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A Path Planning Method for Logistics Oriented Drone Flight Routes

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Abstract. This article mainly studies the path planning of unmanned aerial vehicle logistics delivery, considering the constraints in the process of unmanned aerial vehicle delivery, and establishes a unmanned aerial vehicle flight environment model based on logistics management. Based on the performance constraints and task requirements of logistics drones, a multi constraint logistics drone path planning model is established from the perspectives of transportation safety, economy, and speed. The established constraints include flight altitude, maximum angle constraints, energy consumption constraints, etc. Then, a hybrid algorithm is used to plan the drone path, and dynamic window algorithm is used for local path planning, Finally, the hybrid algorithm was fused through a smoothing strategy, and simulation experiments confirmed that the drone's flight range, energy consumption, and planning time were significantly improved during the delivery process.

Keywords: logistics delivery, planning, hybrid algorithm, UAV

1 Introduction

With the rise of the new retail era, online trading volume is also constantly increasing, which has led to a continuous growth in the volume of express delivery services. Behind the huge business volume is the mismatched number of couriers. When encountering large-scale promotional activities on e-commerce platforms, the express delivery business is prone to compression, especially on typical promotional days such as "Double 11" and "618", where the goods are particularly squeezed. The express delivery that has already arrived at the post station cannot be delivered in a timely manner, and a series of issues such as long pick-up time for customers and long sorting and shelving time for packages have seriously affected their consumption experience.

With the development of technologies such as carbon fiber and lithium polymer batteries, rotor drones are becoming increasingly lightweight, portable, and intelligent. Artificial intelligence and the "5G" craze have provided a theoretical basis and technical support for the logistics distribution of rotor drones. Since 2020, Google has been launching its own drones for logistics and distribution. However, in China, due to the early development of drone technology, SF Express began testing drones for delivery services in 2013. In 2015, JD.com began building its own drone logistics network, and in the same year, Taobao and other express delivery companies also conducted drone delivery experiments. More and more e-commerce companies are investing in the research and development of drone delivery.

However, there are currently several issues with drones in the logistics and distribution process:

1) Part of the problem of logistics drone path planning is simplified as a road vehicle path planning problem, without reflecting the aerial motion characteristics and performance constraints of drones;

2) When planning the path of logistics drones, some did not consider the actual flight environment and did not consider the combination of factors such as task requirements, energy consumption, and cargo quality, resulting in unsatisfactory planning results;

Therefore, in response to the above issues, the work done in this article is as follows:

1) Firstly, the path planning modeling of unmanned aerial vehicle delivery was conducted, mainly focusing on the flight path under multiple constraints.

2) Taking the optimal path as the goal, an improved neural network algorithm is used to solve the model and dynamically obtain the optimal path.

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3) Through simulation experiments, detailed constraint conditions were set, and the experimental results verified the effectiveness of the algorithm proposed in this paper.

The chapter composition is as follows: Chapter 2 mainly studies the relevant research results to determine the idea of this article. Chapter 3 is the establishment of a path planning model. Chapter 4 describes the process of artificial intelligence algorithm solving the optimal path. Chapter 5 is the experimental chapter, which verifies the effectiveness of the method proposed in this paper through simulation experiments. Chapter 6 is the conclusion section, which summarizes the work of this article, And the shortcomings and further research directions of this article were explained.

