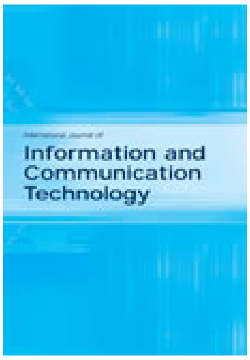

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UAV flight path optimisation based on improved RRT algorithm

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Abstract: The fast search random tree (RRT) algorithm is an algorithm used for path planning, which aims to reduce the search distance of UAV during flight and find the optimal path. Search for viable paths in the environment by building a random tree. The basic steps of UAV RRT algorithm include initialisation, generating random node, finding nearest tree node, extending tree and generating path. The improved algorithm can accelerate the search speed of the whole search space, and can optimise the multi-dimensional environment, and has good adaptability to the uncertain environment. However, the traditional RRT algorithm is not guaranteed to find the optimal path. By improving the centralised RRT algorithm, the flight path of UAV can be optimised, and then the advantages and disadvantages of each can be compared. First, build space model and drone model space. Secondly, the artificial potential field algorithm, pruning algorithm and area limit algorithm are improved to improve the search efficiency.

Keywords: unmanned aerial vehicle; UAV; RRT algorithm; flight path; improve.

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1 Introduction

Path optimisation has always been an important part of unmanned aerial vehicle (UAV) research. The UAV always encounters obstacles during flight. When the camera of the UAV captures the obstacles, the UAV must avoid the obstacles and find a new path during flight. The goal is to find the optimal flight path around obstacles. The traditional RRT algorithm is only aimed at the flight path search of UAV, without setting the corresponding shortest path search in the region, which increases the difficulty of the optimal path search. This paper puts forward a method to optimise the RRT algorithm based on the actual situation. In addition, since the path optimisation of traditional algorithms can no longer satisfy the flight of advanced UAVs, path optimisation can be improved through other kinds of algorithm optimisation.

Uav path planning is one of the key problems in UAV autonomous flight. Traditional path planning algorithms such as fast random tree (RRT) have low efficiency and insufficient path optimisation in large-scale environment. To solve the path optimisation problems, researchers proposed a UAV path optimisation method based on improved RRT algorithm. Here are some possible ways to improve the RRT algorithm for UAV path optimisation:

1 Multi-objective algorithm improvement: Path planning problem is defined as a multi-objective optimisation problem. In addition to the shortest path, other performance metrics such as energy consumption, time, and safety are also considered. Better path planning results can be obtained by introducing appropriate objective functions and constraints.

2 Dynamic environment perception: In consideration of environmental factors in the real world is dynamically changing, the path planning algorithm needs to be able to sense the changes of the environment in real time. Combined with sensor technology, drones can obtain real-time environmental information and make dynamic adjustments during path planning to better adapt to changes in the environment.

3 Multi-UAV collaborative path planning: In special cases, multiple UAVs are required can work together to complete complex tasks. For multi-UAV collaborative path planning, the coordination and division of labour among different UAVs can be considered, as well as the avoidance of collision and conflict. The path optimisation

method based on improved RRT algorithm can be extended to a path planning algorithm suitable for multiple unmanned aerial systems.

4 Application of machine learning: The introduction of machine learning technology enables the path planning algorithm to better adapt to different environments and task requirements by learning and modelling historical data. For example, deep reinforcement learning can be used to achieve autonomous learning of UAV path planning, thereby improving the efficiency and performance of path planning.

5 Improvement of obstacle avoidance strategy: The traditional RRT algorithm has certain limitations in avoiding obstacles. The improved path optimisation method of RRT algorithm can study more effective obstacle avoidance strategies, such as considering dynamic programming methods, local correction, etc., in order to achieve more reliable path planning results.

