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Exploration of UAV Path Planning Methods and Algorithms

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Abstract

With the rapid development of Unmanned Aerial Vehicle (UAV) technology, different kinds of UAVs are widely used in the fields of traffic inspection, disaster rescue, cargo delivery, and target reconnaissance due to their flexibility and low altitude flight capability. Path planning, as an important part of UAV autonomous flight, is of great significance to guarantee flight safety and improve mission efficiency. Therefore, clarifying the basic methods and related algorithm classification for carrying out UAV path planning will help to carry out algorithm improvement research in depth in the next step.

Keywords

Unmanned Aircraft; Path Planning; Algorithm Classification; Intelligent Optimization Algorithm.

1. Introduction

UAV path planning is a technique used to determine the optimal flight path of a UAV from a starting point to a target point in a given environment, taking into account the effects of flight time, energy consumption, safety and environmental characteristics[1] . On this path, the UAV needs to avoid various obstacles and satisfy a variety of constraints such as flight height, flight speed, energy consumption, and so on. The requirements are threefold: first, safety, to ensure that the UAV avoids collision with obstacles during flight; second, high efficiency, the generated path should be as short as possible to minimize flight time and energy consumption; and third, real-time, in dynamic environments, the path planning should be able to respond to environmental changes in real time.

2. Steps for the Implementation of Unmanned Aerial Vehicle Path Planning

2.1 Modeling

2.1.1. Environmental Modeling

Environmental modeling refers to the digital representation and analysis of the flight space and its surroundings. This process aims at identifying and describing terrain features, obstacles, waters, buildings, and other key factors affecting UAV flight, and is the first step in realizing UAV path planning, providing basic data for subsequent path planning[2] . Therefore, the finer the environment modeling is, the better the algorithm plans the path; on the contrary, the coarser the environment modeling is, the worse the path planning effect is[2] .

Depending on the dimension of the modeling, the environment modeling is usually classified into two-dimensional environment modeling and three-dimensional environment modeling. Path planning in 2D modeling environments restricts the UAV to environments with two spatial dimensions (i.e., planes), and the algorithms only need to singularly consider the constraints on the maximum turning angle of the UAV. The common methods used for modeling 2D environments are raster and geometric methods, as shown in Fig. 1 and Fig. 2.

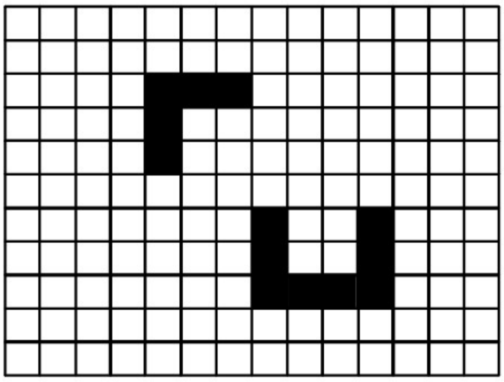

Fig. 1 Raster environment modeling method

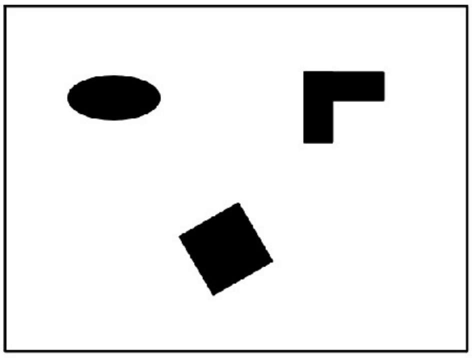

Fig. 2 Geometric method environment modeling

Path planning in a 3D modeling environment is a process of partitioning the 3D space into a number of each uniform cubic spaces using the 2D raster method[3] . As shown in Fig. 3 Compared with the 2D path planning is more rich and three-dimensional, the performance is real and feasible[4] .

