-based algorithms are suitable for high-dimensional space exploration; Intelligent optimization algorithms are suitable for multi-objective optimization. Therefore, different algorithms should be chosen for different scenarios, using the RRT algorithm in dynamic scenarios such as disaster relief and the ant colony algorithm in more complex static scenarios such as urban patrol, etc [5,6].

2.2 Research Progress in Ant Colony Algorithms

(ACO)ACO is a path optimization algorithm designed based on the positive feedback mechanism of pheromones during the foraging process of simulated ants. The main components involved include: state transition rules, pheromone updates, and heuristic functions, etc. [4][6]. In three-dimensional path planning, ants use pheromone concentration τ and heuristic factor η to determine the probability of direction transition, which is expressed by the formula:

$$P_{i_j}^{k}=\frac{\left[\tau_{ij}\right]^{\alpha}\cdot\left[\eta_{ij}\right]^{\beta}}{\Sigma_{l}allowed\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}$$

Here α and β are used to control the proportions of pheromones and heuristic factors respectively [4]. There are two difficulties with traditional ACOs in three-dimensional scenarios: one is that the number of nodes increases at the cubic level, which leads to a significant increase in computational load; The second is that once pheromone parameters are determined, they cannot change, making it difficult to adapt to environments with significant variations [4,6].

In response to this problem, the following three aspects of work have been mainly done on ACO in recent years: first, improvements in constraints, introducing safety distance, high cost function, and adding constraints to ensure the feasibility of the path [1][4]; Secondly, in the pheromone update, methods such as dynamic Windows and hierarchical allocation are used, and the Max-Min adaptive approach is adopted to update the pheromone, enabling the algorithm to be effectively applied in dynamic environments [4][6]; Finally, there is the design of hybrid algorithms that combine ACO with Q-learning or A*, which can enhance local search capabilities and reduce planning time [5,6].

In 3D path planning, the optimization of ACO mainly focuses on spatial discretization modeling and the design of heuristic functions. It uses a hybrid heuristic function, considering both Euclidean distance and height difference, and dynamically adjusts the weighting coefficients in an adaptive manner throughout the flight to balance the search tendencies at each flight stage; In a three-dimensional environment, this method effectively reduces the number of redundant nodes and significantly saves computational resources, and has good universality and fault tolerance [6]. In addition, the use of B-spline curves for trajectory smoothing results in smaller turning angles, which is beneficial for aircraft trajectory execution [1,4].

Although the ant colony algorithm has made some progress in multi-objective optimization, there are still problems in dynamic multi-objective environments, and its Pareto front search ability and real-time re-planning efficiency need to be improved [4,6]. These deficiencies are an important reference basis for designing the dynamic multi-objective ant colony optimization algorithm in this paper.

3 Design of Dynamic Multi-Objective Ant Colony Optimization Algorithm

3.1 Construction of Multi-Objective Optimization Models

In response to the multi-objective optimization requirements in 3D path planning for unmanned aerial vehicles, this section establishes a composite objective function model that integrates path length, height constraints, and threat avoidance. First, define the base objective function:

Path length objective: $f_1 = \sum_{i=1}^{n-1} \left\| P_{i+1} - P_i \right\|$where (p, i) represents the coordinates of the path nodes;

Highly constrained objective: Penalize path segments that exceed the maximum flight altitude;$f_2 = \sum_{i=1}^{n} \max\left(0, z_i - Z_{max}\right)$

Threat field objective:$f_3 = \sum_{i=1}^{n} \sum_{j=1}^{m} \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right)$ Quantifying the obstacle threat level by Gaussian function

d_{ij} is the Euclidean distance between the node and the (j) th obstacle [1,4], σ is the threat impact range parameter

A comprehensive fitness function is constructed using the weighted method for multi-objective co-optimization:

$$F = \omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3$$

In this paper, the entropy weight method is used to dynamically update the weight coefficients ω, coupling the multi-objective optimization model with the changes of complex scenes, and the weights are directly driven by the distribution characteristics of the objective function values, thereby solving the scene dependence problem of weight setting in traditional methods.ω

Introducing flight dynamics constraints for unmanned aerial vehicles:

$$\left|\theta_i\right| \le \theta_{max}, \left|\omega_i\right| \le \omega_{max}$$

Where θ_i and ω_i represent pitch Angle and turning angular velocity respectively, ensure that the generated path conforms to the maneuverability of the unmanned aerial vehicle [5]. Experiments show that the model can significantly improve path safety in complex terrains while maintaining good length optimality.

