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A review of unmanned aerial vehicle path planning techniques

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Abstract. The paper offers an exhaustive scholarly review of the algorithms and techniques employed in Unmanned Aerial Vehicle (UAV) path planning, categorizing these methodologies based on spatial dimensions, planning steps, and the nature of planning maps. It provides a critical evaluation of a plethora of algorithms, including random search methods, particle swarm algorithms, genetic algorithms, and A* algorithms, among others. The study elucidates the advantages and limitations of each algorithm, with a particular focus on their efficacy in real-time planning and navigation within complex three-dimensional environments. It underscores that while the domain of pre-flight path planning has reached a level of relative maturity, there exists a conspicuous gap in the literature concerning real-time obstacle avoidance and optimal path planning, particularly when constrained by limited computational resources. The paper thus serves as both a comprehensive review and a call for further research aimed at addressing these identified lacunae to ensure the generation of safe and feasible UAV trajectories.

Keywords: path planning, UAV, genetic algorithm.

1. Introduction

Unmanned Aerial Vehicle (UAV), referred to as UAV, is a non-manned aircraft controlled by radio or onboard computer program, which has the benefits of low price and tiny size., widely employed in many different sectors [1].

In the early 20th century, the concept of drones was first proposed. Following World War II, nations including the USSR, Australia, and the Soviet Union began to vigorously develop drone technology [2]. After the 1990s, with the Gulf War and the Afghan War, unmanned aerial vehicles were widely used in these wars [3]. So far, our country has gradually paid attention to the research in the field of unmanned aerial vehicles [4]. Quadrotor UAV has the unique advantages of high manoeuvrability, small size and easy control, and is playing an increasingly important role in various fields [5]. Consequently, the UAV's path planning issue has become a key topic of current research. The purpose of path planning is to search out a safe and feasible path through the algorithm under the given starting point and target point, avoid collision with obstacles, and optimize the given cost function under the motion constraints. Real-time planning refers to the fact that UAVs need to continuously obtain and update obstacle information during flight and re-plan a new safe and feasible path when the environmental information obtained by the UAV is limited due to the limitation of sensor detection range. At present, the research on path pre-planning before flight at home and abroad is relatively mature, but there are still deficiencies in-the-moment barrier avoiding and optimal path planning in complex 3D environments. In the case of limited time and computing resources, existing planning methods cannot guarantee to produce safe and feasible trajectories with high success rate.

In addition, the UAV needs to consider the smoothness of the path, the dynamic characteristics of the UAV, the ability to move, and the safe distance from obstacles during the actual flight process [6]. The initial path may not satisfy one or more constraints of the drone. Optimizing the initial path to obtain a flight path that satisfies various constraints is another focus of this paper, and this process is called trajectory optimization process in the following [7]. Sampling-based methods require partial knowledge of the environment. It usually samples the environment as a set of nodes or builds it in the form of a graph or tree, and then conducts a random search to find the best path, such as Rapidly-exploring Random Tree (RRT) and Probabilistic Roadmap Algorithm (Probabilistic Roadmaps, PRM) [8], etc., are representative algorithms in sampling-based methods. The RRT algorithm starts from the starting point to generate random nodes to guide the path points to gradually approach the target point. When the path points expand to the vicinity of the target point or meet certain requirements, the path search is completed. The PRM algorithm can generate a feasible path network diagram from the starting point to the target point. It does not intuitively solve the optimal path, but generates a set of candidate paths [9]. It needs to be further combined with the search algorithm to complete the path planning task. Like the PRM algorithm, there are algorithms that cannot independently generate a single path planning result, such as Voronoi graph method, Rapidly-exploring Random Graph algorithm (Rapidly-exploring Random Graph, RRG), K-PRM and S-PRM. The algorithms similar to the RRT algorithm include the dynamic domain rapid expansion random tree algorithm (Dynamic Domain RRT, DDRRT), RRT*, artificial potential field method, etc. The problem of obtaining the globally optimal path cannot be solved independently for sampling-based algorithms. Xiao proposed an improved PRM that combines the PRM algorithm with the A* algorithm [10]. Liu proposed an improved Voronoi algorithm by combining node-based algorithm and Voronoi algorithm [11]. The algorithm complexity of the artificial potential field method is low, but it is easy to fall into the local optimum. To solve this problem, Sigurd [proposed a new hybrid algorithm, which combines the Voronoi algorithm with the navigation function to realize the global path planning.