Aiming at the path planning problem of autonomous underwater vehicle (AUV) in complex underwater environment, Qi et al. (2023) adopted target point probability bias sampling strategy and target bias expansion strategy to make target nodes become sampling points during random sampling. Feng et al. (2023) aiming at the low search efficiency, weak search ability and long search time of RRT algorithm, an improved RRT algorithm is proposed, which can improve the search efficiency. Yu et al. (2023) aiming at the problem of flight path planning of UAV in the complex unknown environment at low altitude, this paper presents a round-trip flight path planning algorithm for UAV by fully considering the asymmetric characteristics of information in the process of departure and return. The environment information is constantly updated through the real-time detection of UAV airborne equipment, and the improved bidirectional rapidly exploring random tree* (B-RRT*) algorithm combined with rolling planning is used to generate the heading path. The return plan is based on the outbound flight path and global environment information. Han (2023) designed a path planning method based on partition sampling in view of the shortcomings of RRT algorithm in path planning such as strong randomness and many invalid nodes. The method first takes the coordinate values of the long side and the short side of the map as reference, divides the map into several regions, and restricts the nearest point of the random sampling point to search within the region to improve the traversal speed. Xu and Liu (2023) designed an improved RRT algorithm based on dynamic step size by combining the target gravity function and the obstacle repulsive force field function, aiming at the problems of random node sampling, slow convergence and low addressing accuracy in the path planning process of the basic fast search random tree (RRT) algorithm. Zhang et al. (2023) proposed that the traditional RRT algorithm is faced with the problem of large randomness and safety of the driving path, and proposed an improved RRT algorithm, especially in the narrow space environment. Jia et al. (2023) also proposed an improved RRT algorithm for slow search path, low search efficiency and various optimisation problems in the search process. Zhong (2023) proposed a robotic arm adaptive path planning algorithm that integrates artificial potential field and informed-RRT* algorithm, aiming at the problems of planning time, low iteration efficiency and inapplicability of dynamic scenarios in Informed-RRT* algorithm. Li et al. (2023) proposed an improved informed-RRT*FN algorithm to solve the problems of large randomness, low convergence accuracy and long running time of the traditional asymptotically optimal fast extended random tree algorithm (RRT*). Liu et al. (2023) proposed an improved RRT algorithm to avoid the problem of local optimal value in the process of path formation due to the complexity and long time of RRT algorithm to search the path randomly. Ding (2023) made a detailed description based on the acquisition and processing of the basic data of UAV flight space modelling and the operation of relevant software, digitised the terrain and building information of Huaiyin District in Jinan City, and simulated the real space of UAV flight based on the analysis of influencing factors. He (2023) built a single warehouse and multi-warehouse UAV task allocation model in urban areas that saves economic cost and reduces delay penalty, taking into account constraints such as vehicle energy consumption, customer time window and simultaneous pick-up and delivery. Kong (2023) proposed an ant colony algorithm that integrates improved artificial potential field to construct gravitational potential field, and uses the resultant force of improved artificial potential field as a coefficient to initialise pheromones in the pre-search feasible area. He proposed a random pheromone volatile factor updating mechanism, improved the heuristic function and pheromone updating rule of ant colony algorithm, and introduced gravitational potential energy to simulate high-altitude flying of UAV row, and apply it to pheromone updates. Chen (2022) analysed and studied the environmental data management methods and constraints of drones in real-time planning, and established a Euclidean symbolic distance field based on the fact that drones often need to query the distance between their own position and the nearest obstacle to avoid collision. Zhang and Chai (2019) proposed a step-by-step parallel optimisation method based on clustering algorithm and improved particle swarm optimisation (PSO) algorithm to solve the optimal path planning problem of multiple UAVs and multiple targets. Under different test situations, the algorithm proposed by Wang (2020) can provide the optimal path with the minimum number of waypoints and the shortest flight time that completely cover the study area. In particular, it has good planning effect when studying flight path planning of mountains and hills. Chen et al. (2022) searched for the optimal value for the traditional artificial potential field method, the method of ‘moving 90° along the target direction’ is introduced to jump out of the local minimum point, and the path planning, cooperative obstacle avoidance and collision prevention of multi-UAV formation are realised. Liu (2022) aiming at the total logistics distribution cost of only vehicles and only UAVs involved in the distribution mode of end-distribution in rural areas, the results show that under the same logistics distribution environment, the total distribution cost of the logistics mode of collaborative distribution of vehicles and UAVs can be minimised.

2 Model design

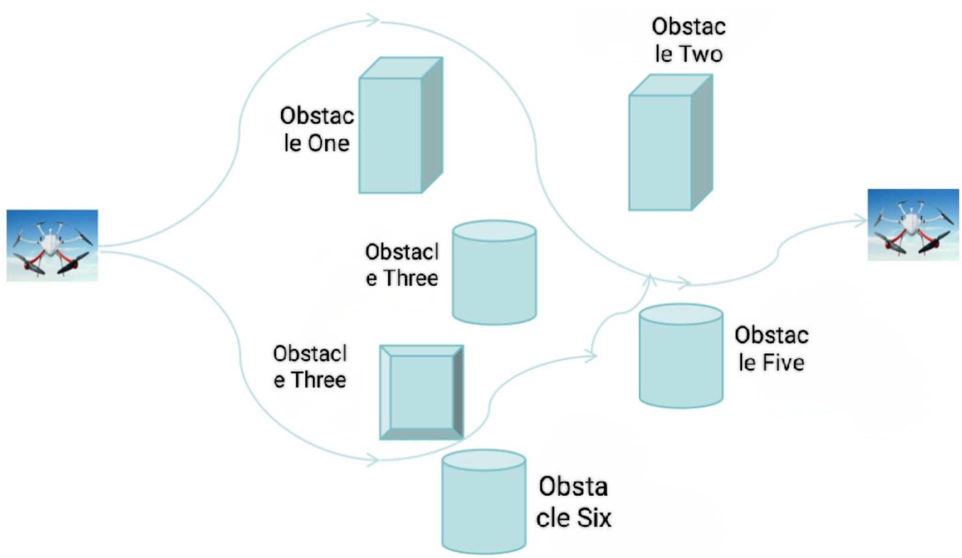
2.1 Establishment of spatial model

For space modelling problems encountered during UAV flight, space physics adopts three-dimensional space modelling method, and the space obstacle modelling model adopts circular and square models. In the process of planning the three-dimensional cell model, using the three-dimensional cell model, form (X, Y, Z) the model, the model steps are as follows:

- Set the coordinate system: First, you need to set a coordinate system to describe the three-dimensional space. The common coordinate systems are Cartesian coordinate system and polar coordinate system. In the Cartesian coordinate system, each point is represented by a triplet (x, y, z), which x represents a position on the horizontal axis, y represents a position on the vertical axis, and z represents a position on the vertical axis.

- Create basic geometry: In 3D modelling, you can use basic geometry (such as cubes, spheres, cylinders, etc.) as a starting point for modelling. These basic geometers can be placed in three dimensions by determining their position, size, and rotation Angle.

Figure 1 3D flight path simulation diagram (see online version for colours)



- Composition and deformation: By combining different basic geometries, you can create more complex objects or scenes. This can be achieved by translating, rotating, scaling and other transformations of the geometry. In addition, curves, surfaces and other tools can be used for shape adjustment and detail shaping. Figure 1 is a 3D flight path simulation diagram.