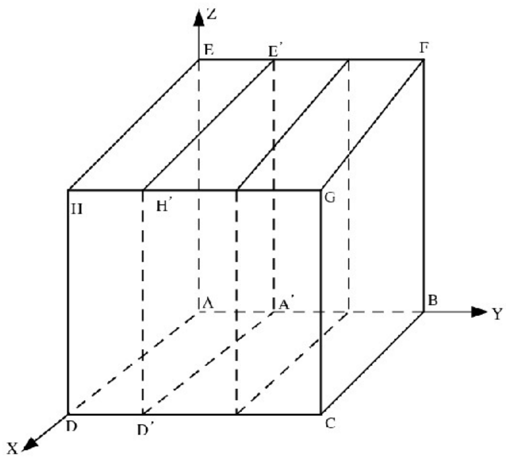

Fig. 3 Schematic diagram of uniform division of three-dimensional space

2.1.2.Constraint Modeling

Different UAVs have disparities in their flight performance in terms of airframe mass, motor speed, communication equipment, and processor model. Therefore, the UAV's own constraints should also

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be fully considered. A wide range of scholars have proposed the farthest path length condition based on the UAV's own power capacity such as fuel quantity and battery endurance; the constraint of minimum flight distance is proposed by considering that the actual path executed by the UAV will not be lower than the shortest safe distance or minimum range limit of the flight when it performs the mission; the constraint of maximum steering angle is proposed for the maximum turning arc that the UAV is able to make when it steers; and the constraint of maximum steering angle is proposed in order to avoid collision with obstacles when UAV is flying, the flight altitude constraint is proposed. The above general constraints are proposed to quantitatively describe the UAV more accurately and lay the foundation for the subsequent path generation.

2.1.3. Modeling the Fitness Function

In order to evaluate the high quality of the path searched by the algorithm, and also to provide a basis for the iteration of the algorithm population, and to comprehensively consider the influence of the path length, the cost of the threat area, the cost of the altitude change, and the cost of the collision of the obstacles[5] , scholars express the path adaptation function of UAV as Eq:

$$F = \varphi_1 f_L + \varphi_2 f_R + \varphi_3 f_H + \varphi_4 f_C$$

In the above equation, F represents the fitness value of the path, which is a comprehensive index describing the path, and the smaller the value of F, the higher the comprehensive quality of the path; f_L represents the cost of the path length; f_R represents the cost of the threatened area; f_H represents the cost of the altitude change; f_C represents the cost of the obstacle collision; φ_1 , φ_2 , φ_3 , φ_4 are the coefficient of the cost of the path length, the coefficient of the threatened area cost, the coefficient of the cost of the altitude change, and the coefficient of the cost of the obstacle collision, all of which are constants, respectively. They are all constants, which represent the proportion of several costs in a specific environment.[6] The cost coefficients of path length, threat area cost coefficient, height change cost coefficient and obstacle collision cost coefficient are all constants. The specific formulas of the above four costs can be found in the cited literature.

2.2 Path Generation

Path generation is the process of applying an algorithm to create an optimal path for a UAV based on a model of the UAV itself and the environment in which it is embedded, while satisfying various constraints. The commonly used conventional algorithms are shown in Fig. 4.

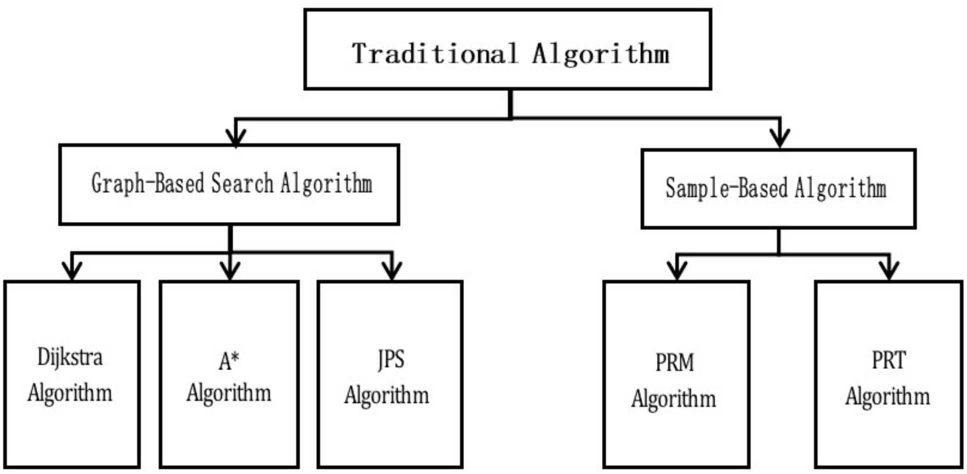

Fig. 4 Classification of traditional algorithms

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2.2.1. Algorithms based on Graph Search