2 Related Work

In terms of civilian drones, China has always been at the forefront of the international community and is constantly exploring and innovating the application of drones. Therefore, it has searched for relevant research from domestic scholars. Guangqin He regards the improved ant colony algorithm as the main algorithm for unmanned aerial vehicle path planning, adaptively adjusting the pheromone volatility coefficient P value to limit the update of pheromones on the path to a reasonable range, avoiding falling into local optima during path optimization search. The algorithm performance has been verified in simulation results [1]. Jingran He used the maximum minimum distance product method to process the initial honey source, combined the K-means clustering algorithm with the artificial bee colony algorithm, and proposed an improved artificial bee colony algorithm to solve the problem of drone path planning, making the path adaptability of drone planning better [2]. Dingding Hu used an improved particle swarm optimization algorithm and optimized various parameters in the algorithm through filters. Finally, simulation experiments proved that the improved algorithm has excellent performance in improving the robustness of unmanned aerial vehicles [3]. Yuan Jiale proposed an improved artificial potential field (APF) based universal obstacle avoidance maneuver strategy for unmanned aerial vehicles (UAVs) to address the avoidance problem when encountering sudden obstacles during flight. This strategy enhances the dynamic obstacle avoidance and real-time path planning capabilities of UAVs during flight [4]. Yonghong Xie proposed a hybrid inertial traction particle swarm based 3D path planning method for unmanned aerial vehicles, incorporating adaptive weight assignment methods. Through experimental analysis, the method can improve the stability of path planning [5]. Qingyu Jiao mainly studied how to ensure the safety of the bottom crowd when the number of drones increased. Therefore, an improved A^* algorithm was used for real-time path planning of drones. Finally, Beijing was used as an experimental city to demonstrate the feasibility of the proposed method in dynamic path planning [6].

3 Modeling of Logistics Drone Path Planning

This article starts from the perspective of flight safety and transportation efficiency of logistics unmanned aerial vehicles, with minimizing path flight time, energy consumption, and danger as the objective functions. It constructs a logistics unmanned aerial vehicle path planning model that reduces operating costs while meeting the autonomous safety obstacle avoidance requirements during the transportation of goods by unmanned aerial vehicles.

3.1 Flight Environment Modeling

Divide the environment into cells and classify them based on the presence of obstacles: if there are obstacles such as terrain and ground attachments, it is an obstacle grid and assigned a value of 1; otherwise, it is a free grid and assigned a value of 0. Due to the fact that the grid center point is the flight path point of logistics drones and the path needs to meet drone performance constraints, the grid granularity size needs to match the performance constraints [7].

Set up a rectangular area with length, width, and height of x, y, and z in the transportation task planning environment, denoted as $OABC-O'A'B'C'$, and establish a three-dimensional Cartesian coordinate system with O as the origin. The length of OA is x, the length of AA' is y, the length of OC is z, and the particle size of the grid is l.

Divide $OABC-O^{'}A^{'}B^{'}C^{'}$ along $OO^{'}$ by m to obtain $m-1$ planes, γ_j (j = 1, 2, ..., m). Where m = int(y/l) and int()are rounding functions.

Divide any of the above planes γ_i along OA by u and OC by h, where u = int(x/l), u = int(x/l), and γ_i are discretized into $u\times h$ plane grids, and the drone path point can be marked as $p(i,j,k), i=1,2,\cdots,m, j=1,2,\cdots,u, k=1,2,\cdots,h$.

3.2 Modeling of Path Planning for Logistics Unmanned Aerial Vehicles with Multiple Conditions

Logistics drone cargo transportation needs to consider multiple influencing factors. This article comprehensively considers the performance constraints and task requirements of logistics drones, and establishes a multi constraint logistics drone path planning model from the perspectives of transportation safety, economy, and speed [8].

1) Performance constraints

The distance between adjacent flight path points in the logistics drone path cannot be less than the minimum path segment length, with the following constraints:

$$\forall l_i \geq l_{\min} \quad i=1,2,\cdots,\rho \tag{1}$$

In the formula, l_i represents the range of each path segment, ρ represents the number of path segments, and $l_{\min}$ represents the minimum path segment length. The flight range of logistics drones is the sum of the flight ranges of each path segment. The single cargo transportation range of logistics drones should not be greater than their farthest range, subject to the following constraints:

$$\sum_{i=1}^{\rho} l_i \leq L_{\max} \tag{2}$$

$L_{\max}$ is the farthest range.