2.1.1 UAV flying obstacle model design

Since the geographic information of the UAV will be displayed in the map information during flight, based on this information, the geographic information of the obstacle area is constructed, and the construction model is as follows:

$$T_{(x,y,z)} = \sum_{i=1}^{n} b_i b_i' \left(\frac{x - x_i'}{\hat{x}} - \frac{y - y_i'}{\hat{y}} - \frac{z - z_i'}{\hat{z}} \right)$$

$T_{(x,\,y,\,z)}$ is the maximum height of the obstacle, is the shape of the obstacle, is the shape size factor, b_i is obstacle shape, b_i' is the shape size coefficient, n is the number of obstacles, (x_i', y_i', z_i') is the centre point coordinate, $(\hat{x}_i, \hat{y}_i, \hat{z}_i)$ respectively are the slope x, y, z, this model forms three-dimensional coordinates (x, y, z) and generates an obstacle model.

2.2 Smoothing path of Bessel curve

Bell curve is a common mathematical curve, often used in computer graphic design, its role is mainly used to connect discrete path points after algorithm path optimisation. The Bell curve can be shaped by n control point $\{P_1, P_2, \ldots, P_n\}$, the resulting curve passes through the starting point P_1 and the ending point P_n, without going through the P_2 and P_{n-1}, through the algorithm, all the waypoints are obtained and grouped to form a number of second-order Bell curves. After second-order Bessel, the recursive Bessel formula is trained to take all waypoints into account n. Bessel's formula is as follows:

$$p(t) = \sum_{i=0}^{n} P_i B_{i,n}(t),\ 0 \le t \le 1$$

$$\begin{cases} B_{i,n}(t) = C_n^i i(1-t)^{n-i} \\ C_n^i = \dfrac{n!}{i!(n-i)!}(i = 0, 1 \ldots n) \end{cases}$$

The second order Bessel curve formula is as follows:

$$B(t) = (1-t)^2 P_0 + 2t(1-t)P_1 + t^2 P_2,\ t \in [0, 1]$$

2.3 Design of UAV flight motion model

Based on the four-wing dynamics model, the following problems should be ignored in designing this model:

1 air resistance should not be considered

2 the shape of the drone does not change during flight

3 the angle variation of UAV is small during flight

4 the coordinates of this drone model are based on the land.

Input external variable $M = \begin{bmatrix} M_1 \\ M_2 \\ M_3 \\ M_4 \end{bmatrix}$; M_1 is the lift of a four-wing drone, $M_1 = \sum_{i=0}^{4} F_i$;

M_2 is the upturning moment of the UAV, $M_2 = -F_1 - F_2 + F_3 + F_4$; M_3 is the roll pitch of the drone, $M_3 = F_1 - F_2 - F_3 + F_4$; M_4 is the roll pitch of the drone, $M_4 = F_1 - F_2 + F_3 + F_4$. Then through the transformation of the coordinate system:

$$\text{Input variable}: X = \begin{bmatrix} x \\ y \\ z \\ \alpha \\ \beta \\ \gamma \end{bmatrix}, \text{output variable}: Y = \begin{bmatrix} x \\ y \\ z \\ \alpha \\ \beta \\ \gamma \end{bmatrix}.$$

For the analysis of the coordinate system of the four-wing body, the resultant force of the four-wing aircraft driven by the motor in the process of flight is M_1, $F_\nabla = \begin{bmatrix} 0 \\ 0 \\ M_1 \end{bmatrix}$, the conversion coordinates to earth are

$$\begin{aligned} F_\infty &= C_\nabla * F_\nabla \\ &= \begin{bmatrix} \cos\alpha\cos\gamma & \sin\alpha\sin\beta\cos\gamma-\cos\beta\sin\gamma & \sin\alpha\cos\beta\cos\gamma+\sin\beta\sin\gamma \\ \cos\alpha\sin\beta & \sin\alpha\sin\beta\sin\gamma+\cos\beta\cos\gamma & \sin\alpha\cos\beta\sin\gamma-\sin\beta\cos\gamma \\ -\sin\alpha & \sin\beta\cos\alpha & \cos\alpha\cos\beta \end{bmatrix} \\ &* \begin{bmatrix} 0 \\ 0 \\ M_1 \end{bmatrix} = \begin{bmatrix} M_1\cdot(\sin\alpha\cos\beta\cos\gamma+\sin\beta\sin\gamma) \\ M_1\cdot(\sin\alpha\cos\beta\sin\gamma-\sin\beta\cos\gamma) \\ M_1\cos\alpha\cos\beta \end{bmatrix}, \end{aligned} \tag{7}$$

The dynamics equation of the four-wing aircraft is as follows:

$$\begin{cases} m\ddot{x} = \mu(\sin\beta\sin\gamma+\cos\alpha\cos\gamma\sin\beta) \\ m\ddot{y} = \mu(\cos\gamma\sin\alpha\sin\beta-\cos\alpha\sin\gamma) \\ m\ddot{z} = \mu\cos\beta\cos\gamma-mg \\ \ddot{\alpha} = \tau_\alpha \\ \ddot{\beta} = \tau_\beta \\ \ddot{\gamma} = \tau_\gamma \end{cases}$$

3 Research on traditional RRT algorithm

According to raster map analysis, the RRT algorithm forms a tree search network graph from the start search position to the end search position. Its search method is to optimise search section by section according to the nodes of the tree through random search points, so as to form a search path graph. Figure 2 shows the search path diagram of the traditional algorithm.