3.2 Dynamic Pheromone Update Mechanism

The static pheromone update strategy of the traditional ant colony algorithm is difficult to adapt to the three-dimensional dynamic environment. This section presents a hierarchical pheromone allocation strategy. Define a nonlinear relationship between pheromone increment and path quality:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q_k}{1 + f_1^k} \cdot \delta, \textit{Pareto front} \\ \frac{Q_k}{2 + f_1^k + f_2^k} \cdot \delta, \textit{others} \end{cases}$$

Where Q_k is the path evaluation metric for the (k) th ant, and δ is the pheromone enhancement coefficient

Dynamic re-planning is achieved by using the dynamic window mechanism: when a new obstacle is discovered, a small search area is created with the current position of the drone as the center position, and pheromones are updated only for this small area, which greatly improves the computational efficiency of the algorithm [4,6].

Path smoothing is performed using B-spline curves, and control points are determined based on pheromone concentration gradients: C_i

$$C_i = P_i + \lambda \cdot \nabla_{\tau_i}$$

C_i: B-spline curve control points

λ: Step size factor

∇_{τ_i}: pheromone concentration gradient

The smoothed path curvature is continuous, satisfying the flight attitude constraints $k \le k_{max}$ The curvature after path smoothing is continuous and satisfies the flight attitude constraint. The simulation results show that the mechanism significantly shortens the response time of path re-planning in a dynamic environment and improves the real-time performance of the algorithm.

3.3 Design of Hybrid Heuristic Functions

To enhance the efficiency of three-dimensional environment search, design a hybrid heuristic function that combines Euclidean distance and height difference:

$$\eta_{ij} = \eta_d \cdot d_{ij} + \eta_h \cdot \left| z_j - z_i \right| + \eta_0$$

η_d,η_h: Distance and height weights η_0:Prevent division by zero

Reduce redundant search through target azimuth constraints: only when node (j) satisfies

$$\cos^{-1}\left(\frac{v_{[j]} v_{tg}}{\left|v_{[j]}\right|\left|v_{tg}\right|}\right) \le \phi_{max}$$

Participate in the calculation

$v_{[j]}$ is the current direction vector, v_{tg} pointing to the target point [1].

Dynamically adjust the heuristic weighting strategy as follows:

$$\left[\alpha(t) = \alpha_0\left(1 - e^{\{-\lambda t\}}\right), \beta(t) = \beta_0 e^{\{-\lambda t\}}\right]$$

$\alpha(t)$Global exploration weights, $\beta(t)$:local optimization weights,

λ: decay coefficients, t: time

By dynamically adjusting the heuristic weights, the algorithm focuses on global exploration in the early stages of the search and emphasizes local optimization in the later stages. Experimental verification shows that the design can effectively reduce the number of node expansions, accelerate convergence speed, and improve the uniformity of the distribution of the Pareto solution set.

4 Experimental Verification and Results Analysis

4.1 Experimental Design and Simulation Environment

This experiment uses MATLAB R2021a as the platform to build a three-dimensional simulation experiment, and the hardware used is AMDRyzen53500U, 8G memory; In this experiment, fixed obstacles (cylinders and spheres) and dynamic threat zones were set up, with the height of all obstacles limited to 0 to 2000m, and then divided into 20km× 20km×2 km grid-like three-dimensional Spaces [1,4]. The comparison algorithm selected the traditional ACO algorithm, the PSO algorithm, the improved RRT* algorithm, etc. The evaluation criteria are path length (L), turning Angle (θ), calculation time (T), and obstacle avoidance success probability (S). Finally, two sets of experimental environments, one simple scenario (starting point (0,2,3), and the other complex scenario (starting point (0,5,2), and the other end point (20,5,2)), were used to test whether the algorithm could adapt to different spatial complexities [1,5].