2) Maximum angle constraint

The maximum turning angle restricts the movement in the horizontal plane, constraining it to only change a certain angle from the current path point to the next path point. Essentially, it limits the minimum turning radius. Assuming that the coordinates of the adjacent path points of the logistics drone after excited flight are $p_i(x_i, y_i, z_i)$ and $p_{i+1}(x_{i+1}, y_{i+1}, z_{i+1})$, the turning angle is denoted as β, and the maximum turning angle is denoted as $\beta_{\max}$, the maximum turning angle is represented as:

$$0 \leq \arccos\left(\frac{(x_i-x_{i-1})(x_{i+1}-x_i)+(y_i-y_{i-1})\cdot(y_{i+1}-y_i)}{\sqrt{(x_i-x_{i-1})^2+(y_i-y_{i-1})^2}\cdot\sqrt{(x_{i+1}-x_i)^2+(y_{i+1}-y_i)^2}}\right) \leq \beta_{\max} \tag{3}$$

3) Flight altitude

The logistics drone has a flight limit due to manufacturing level and load limitations, and path point A meets the following requirements:

$$\forall z_i \leq H_{\max} \tag{4}$$

$H_{\max}$ is the maximum flight altitude.

4) Energy consumption constraints of unmanned aerial vehicles

Unlike other drone flight situations, each battery of the drone should meet the requirements to ensure that the goods are transported to the delivery point or to the power station, so the energy consumption constraint is expressed as:

$$E_{\cos t} \leq E_{total} \tag{5}$$

After the above analysis, in addition to meeting the requirements of flying to the delivery point, the entire drone should also meet the requirements of shortest flight time, lowest energy consumption, and the safest flight route. Therefore, the constraint model is as follows:

$$\min z = f_1 t_f + f_2 E_{\cos t} + f_3 S \quad \textbf{(6)}$$

Simultaneously satisfying formulas (1), (2), (3), (4), and (5), where t_f represents flight time, S represents safety level, f_1 , f_2, and f_3 represent their respective coefficients, and z represents the constraint objective.

4 Improvement Process of Path Planning Algorithm

This article uses a hybrid path planning algorithm. The global path planning uses the $APF-IRRT^*$ algorithm [9], while the local path planning uses the dynamic window algorithm [10]. Then, the paths of the hybrid algorithm are smoothly fused, and the optimal goal is ultimately obtained under global information. The process of the hybrid algorithm is as follows:

1) In the environment where the global obstacle map is known, the $APF-IRRT^*$ global path planning algorithm is used to find the optimal path and calculate the information of each coordinate point.

The algorithm pseudocode is as follows:

$APF-IRRT^*$
1 Input: M, x_{start} , x_{goal}
2 Output: A path T from x_{start} to x_{goal}
$X_{so\ln} \leftarrow \phi$
T = (V, E)
for interation = 1 to n do
$c_{best} \leftarrow \min_{x_{so\ln} \in x} \{\operatorname{Cos} t(x_{so\ln})\}$
$x_{rand} \leftarrow Sample(x_{star}, x_{goal}, c_{best})$
if CollisionFree($x_{nearest}$, x_{new}) then
$X_{near} \leftarrow Nearest(T, x_{new}, r_{RRT*})$
$x_{parent} \leftarrow Parent(x_{near})$;
if InGoalRegion(x_{new}) then
$X_{so\ln} \leftarrow X_{so\ln} \cup \{x_{new}\}$
$T \cdot addNode(x_{new})$
Return T;

2) The calculated coordinate points will be sequentially used as the sub target points of the drone, and the local path planning will use the dynamic window algorithm (DWA) to enable the drone to reach each sub target point separately, enabling the drone to avoid obstacles in a timely manner with partial global obstacle map information. When the drone cannot reach the current sub target point, static or dynamic obstacles occupy the current target point position, The hybrid algorithm will replace the new target point. In order to control the speed of the drone within a reasonable range, ensure that the motion trajectory is smooth enough, and limit the acceleration range in dynamic constraints, the acceleration range is shown in Fig. 1.