3.1 Algorithm steps

The traditional RRT algorithm takes an initial point as the starting point, then randomly increases the nodes of the tree, and searches for the final target step by step. Since there are many target nodes in the random tree, it searches and searches through each node, and an optimal path can be found among multiple nodes. That is, the execution process of the RRT algorithm is as follows:

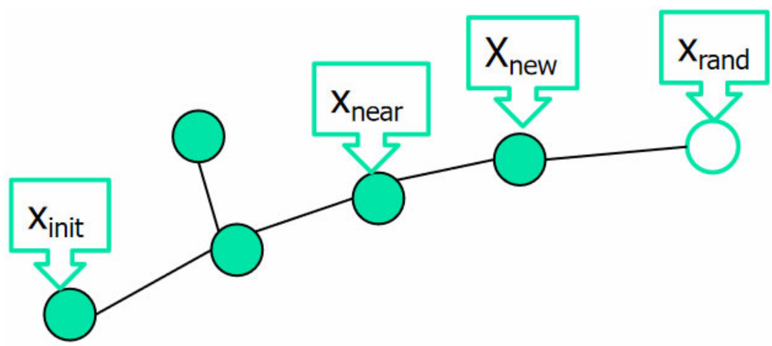
1 The next random point is x_{rand} generated through the starting point x_{init} of the path;

2 Secondly, after the random points are generated, find the path from the starting point to all the random points, and find the new random point closest to the random point x_{new}.

3 Define a distance d, then this defined distance is x_{rand}, the actual distance is x_{new}, if the new random point is not the optimal path, then the loop.

4 Find out the latest x_{new} to the distance x_{rand}, if less than, the latest distance, exit the loop.

Figure 2 Traditional algorithm path search diagram (see online version for colours)



3.2 *Improvement of RRT algorithm*

3.2.1 *Improvement of RRT algorithm based on artificial potential field method*

The gravitational potential field is mainly related to the distance between the UAV and the obstacle. Because the distance between the UAV and the obstacle during flight is farther, the potential energy value is larger; if the distance is closer, the potential energy value is smaller. Then the function to define the gravitational potential energy is as follows:

$$U_{att}(q) = \frac{1}{2}\eta\rho^2(q, q_g)$$

where η is the proportional gain coefficient, $\rho(q, q_g)$ is the vector, then represents the Euclidean distance between the UAV q and q_g the target point, then the negative gradient of the gravitational field is:

$$F(X) = -\nabla U(X) = \eta\rho(q, q_g)$$

When the UAV enters the obstacle area, there will be a force field between the UAV and the obstacle. If the distance between the two is closer, the repulsion force between the two is greater; if the distance between the two is farther, the repulsion force is smaller. The artificial function of the repulsion potential field is as follows:

$$U_{rex}(X) = \begin{cases} \frac{1}{2}k\left(\frac{1}{\rho(q, q_0)} - \frac{1}{\rho_0}\right)^2; & 0 \le \rho(q, q_0) \le \rho_0 \\ 0; & \rho(q, q_0) \ge \rho_0 \end{cases}$$

where k is the direct proportional coefficient and $\rho(q, q_0)$ is a vector, then it is the obstacle pointing to the UAV, the size $|q - q_0|$ is the distance between the UAV and the obstacle,

ρ_0 is a constant, indicating the maximum distance of the UAV to the obstacle, then the corresponding negative gradient of the repulsive force field is:

$$F_{n0}(X)=\begin{cases} k\left(\frac{1}{\rho(q,q_0)}-\frac{1}{\rho_0}\right)\frac{1}{\rho^2(q,q_0)}\nabla\rho(q,q_0); & 0\le\rho(q,q_0)\le\rho_0 \\ 0; & \rho(q,q_0)\ge\rho_0 \end{cases}$$

where $\Delta\rho(q, q_0)$ represents q to q_0 the unit vector :

$$\nabla\rho(q,q_0)=\frac{q-q_0}{\|q-q_0\|}$$

Then the combined potential field:

$$U=U_{att}(q)+U_{rex}(X)$$

3.2.2 Improvement of RRT algorithm for pruning random trees

As the RRT algorithm optimises the selection of parent nodes and pruning some redundant nodes, there is still a phenomenon of node redundancy in the obstacle avoidance process of UAV flight, resulting in the lack of optimal path optimisation in the obstacle avoidance process. In view of such cases, branches in the random tree should be pruned, and the remaining branches are the optimal branch paths. Specific implementation steps are as follows:

1 Assume that the order of all nodes is set as $\{x_1, x_2, x_3, \ldots, x_n\}$.

2 If the obstacle node is selected, then this is the key step of the node. At this time, there are many redundant nodes. If the redundant nodes are pruned, the node can be selected, and the path at this time is the optimal route for UAV flight;

3 Start from the starting point to find the end point, is the flight path.

As shown in the figure above, during the process of pruning random trees, the flight Angle of the drone changes, let's say x_t to x_{t+1} the turning angle is α_1, x_t to x_{t+2} the turning angle is α_2, when its steering angle changes in the same path, the original path will change when it encounters an obstacle, and it will fly around the obstacle.