Dijkstra's algorithm was first proposed by Dijkstra in 1959[7]Its function is to solve the shortest path problem between fixed points in a raster map.A* algorithm was first proposed in 1968 by P. Hart et al.[8]It combines the features of best-first search and Dijkstra's algorithm, and has better accuracy and performance, but when the state space is extremely complex, its computational memory consumption will also increase relatively.Prof. Daniel Harabor et al. proposed the JPS (JumpPoint Search) algorithm in 2014.[8] This algorithm is an optimization algorithm for graph search, a variant of the A-algorithm, which accelerates the search process by exploiting the geometric properties of lattice maps, thus making it faster than the traditional A-algorithm in many cases.Moore et al. on the other hand, proposed to improve the search efficiency of the JPS algorithm by recording the locations of the boundaries of the obstacles, and then using these locations in a direct lookup manner[9] .

2.2.2. Sampling-based Methods

Kavraki et al. proposed the PRM (Probabilistic Roadmap) algorithm in 1996.[10] Kavraki et al. proposed the PRM (Probabilistic Roadmap) algorithm in 1996, which is a sampling-based path planning algorithm, the core idea is to construct a probabilistic roadmap, which consists of randomly sampled nodes and edges connecting these nodes, which represent feasible paths. Due to the probabilistic random sampling characteristics of the algorithm, the algorithm does not have probabilistic completeness.Lavalle proposed RRT (Rapidly Exploring Random Trees) algorithm in 1998, the core idea of this algorithm is to utilize the probabilistic random sampling characteristics of the algorithm.[11] Lavalle proposed RRT (Rapidly Exploring Random Trees) algorithm in 1998, the core idea of the algorithm is to explore the configuration space using random sampling and tree expansion. The algorithm starts from a single root node (starting point), randomly generates new nodes and connects them to the tree, thus gradually constructing a tree structure covering the feasible region. Although the algorithm may not always find the optimal path, its fast response and adaptability make it a powerful tool for solving path planning problems in dynamic and complex environments. Subsequently Reza[12] , Xinpeng et al.[13] respectively, improved and utilized the RRT algorithm to obtain a path energy that not only better meets the safety of UAV driving, but also reduces energy consumption.

2.3 Obstacle Avoidance

The presence of obstacles can have a significant impact on UAV path planning. Therefore, in order to avoid the static and dynamic obstacles that already exist or suddenly appear in the path, the UAV in flight must adjust the path in real time through local planning algorithms to ensure its safe flight. Common local planning algorithms are shown in Fig. 5:

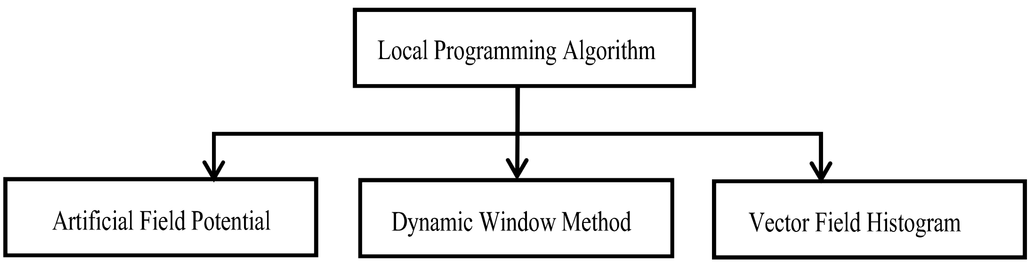

Fig. 5 Classification of traditional algorithms

Static obstacle avoidance is the ability of a UAV to detect and avoid fixed obstacles (e.g., mountains, buildings, trees, power lines, etc.) in real time during flight. The location and shape of these obstacles remain constant over a short period of time. Effective static obstacle avoidance techniques rely on a variety of sensors (e.g., LIDAR, cameras, and radar) to construct a real-time map of the environment and utilize traditional path-planning algorithms (e.g., Dijkstra's algorithm and A* algorithm) to compute a safe flight path. Dynamic obstacle avoidance, on the other hand, refers to the ability of a UAV to recognize and avoid dynamic obstacles (e.g., other flying vehicles, birds, etc.) in real time during flight. Realizing dynamic obstacle avoidance usually involves fast processing of sensor data, real-time updating of path planning algorithms, and timely decision making in response to changes in the surrounding environment[14] Khatib proposed the artificial field potential algorithm in 1986[15] Khatib proposed the artificial field potential algorithm in 1986, the core idea of the algorithm is to establish a gravitational potential field around the target point similar to the electromagnetic field, and to establish a repulsive potential field around the obstacles, the UAV flying in such a composite field, not only to bear the gravitational force of the target point, but also to bear the repulsive force of the obstacles, guided by the combined force, the UAV will find a collision-free obstacle avoidance route.Dieter Fox et al. proposed the dynamic window method (Dynamic Window Method) in 1997, which is the best solution to the problem of collision avoidance. Dynamic Window Approach (DWA) was proposed by Dieter Fox et al. in 1997.[16] In 1997, Dieter Fox et al. proposed the Dynamic Window Approach (DWA), in which the core of the algorithm lies in defining a "dynamic window" for the robot, which represents the range of speeds and steering angles that can be safely executed by the robot in the current time step. Virtual Force Field (VFF)[17] The vector field histogram (VFH) method was proposed based on the Virtual Force Field (VFF) method.[18] The VFH method was proposed on the basis of the Virtual Force Field (VFF). With the in-depth research of subsequent scholars, the VFH algorithm has been improved, and the VFH+ and VFH* algorithms for obstacle avoidance have been proposed one after another.

3. Intelligent Optimization Algorithm

In order to further improve the efficiency and effectiveness of UAV path planning, researchers have proposed a variety of intelligent optimization algorithms in recent years. Compared with traditional algorithms, intelligent algorithms can quickly find the best path in complex environments while considering multiple constraints. Commonly used intelligent optimization algorithms can be further divided into bionic search algorithms and reinforcement learning algorithms. As shown in Fig. 6.

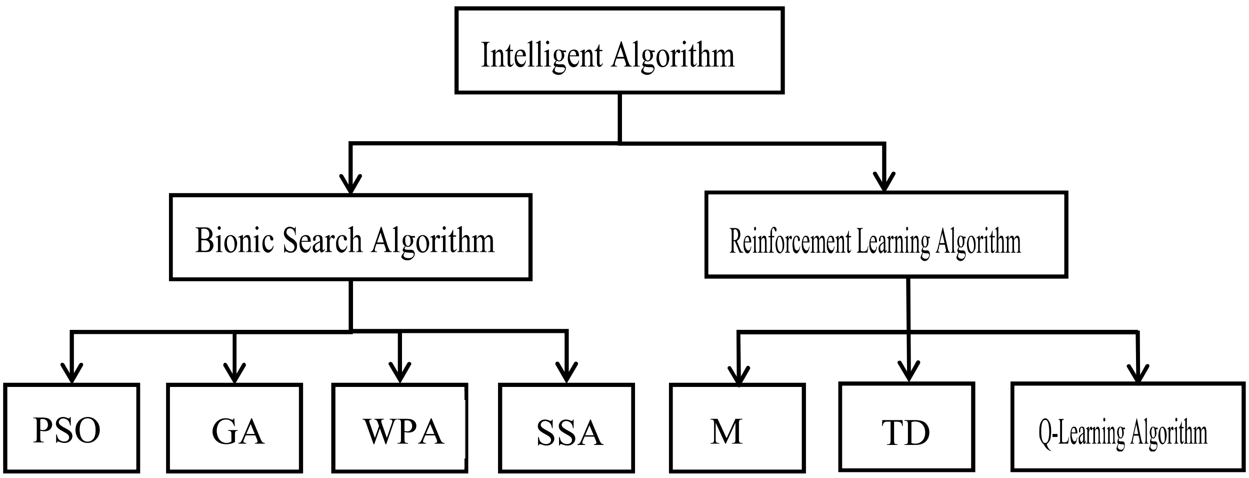

Fig. 6 Classification of intelligent algorithms

3.1 Bionic Search Algorithms

Particle swarm algorithm was proposed in 1995 by Eberhart et al.[19] The algorithm performs path search by simulating the behavior of birds foraging to find the best path, it has good global search ability and fast convergence speed, but sometimes it is easy to fall into the local optimum, especially when dealing with discrete optimization problems.Prof. J.H. Holland proposed the Genetic Algorithm