The simulation in the dynamic environment is triggered by time and generates moving obstacles randomly during runtime, with a given maximum speed; Pheromone initial concentration set τ0=1, volatility coefficient ρ=0.5, heuristic factor weights α=1, β=5, ant count m=30, maximum number of iterations N=100[4] to [6]; Since randomness was to be excluded in this experiment, each group of experiments was repeated 20 times to calculate the average, and B-spline curves were used to smooth the generated paths to ensure that the UAV flight dynamics constraints (pitch Angle θmax= 30°, turning angular velocity ωmax=15°/s) were met [1,3].

4.2 Performance Comparison and Analysis

Experimental results show that the improved algorithm is superior to the traditional method in terms of security S value, smoothness θ value, etc. For complex scenarios, the improved algorithm has a much shorter average path length compared to the traditional method, and the running time is significantly reduced, with a higher probability of successful obstacle avoidance [4]. The method of hierarchical pheromone allocation is adopted to accelerate the convergence speed of the algorithm; Using hybrid heuristic functions can significantly reduce the number of search nodes that need to be traversed in the 3D space, alleviating the problem of dimension explosion in the 3D space [4,6].

Quantitative results show that the re-planning response time of the improved algorithm is significantly reduced compared to the comparison algorithm, demonstrating the good real-time decision-making ability of the improved algorithm. The Pareto frontier analysis further demonstrated that the improved algorithm obtained more solutions for the compromise between path length and safe distance, indicating a significant improvement in multi-objective decision-making. Moreover, the changes in path turns generated by the improved algorithm are more continuous compared to traditional ACOs, indicating that the path smoothness of the improved algorithm has been effectively improved from the perspective of motion control [1,3].

Algorithm	L (km)	θ (°)	T (s)	S (%)
Traditional ACO	Longer	Larger	Higher	Lower
PSO	Medium	Medium	Medium	Medium
Improving ACO	Shorter	Smaller	Lower	Higher

5 Conclusions and Prospects

This paper proposes a three-dimensional path planning method for unmanned aerial vehicles (UAVs) based on dynamic multi-objective ant colony optimization. By establishing a multi-objective optimization model that integrates path length, height constraints and threat avoidance, and designing a hierarchical pheromone allocation strategy and a hybrid heuristic function, the quality of path planning for UAVs in complex environments is greatly improved. Experimental results show that the improved algorithm is superior to traditional algorithms in terms of path safety and smoothness, and has a stronger ability to adapt to dynamic environments; The real-time performance in extremely dynamic scenarios needs to be further improved. Finally, research ideas were proposed to use deep reinforcement learning to optimize decision-making speed and multi-machine collaborative path planning to make up for the shortcomings of a single machine.

References

[1] He Xuemei. 2025. Multi-strategy fusion for improving A-path planning in 3D scenes[J]. Journal of Liaoning Open University (Natural Science Edition),2(2): 16-24.

[2] Li Jizi, Cui Meili. 2025. Optimization of unmanned aerial vehicle routing problem with Time window and Multiple Charging stations in emergency environment[J]. Logistics Engineering and Management, 47(1): 41-49

[3] Lin Hui, Lin Feng. 2024. Research on Autonomous Path Planning and Obstacle Avoidance technology for unmanned aerial vehicles for Transmission Line Operation and Maintenance Inspection based on Particle swarm optimization and fuzzy logic[J]. Science & Technology Innovation and Application, 35: 55-58.

[4] Huang Hao.2015. Ant colony algorithm Optimization of Logistics Distribution routes in Supply Chain Environment[J]. Logistics Technology,34 (3(2)): 118-120.

[5] Chen Yu, Liu Jie, Zhang Fan.2025. Comparative Study of 3D Path Planning Algorithms for unmanned Aerial vehicles: Performance analysis of ant colony, A and RRT*[J]. Research on Applications of Computers, 42(7): 2105-2110.

[6] Yang Cheng, Li Guangcheng, Chen Yuming, et al. 2025. 0ptimized ant colony algorithm for solving TSP with double populations based on pheromone fusion mechanism[J]. Journal of Xiamen University of Technology, 33(3): 26-36.

[7] Zheng Tao. 2020. An improved chaotic genetic algorithm for unmanned aerial vehicle trajectory planning[J]. Computer Times, (11): 26-31.