The path of the flight distance before pruning is:

$$d_1=\sqrt{(x_{t+2}-x_t)^2+(y_{t+2}-y_t)^2+(z_{t+2}-z_t)^2}$$

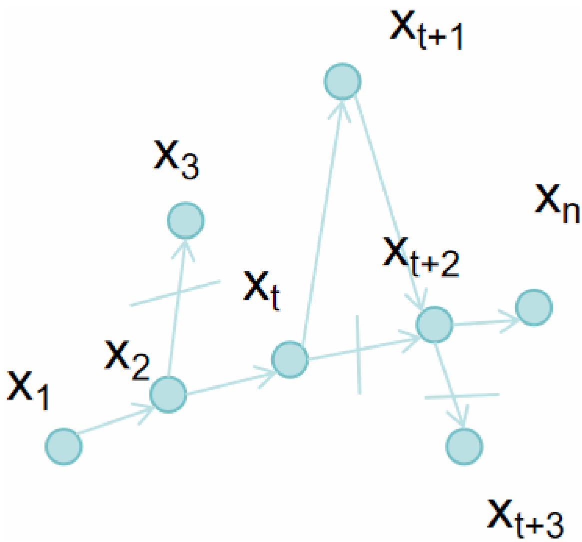
Distance of the trimmed part of the flight path:

$$d_2=\sqrt{(x_{t+1}-x_t)^2+(y_{t+1}-y_t)^2+(z_{t+2}-z_t)^2}+\sqrt{(x_{t+2}-x_{t+1})^2+(y_{t+2}-y_{t+1})^2+(z_{t+2}-z_{t+1})^2}$$

$$\alpha_1=\frac{(x_{t+2}-x_t)*(y_{t+2}-y_t)}{(x_{t+2}-x_t)+(y_{t+2}-y_t)}$$

$$\alpha_2 = \frac{(x_{t+1} - x_t)*(y_{t+1} - y_t)}{(x_{t+1} - x_t)+(y_{t+1} - y_t)} * \frac{(x_{t+2} - x_{t+1})*(y_{t+2} - y_{t+1})}{(x_{t+2} - x_{t+1})+(y_{t+2} - y_{t+1})}$$

Figure 3 Building a random tree path search graph (see online version for colours)



The angle in the climbing process and the angle in the descending process produced by the aircraft during flight are respectively as follows:

1 Since the 3D simulation introduces coordinate axes z, assume that the angle of climb and angle of descent are set as σ:

$$\sigma_1 = \frac{|z_{t+2} - z_t|}{\sqrt{(x_{t+2} - x_t)^2 + (y_{t+2} - y_t)^2}}$$

$$\sigma_2 = \frac{|z_{t+1} - z_t|}{\sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2}} * \frac{|z_{t+2} - z_{t+1}|}{\sqrt{(x_{t+2} - x_{t+1})^2 + (y_{t+2} - y_{t+1})^2}}$$

2 Assume that the maximum allowable flight height of the UAV is $z_{\max}$, the lowest flight height is $z_{\min}$, and the flight height range after the corner is:

$$z_{\min} \le z \le z_{\max}$$

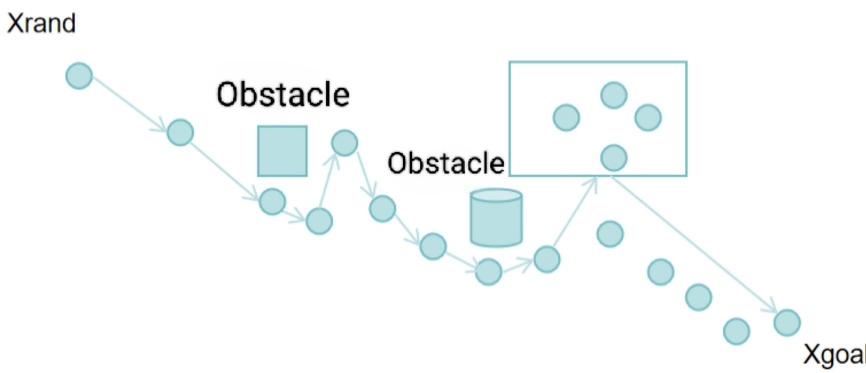
3 Assuming that the longest flight distance of the UAV is $d_{\max}$ and the shortest flight distance is $d_{\min}$, the setting range is $d_{\min} \le d \le d_{\max}$.

3.2.3 Limit the selection of random points

In order to reduce search times and search scope and improve computing efficiency, the region of random points is randomly selected for range delineation. In the process of region setting, the target bias strategy is introduced and sampling points X_{rand} are selected according to random probability. If the target point of the UAV is temporarily uncertain during flight, it is only necessary to select the barrier-free path, which is the optimal path.

Then the target point X_{goal} can be arbitrarily selected, which r is the radius of the target point in the search process. In addition, the reference value $s_{val}(0 \leq s_{val} \leq 1)$ is set. Before the random point is generated, set $p(0 \leq p \leq 1)$. Then, the target point is the sampling point. When $0 \leq p \leq s_{val}$, then the target point is the sampling point, when $s_{val} \leq p \leq 1$, randomly generate random points, so repeat this step over and over again to form a complete path. Figure 4 shows the restricted search diagram of random points.

Figure 4 Restricted search map of random points (see online version for colours)



As shown in the figure above, the region is demarcated, the search is carried out in the specific area, and the barrier-free path of UAV flight is searched. This method can accelerate the number of convergence times in the search path within a fixed range, and find the optimal path.