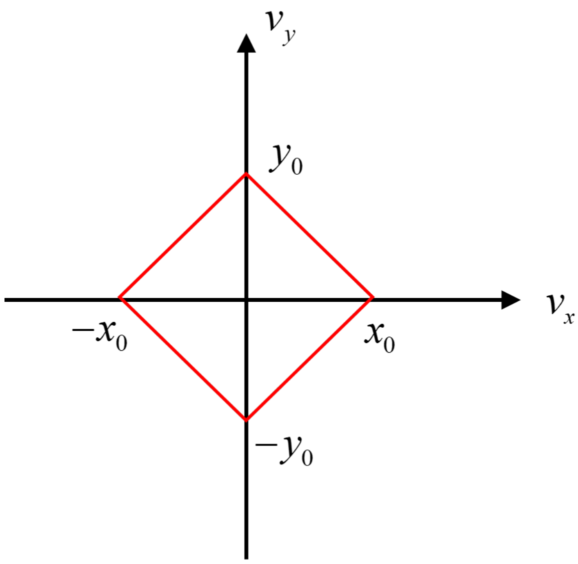

Fig. 1. Acceleration range

To reduce the number of drone turns, curvature radius constraint optimization is added to the planning process. The expression for curvature constraint optimization is as follows:

$$curvature(v,\omega)=\left|curvature_i(v,\omega)-curvature_{i-1}(v,\omega)\right| \quad (7)$$

$curvature_i(v,\omega)$ represents the curvature radius of the drone simulated by the current mouseshike, and $curvature_{i-1}(v,\omega)$ represents the curvature radius of the optimal trajectory of the drone at the previous moment. The constraint is normalized using the following formula:

$$heading=\frac{heading_t(v,\omega)}{\sum_{i=1}^{n}heading_i(v,\omega)} \quad (8)$$

$$dist=\frac{dist_t(v,\omega)}{\sum_{i=1}^{n}dist_i(v,\omega)} \quad (9)$$

$$velocity=\frac{velocity_t(v,\omega)}{\sum_{i=1}^{n}velocity_i(v,\omega)} \quad (10)$$

$$curvature(v,\omega)=\frac{\left|Curvature_i(v,\omega)-Curvature_{i-1}(v,\omega)\right|}{\sum_{i=1}^{n}\left|Curvature_i(v,\omega)-Curvature_{i-1}(v,\omega)\right|} \quad (11)$$

The improved evaluation trajectory standard function is as follows:

$$G(v,\omega)=\sigma\begin{bmatrix}a\cdot heading(v,\omega)+\beta\cdot dist(v,\omega)+\\ \gamma\cdot velocity(v,\omega)+\delta\cdot curvature(v,\omega)\end{bmatrix} \quad (12)$$

Using the $APF-IRRT^*$ algorithm for global path planning, the obtained global path waypoint information is sent to the DWA local path planning. By sampling the velocity space of the drone and optimizing its dynamic constraints, the optimized velocity space is sampled for velocity, and the trajectory calculated after velocity sampling is scored to select the optimal trajectory and velocity control drone motion.

The flowchart of the entire process is shown in Fig. 2:

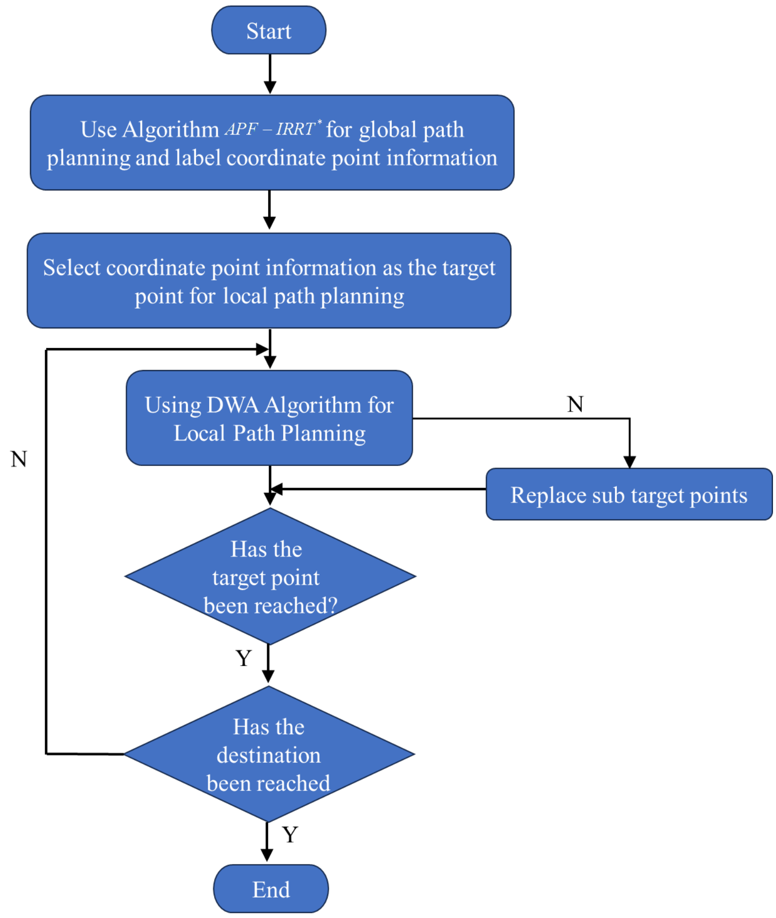

Fig. 2. Path planning flowchart

5 Path Planning Simulation

To verify the effectiveness of the algorithm proposed in this article, Matlab2019a was used for simulation. Use Matlab to simulate a high-rise building scene in a certain city, and use grid method for 3D environmental modeling. To be as close as possible to the actual flight process of logistics drones, the specific parameter settings in this article are shown in Table 1:

Table 1. Drone flight parameter settings

Name	Symbol	Parameter value
span	W_{UAV}	1m
aircraft commander	L_{UAV}	0.7m
The height of the drone	H_{UAV}	0.45m
Weight	M	5 kg

Speed	v	5 m/s
Start point		(40, 40, 50)
End point		(420,380,45)
Grid edge length	N_{length}	5m
Range		3000m
Minimum Path		5m
Flight altitude range		[5m, 120m]
Maximum turning angle		60°
Maximum pitch angle		60°
Maximum energy consumption	$E_{\max}$	1345KJ
Maximum load-bearing capacity	Q_k	9Kg
Actual weight of load		5.5Kg
Payload penalty coefficient	ψ_E	3
Air operation risk coefficient	I_R	2
Self failure probability		6.2×10^{-5}
Crowd density	ρ	0.02
Shading Coefficient	P	0.5
Weight coefficient	$\alpha_1,\alpha_2,\alpha_3,\alpha_4$	0.2,0.2,0.3,0.3
	k_1,k_2,k_3	10,0.2,120

In the established three-dimensional environment model, the final path planning results during the unmanned aerial vehicle delivery process are simulated using the algorithm proposed in this article, as shown in the red curve in Fig. 3. From the figure, it can be seen that the logistics drone departed from the starting point of takeoff and landing, safely avoided obstacles along the way and successfully arrived at the ending point of takeoff and landing. It can accurately plan the route and achieve obstacle avoidance.