Node-based optimization methods usually need to discretize the task space into a topological space. This type of algorithm is a special form of dynamic programming [12]. It generally needs to construct a graph in advance, and then define the corresponding fitness function or cost function. By searching each node or arcs to find the optimal path. For example, Dijkstra algorithm, Theta*, Lazy Theta*, D*-Lite and other algorithms are all node-based optimization algorithms. Musliman [proved that Dijkstra's algorithm can find the shortest path in a graph. Filippis devised a heuristic cost estimating approach to speed up the algorithm's convergence while reducing the overall number of states in Dijkstra's algorithm [13]. The algorithm based on the mathematical model abstracts the problem into a mathematical model, and then solves the optimal path through the mathematical model [14]. Such methods model the environment and the UAV, consider the UAV kinematics and dynamics constraints, and combine cost functions with inequalities or equations to obtain optimal solutions. Linear programming and optimal control are representatives of such methods, among which linear programming includes mixed integer linear programming, binary linear programming, nonlinear programming, etc [15]. This type of algorithm considers almost all factors, and defines a cost function to evaluate whether the current choice meets the requirements, so as to find an optimal path. Biologically inspired intelligent optimization methods rely on simulating biological behavior characteristics to deal with optimization problems. This method omits the process of building a complex environment model, and proposes an efficient search mechanism that can converge steadily to the target. Such algorithms can be divided into evolutionary algorithms (Evolutionary Algorithms, EA) and algorithms based on neural networks (Neural Network, NN). As far as evolutionary algorithms are concerned, they include genetic algorithms, particle swarm optimization algorithms, ant colony optimization algorithms, and hybrid leapfrog algorithms. The evolutionary algorithm randomly selects some feasible solutions at the beginning of the iteration, and then evaluates the fitness of each candidate feasible solution by comprehensively considering the environment, optimization objectives and other constraints. In the next step, a group of individuals is

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selected according to the fitness as the basis of the next generation of individuals. After a series of mutation and crossover operations, the iteration is stopped until the expected goal or condition is met. The individual with the best fitness will be decoded as the best path. The current swarm intelligence algorithm is often combined with other algorithms. Practice has proved that the mixed heuristic intelligent optimization algorithm can significantly improve the efficiency of path planning.

2. Research status of path planning algorithms

The UAV path planning problem refers to searching for a path from the starting point to the goal in the planning space according to one or more criteria (such as the shortest flight distance, the smallest energy consumption, the shortest flight time, etc.) when the UAV performs a task. The optimal safe path for the point. There are many ways to classify the path planning method. Based on the spatial dimension, it can be divided into two-dimensional path planning and three-dimensional path planning; based on the planning steps, it can be divided into single-step path planning and multi-step path planning; based on the planning map It can be divided into path planning on raster maps and path planning on vector maps.