3.2.4 Steps of the improved algorithm

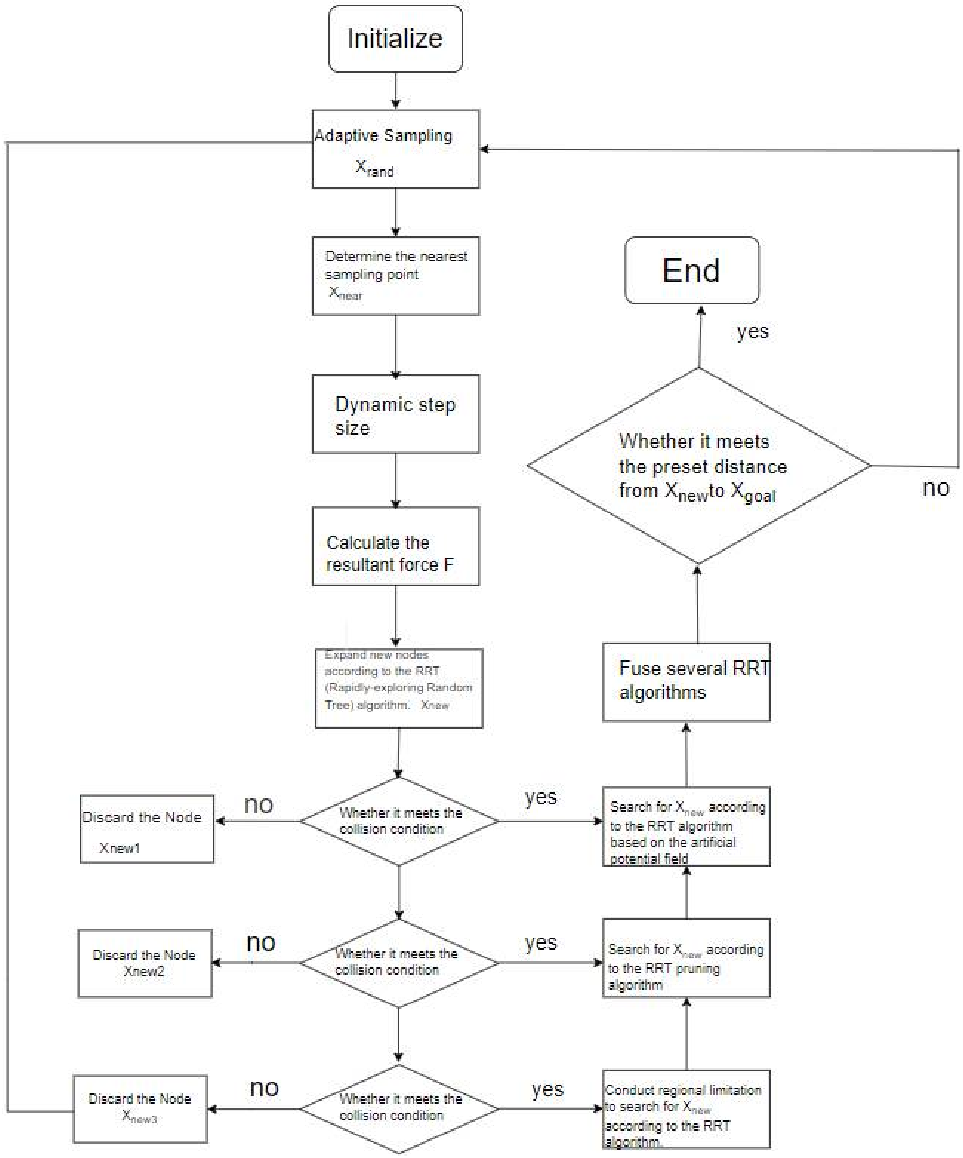
1 Through the starting point x_{init} of the path, the next random point x_{rand} is generated;

2 Secondly, if the random points meet the random points x_{new} at this time, the RRT artificial potential field method is improved; If the rejected node is not met, the collision of random points will continue. If the new node is met, the RRT pruning and region-restricted RRT algorithm will be used for search.

3 In addition, the three improved algorithms are integrated, namely, the artificial potential field method is improved, RRT pruning is improved and the RRT algorithm of area restriction is improved.

4 Find out the latest x_{new} to x_{rand} the distance, if less than d, the latest distance, exit the loop. Figure 5 is the algorithm flow chart of this paper.