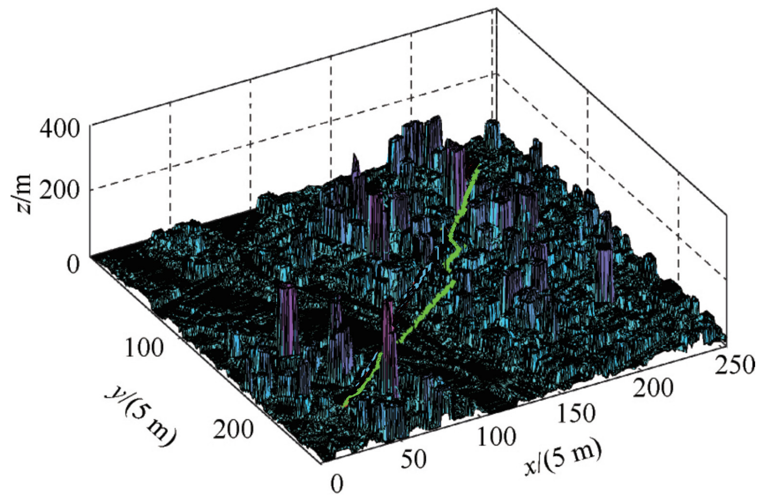

Fig. 3. Path planning 3D map

To further analyze the performance of the algorithm proposed in this article, while maintaining the simulation environment and parameter settings unchanged, the path was compared with the improved algorithm and the artificial potential field method route. The planned path comparison results are shown in Fig. 4.

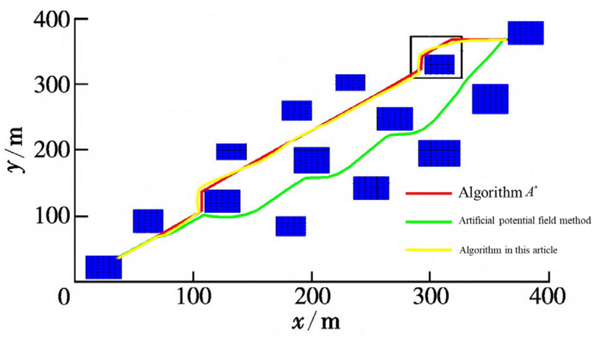

Fig. 4. Comparison of three algorithms for path planning

Compare various algorithms in terms of drone flight range, energy consumption, and planning time. The comparison results of each algorithm are shown in Fig. 5.

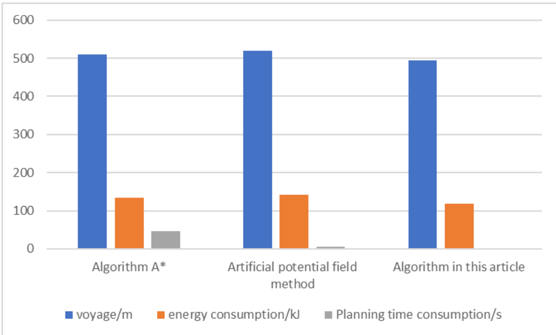

Fig. 5. Performance comparison of various algorithms

All three algorithms can complete the path planning of logistics unmanned aerial vehicles, but the improved algorithm A^* mostly plans routes with broken lines, large turning angles, and close to the boundary of obstacles, resulting in higher operational risks; However, the artificial potential field method is prone to falling into local minima due to the lack of global information, and the shortcomings of both algorithms seriously affect the planning effectiveness of the path. The algorithm proposed in this article outperforms the improved algorithm and the artificial potential field method in all indicators, especially in terms of reduced planning time by 97.1% and 65.2%, energy consumption by 6.4% and 10.2%, air operation risk and ground impact risk by 46.2% compared to the artificial potential field method.

6 Conclusion

This article completes the path planning modeling of unmanned aerial vehicle delivery and considers the flight path under multiple constraints. Then, the optimal path is used as the goal, and an improved hybrid algorithm is used to solve the model to dynamically obtain the optimal path. Finally, through simulation experiments, detailed constraint conditions were set, and the experimental results verified the effectiveness of the algorithm proposed in this paper, resulting in improved path planning performance.

Although a relatively realistic simulation environment has been established based on the real city situation, the 3D model lacks the non constraint of the real environment. Therefore, further research plans are to run logistics drones in a real experimental environment, test the effectiveness of algorithms, and make further improvements.

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