2.1. Classification by spatial dimension

2.1.1. Two-dimensional path planning method. The two-dimensional path planning method can plan the trajectory of the unmanned aerial vehicle flying at a fixed height, and can also carry out two-dimensional planning in the two directions of horizontal and height in turn (the so-called two-dimensional semi-planning), and then obtain an unmanned aerial vehicle with a variable height. aircraft flight path. Yao et al. proposed an improved artificial potential field method combining reinforcement learning and Black-Hole Field (BHF), which solves the problem of dealing with local stable points in complex environments in traditional artificial potential field methods and increases the complexity of the algorithm. question of degree. However, this method is difficult to select the appropriate size of the black hole potential field. If the potential field range is too large, multiple gravitational fields will be superimposed, and if the potential field range is too small, it will be difficult to be detected. Magid et al. proposed a path planning algorithm based on the Voronoi diagram, which uses the global information of the environment to obtain the initial path, and then dynamically adjusts the path in real time by changing the weight of each parameter in the objective function. Probabilistic Roadmaps (PRM) is a path planning method that requires a large amount of sampled data, which results in exponentially increased computation time. Chen et al. proposed an improved PRM algorithm that introduces a potential field in the entire planning space, which is superior to the traditional PRM algorithm in terms of calculation time or path length, but it does not consider the kinematics and dynamics constraints of the UAV, it is difficult to apply to actual flight. Stanford University proposed a new algorithm in 2008 to solve the unmanned vehicle planning problem in a two-dimensional environment. The benefits of the A* algorithm and the state grid planning method are combined in this algorithm., so it is called the hybrid A* algorithm. This method considers the kinematic constraints of the vehicle, but the quality of the planned path is worse than that of the traditional A* algorithm.

2.1.2. Three-dimensional path planning method. Zhang Biao and others used the improved D* algorithm for 3D planning, and converted the point cloud data into an octree data structure for storage, which effectively improved the efficiency of planning in 3D space. Scharff et al. apply the hybrid A* algorithm to 3D environments and prune trees that collide with obstacles, reducing planning time in various environments. Mohammed et al. proposed an improved Rapidly Exploring Random Tree star (RRT*) algorithm. This method generates new nodes according to the probability distribution. Nodes closer to the target point have a higher generation probability. In the same environment, this approach can be three times faster than conventional RRT*. Sun proposed to use the improved layered Deep Q network to plan in a three-dimensional environment, which realized the dimensionality reduction of the state space and solved the problem of dimensionality disaster. Han classifies obstacles according to their importance to the planned path, which significantly improves the efficiency of path planning by reducing

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the number of obstacles and grid points in the 3D environment, but the method must be planned under a complete map, it is difficult to apply to the field of real-time planning. Dewangan et al. used the Gray Wolf Optimizer (GWO) to solve the path planning problem of UAVs in three-dimensional space, and compared it with the A* algorithm and other intelligent optimization algorithms through simulation experiments. part of the algorithm. Fang Qun and others made a suggestion for a better particle swarm method, which introduced the concept of minimum threat surface, and combined the constraint and search algorithm with a specific particle swarm position encoding method to improve planning efficiency.

2.2. Classification by planning steps

2.2.1. Single-step path planning method. An enhanced crossover operator was suggested by Lamini et al. based on the Genetic Algorithm, which avoids premature convergence. Aiming at the common problems that in 3D path planning, the ant colony method is prone to run into local optimums and take a lengthy time., Wang proposed an improved pheromone update method and heuristic function, which greatly improved the planning efficiency in 3D environment. Guo et al. proposed an improved artificial potential field method, and set a heuristic sub-target point for the problem that a local optimum solution is simple to get using the conventional artificial potential field approach, and verified the effectiveness of the algorithm in three-dimensional space planning through simulation experiments. sex. Luo et al. proposed an improved ant colony algorithm for the problem of local optima in the ant colony algorithm, and improved the global pheromone update method by introducing the solution that is the best and the one that is the worst. Song solves the local optimum problem through the improved particle swarm optimization algorithm combined with continuous high-order Bezier curves. Yonetani combined machine learning to propose Neural A* (Neural A*) algorithm. The spherical vector-based particle swarm optimisation technique (SPSO) that Phung devised has been shown through trials to be superior than the conventional particle swarm optimisation.