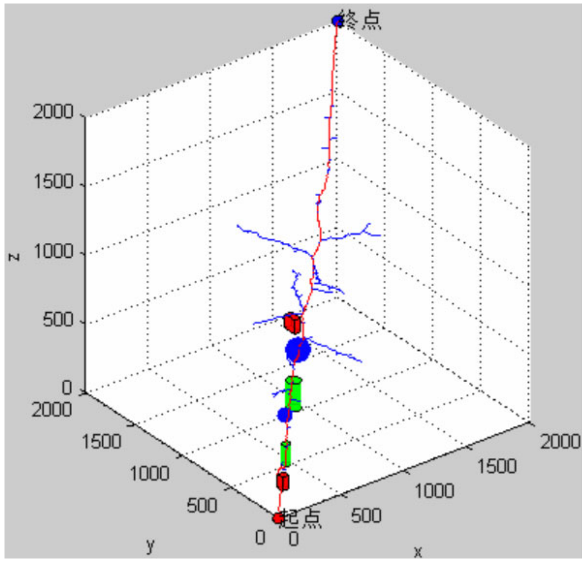
Figure 5 Algorithm flowchart



4 Simulation results and analysis

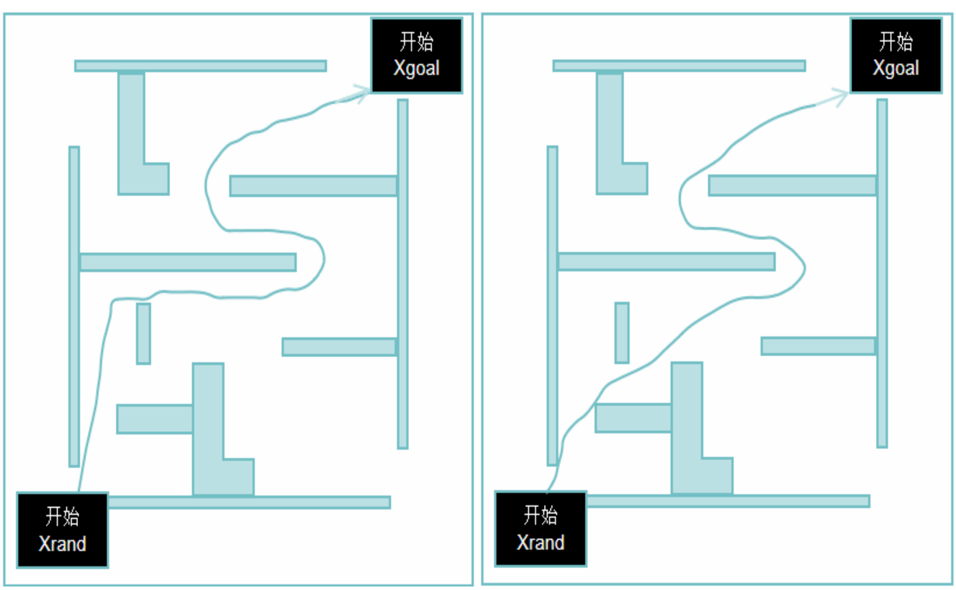
This UAV flight mainly uses three-dimensional path optimisation. The following figure is a basic three-dimensional diagram of UAV flight, and its flight path and obstacle path are set through the model. Figure 6 shows the three-dimensional flight path diagram.

Figure 6 3D basic flight diagram (see online version for colours)



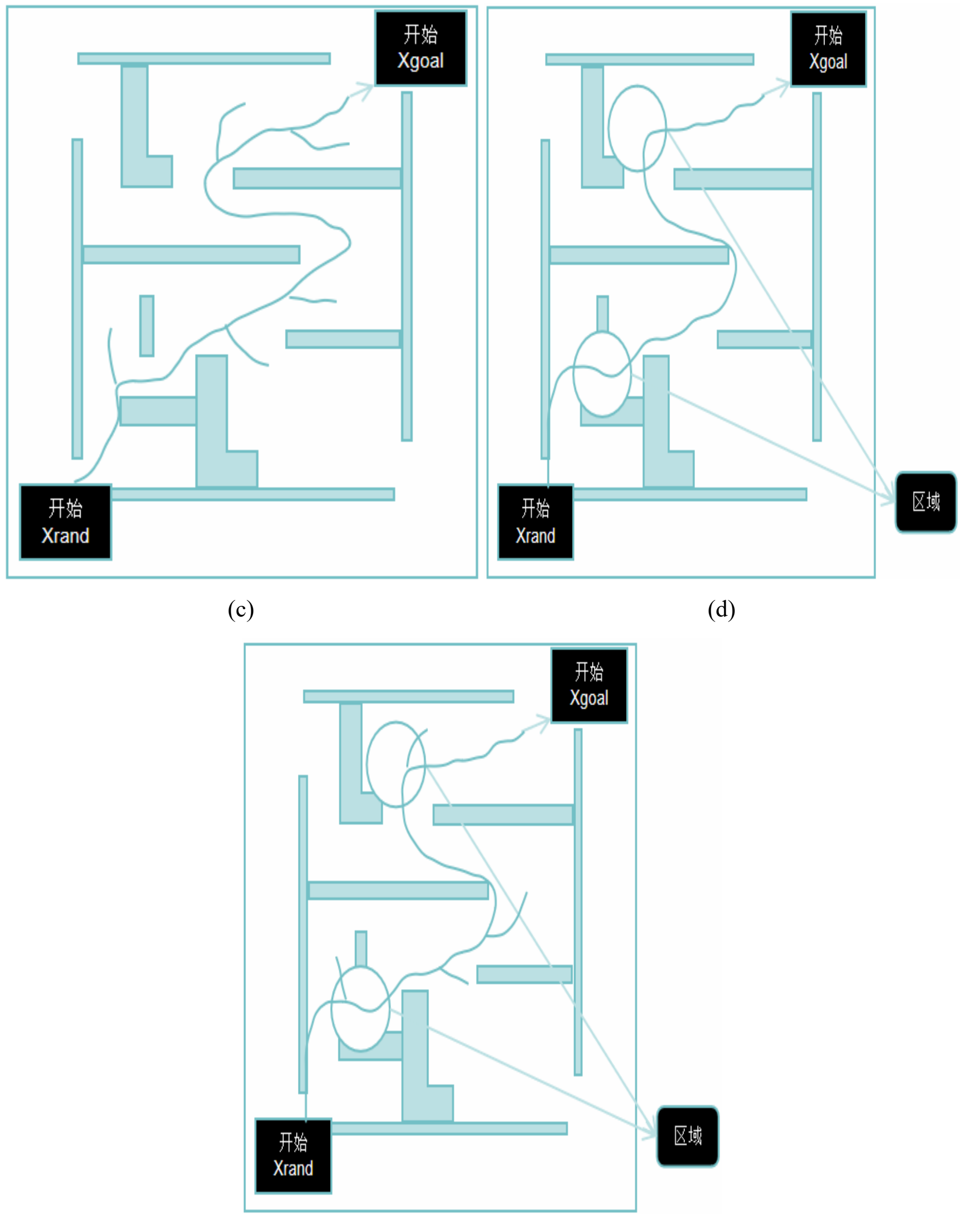
After the previous algorithm research, the flight path of the three-dimensional path casts a shadow of the two-dimensional path. The following figure shows the two-dimensional mapping of the UAV flight path before and after the improvement. Figure 7 is a two-dimensional mapping.