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in 1975, it is a search optimization algorithm simulating the principles of natural selection and genetics, its core idea is to extract and explain the self-adaptive process of natural systems, and design a natural system with self-adaptation.[20] , which is a search optimization algorithm that simulates the principles of natural selection and genetics, and its core idea is to extract and explain the adaptive process of natural systems and design artificial systems with the mechanism of natural systems. Genetic algorithm has been widely used in engineering optimization, economic scheduling, machine learning, artificial intelligence and other fields, and so far has been considered as the basis of intelligent optimization algorithms. Wolf Pack Algorithm (WPA)[21] is a new intelligent optimization algorithm proposed by Husheng Wu et al. in 2013, inspired by the hunting behavior and social structure of wolf packs. The algorithm mimics the collaboration between leaders and followers in a wolf pack, as well as the decision-making strategy of the wolf pack during the hunting process. The algorithm is easy to implement with fewer parameters, has good global search ability and the ability to avoid falling into local optimum, especially suitable for dealing with high dimensional and complex optimization problems. Sparrow Search Algorithm (SSA)[22] Sparrow Search Algorithm (SSA) is a swarm intelligence optimization algorithm proposed by Jiankai Xue and Bo Shen in 2020, which is inspired by the group intelligence, foraging and anti-predation behaviors of sparrows. They compared the optimization effect of the sparrow search algorithm on standard test functions with particle swarm algorithm, grey wolf optimization algorithm, and gravitational search algorithm, and the results show that the sparrow algorithm has good stability and convergence speed, and is able to explore the unknown region and avoid falling into local optimal solutions.

3.2 Reinforcement Learning Algorithms

Monte Carlo Algorithm (Monte Carlo, MC)[23], The fusion of game tree search algorithm and Monte Carlo simulation method is a kind of game tree algorithm in the field of machine learning. The algorithm can selectively expand the game tree, and gradually adapt and improve the simulation strategy, as the number of simulations increases, the simulation results are closer to the optimal value. Temporal Difference Learning (TD) Algorithm[24] Temporal Difference Learning (TD) algorithm is a reinforcement learning algorithm that combines the dynamic programming method and Monte Carlo algorithm, the concept of the algorithm is to gradually update the action value function and state value function during the execution process, and use the estimate of the current step to update the estimate of the previous step, which optimizes the shortcomings of the Monte Carlo algorithm that requires a high degree of completeness of the trajectory, and it can learn autonomously.In 2021, Tu Guan-Ting[25] et al. proposed to use the Q-learning algorithm for global path planning of UAVs, and then apply the deep Q-learning algorithm for local path planning, so that the reinforcement learning algorithm can be more fully utilized for path planning of UAVs.

4. Future Development Trends

Based on the maturity and wide application of "swarm", the research on path planning will face new challenges and development opportunities as a prerequisite for individual UAVs to accomplish tasks efficiently. In the near future, UAVs will have high autonomy without human intervention, and their autonomous path planning capability will become stronger and stronger; in order to accomplish complex tasks with multiple UAVs, the collaborative mechanism of path planning will be more complete; combined with artificial intelligence technology, and highly adapted to changing environments and mission requirements, UAV path planning will become smarter and smarter.

5. Conclusion

Path planning, as a key technology for UAV to accomplish tasks efficiently, is a complex and important research field. With the continuous progress of technology, the application scenarios of UAV will be more extensive, and the research on path planning will continue to deepen. In order to improve the path planning ability of UAV in complex environments, it is difficult for any single algorithm to perform well, and complementing the advantages of multiple algorithms based on the

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idea of fusion will surely become an important breakthrough to improve the efficiency of path planning in the future.

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