2.2.2. Multi-step path planning method. Nie divides the path planning into two steps, first uses the Dijkstra algorithm for initial path planning, and then uses the ant colony algorithm to optimize the initial path. Based on the idea of sequence planning, Liu Li et al. first used the Particle Swarm optimization (PSO) algorithm to plan the initial path, and then used the improved sparse A* algorithm for online planning, which effectively improved the planning speed. Zhou et al. first use topological path search to generate initial paths, and then use path-guided optimization for further planning. In order to solve the problem of planning in a dynamic unknown environment, Wang et al. first planned the initial path through the Theta* algorithm, and then performed local planning. Chang et al proposed a dynamic window approach (DWA) based on Q-learning for local path planning, which has good performance in complex unknown environments. Classified by planning map:

(1) Vector method

Zhou et al. established a vector geographic information system (Geographic Information System, GIS), on this basis, used the jump point search method for local planning, and proved through experiments that the optimal safe path can be successfully searched. Li et al. proposed a low-cost vector map navigation method for autonomous vehicles. By recording the vector map offline, any starting point and end point on the map are given to plan the global optimal path.

(2) Grid map method

Dijkstra's algorithm is a classic path planning algorithm. Li et al. considered the properties of the two-dimensional eight-nearest neighbor grid, and proposed an improved Dijkstra's Algorithm (IDA), which ensures that each grid only needs to be calculated once in the IDA planning process to get the target. The shortest distance of the grid, so it can save a lot of time compared to Dijkstra's algorithm. Mohajerin uses Recurrent Neural Network (RNN) to perform multi-step prediction on the occupancy grid map, which effectively improves the path planning algorithm. Panov et al. used a neural network algorithm for path planning on a square grid map, and proved through experiments that the Q-learning algorithm can learn on a small map to achieve planning goals and has good generalization performance.

3. Research status of trajectory optimization algorithm

The trajectory optimization problem is a process of local optimization on the paths generated by path planning. Constraints are generally divided into hard constraints and soft constraints.

3.1. Trajectory optimization under hard constraints

Hard constraints are constraints that must be satisfied under all circumstances. Trajectory optimization through hard constraints is highly efficient and can quickly solve optimization problems within limited resources. Richter proposed a method for jointly optimizing polynomial path segments, which can generate high-quality trajectories faster, but cannot guarantee asymptotic convergence to the global optimum. Ding proposed a B-spline based kinematic search algorithm to find the initial trajectory, which was then refined by an elastic band optimization method. Gao uses a Bernstein polynomial base to represent trajectories as piecewise Bezier curves that fully constrain the trajectory's position within a safe region. The problem with the hard constraint method is that the cost of all positions in the safe area is considered equal, so it may cause some places on the trajectory to be too close to obstacles, and if there is an error in the flight process, it will still cause a collision.

3.2. Trajectory optimization under soft constraints

Soft constraints do not require strictly satisfying constraints, but express a preference that the trajectory is expected to be as far away from obstacles as possible, and it uses gradient information to push the trajectory away from obstacles. Zucker uses the gradient descent method to optimize the smoothing cost of the path and the collision cost with obstacles. Kalakrishnan et al. proposed a method for stochastic trajectory optimization framework. The method generates a series of trajectories around the initial trajectory to explore the space around the initial trajectory, and then combines these trajectories to generate new trajectories with lower cost. Oleynikova proposed a continuous-time trajectory optimization method for multi-rotor UAVs. When the UAV detects new environmental information around it, the algorithm will recalculate the safe trajectory at a fast speed, solving the problem of partially unknown security issues in the environment. Gao used a sampling-based path search method to find a collision-free initial path that can be used as an initial path for nonlinear optimization. Sun Yong proposed an improved Gauss pseudospectral method, which can effectively reduce the number of nonlinear constraints. Usenko transformed the local trajectory replanning problem into a B-spline optimization problem. On the whole, the research on UAV path planning algorithm and trajectory optimization has achieved many results, but there are still deficiencies in some aspects:

Some path planning algorithms focus on the optimal path search, which has the problems of low efficiency and long planning time. Real-time planning refers to the fact that UAVs need to continuously obtain and update obstacle information during flight and re-plan a new safe and feasible path when the environmental information obtained by the UAV is limited due to the limitation of sensor detection range. The algorithm is required to be highly efficient. Therefore, too much pursuit of the optimality of the path in the planning process will often outweigh the gains.

The objective function established in the field of trajectory local optimization is relatively complex, and the iterative optimization algorithm used usually has a slow convergence speed, so the optimization algorithm may not be fast enough in the real-time planning process.