Figure 7 Flight path diagram of UAV, (a) traditional algorithm (b) improved algorithm 1 (c) improved algorithm 2 (d) improved algorithm 3 (e) improved algorithm 4 (see online version for colours)



(a) (b)

Figure 7 Flight path diagram of UAV, (a) traditional algorithm (b) improved algorithm 1 (c) improved algorithm 2 (d) improved algorithm 3 (e) improved algorithm 4 (continued) (see online version for colours)

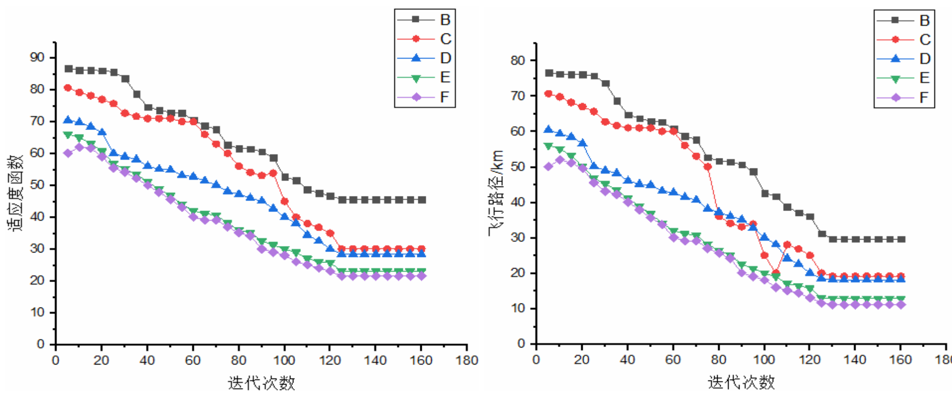


(c) (d)

(e)

As can be seen from Figure 7, the improved algorithms mainly fall into four categories: one is to improve the RRT algorithm by artificial potential field, the other is to improve the RRT algorithm by pruning, the third is to delimit a specific area to improve the RRT algorithm, and the fourth is to merge the three improved algorithms, and it can be seen that the path has changed significantly. Then its fitness function and the flight path of the UAV will also change. Figure 6 shows the change curve of fitness function and flight path. Figure 8 shows the fitness and path diagram.

Figure 8 Fitness function and path diagram, (a) fitness function (b) flight path (see online version for colours)



(a) (b)

The UAV flight is set to five different RRT algorithms, which are respectively set to five levels: B, C, D, E and F. B represents the research of traditional algorithms, C represents the research of artificial potential field algorithm, D represents the research of pruning random tree algorithm, E represents the research of random point area restriction, and F represents the research of four algorithms based on fusion CDEF. It can be seen from the figure that with the increase of iteration times, function fitness and flight path will decrease. At the same time, it can be seen that the CDEF of the four algorithms based on the improvement is obviously better than the traditional algorithm with the increase of the number of iterations. Secondly, F integrated with CDF algorithm has more advantages, which greatly reduces the fitness function value and path distance. Table 1 shows the final parameters of UAV path optimisation.

Table 1 The final parameters of unmanned aerial vehicle path optimisation

Algorithm	*Traditional algorithm*	*Improved algorithm 1*	*Improved algorithm 2*	*Improved algorithm 3*	*Improved algorithm 4*
Fitness function	28.115	18.678	17.223	15.118	14.128
Flight path/km	29.765	19.287	18.223	12.998	11.254

According to Table 1, it can be seen that after the algorithm is improved, its fitness function and flight path optimisation become the final parameters, indicating that the UAV flight with the improved algorithm has obvious results.

5 Concluding remarks and prospects

5.1 Concluding remarks

This paper aims at the path optimisation of UAV based on traditional algorithms, which greatly reduces the flight distance, automatically searches the obstacles in flight when encountering obstacles, selects the most suitable path, reduces the collision risk, shortens the flight distance and saves time. Secondly, this paper uses several improved algorithms, including artificial potential field method, random tree construction method and random point area restriction method. The fitness function parameters and flight distance can be significantly reduced. Finally, the integration of the three algorithms is more conducive to the optimisation of UAV flight path.

5.2 Outlook

Fast search random tree (RRT) algorithm, as a classical method widely used in the field of path planning, especially in the case of obstacles or high dimensional space, shows its unique advantages. However, RRT algorithm also has some limitations, such as the generated path may not be the shortest or optimal, and the path quality and computational efficiency are greatly affected by random samples. To address these limitations, researchers have proposed a variety of improvement methods, and the improvement of RRT algorithms will continue in the future.

1 Enhance goal orientation:

   By increasing the sampling tendency of the direction of the target point, the algorithm expands to the target point faster, reduces the blindness and randomness of the search, and improves the search efficiency and convergence speed.

   By setting a probability threshold, random points can be generated in the direction of the target point with a certain probability, or some specific random points towards the target point can be generated in each iteration according to a certain proportion.

2 Dynamic adjustment of step size:

   Dynamically adjust the expansion step size of the tree according to different circumstances of the environment. Use larger steps in open areas to speed up the search, and smaller steps in narrow or obstruction-dense areas to improve the accuracy and safety of the search.

   The step size can be determined based on factors such as the distance from the obstacle and the distance from the current node to the target point, or fuzzy logic, neural network and other methods can be used to calculate the appropriate step size in real time based on environmental information.

Declarations

All authors declare that they have no conflicts of interest.

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