4. Four common algorithms

4.1. Random search method

The random search method is a method that obtains a series of subsets by repeatedly scanning the known area, and then finds the optimal solution of the objective function by traversing all the subsets. Although this method can find the world's best answer, it requires a lot of time and computing resources, and it cannot guarantee that the obtained solution is the global optimal solution. Singh et al. proposed a local path planning algorithm based on the random search method. This algorithm does not need global planning during the search process, but determines the next search direction according to local information. In this algorithm, a random heuristic function and a node search method are used to determine the next path. Simulation results show that the algorithm can effectively solve the UAV path planning problem. Li et al. realized the optimization of UAV paths by improving the random tree (RB) algorithm. In the RB algorithm, there are various possible connections between nodes, and each node has a probability to move from the current position to another position. The RB algorithm can not only avoid planning in the whole process, but also effectively deal with the collision problem. Zhang et al. proposed a local path planning algorithm based on genetic algorithm on the basis of random search method. The algorithm uses genetic algorithm to deal with the global programming problem, and proposes a new heuristic function to divide the population into two subpopulations to increase the diversity of the population and speed up the convergence. In this algorithm, the linear search is used to replace the crossover operation in the genetic algorithm, and then the convergence speed and precision are improved by the genetic operation. However, these methods require a lot of computing resources and time resources, and cannot guarantee to obtain the global optimal solution, so they have not been widely used in actual engineering.

4.2. Particle swarm algorithm

A swarm intelligence optimisation algorithm is the particle swarm algorithm that simulates the the way that birds forage. The basic principle is to regard all particles as an optimization group, and evaluate the individual according to the particle with the best individual fitness function. Therefore, the algorithm has strong robustness and adaptability when solving complex combinatorial optimization problems. The main advantages of this algorithm are: fast convergence, less iterations, high solution accuracy, and stable calculation results. The disadvantage is that the solution speed is slow, and it is easy to fall into a local optimal solution in practical applications. The particle swarm optimization algorithm has three advantages: (1) the algorithm is simple, easy to understand, and easy to implement; (2) it has certain limitations: it is easy to fall into local optimum; (3) it is easy to combine with other intelligent optimization methods such as genetic algorithm. However, when the particle swarm optimization algorithm solves complex combinatorial optimization problems with multiple constraints, it will have issues like delayed convergence and easy settling into local optimum. Therefore, it is rarely used in the field of UAV path planning. In recent years, the particle swarm optimization algorithm has also been applied to the UAV path planning problem.

4.2.1. Basic PSO algorithm. Particle swarm optimization is to convert complicated optimisation issues into group of discrete variables for solving linear programming by mathematically modeling the problem, and then use a set of random variables to update the particles to find the optimal solution of the objective function. The process of the PSO algorithm: (1) Initialize the particle swarm and give a set of initial parameters; (2) Calculate the fitness of the particles, if the fitness is higher than the optimal solution, update the position and speed of the particles; (3) Calculate the individual optimal solution, and if it is greater than the group ideal solution, update the person's position and speed; (4) provide the population's starting position as the updated optimal solution. There is a fitness function for each particle. The particle swarm is updated by the fitness function. The PSO technique offers great accuracy and quick convergence, but it is seldom used for UAV route planning issues since it is easy to become stuck in a local optimal solution.

4.2.2. Improved PSO algorithm. In the UAV path planning problem, the objective function is a complex nonlinear function, so it is difficult to describe it with traditional mathematical methods. Based on this, some scholars have improved the particle swarm algorithm to make it more suitable for UAV path planning. For example, Wei Zhipeng et al. proposed an improved particle swarm optimization algorithm (LS-PSO) based on learning factors. It allows it to more effectively balance the local search capability and the global search capability in issues involving multi-objective optimisation. Liu et al. proposed a chaos-based particle swarm optimization algorithm (CPSO) and applied it to the UAV path planning problem. Compared with other particle swarm optimization algorithms, CPSO provides the benefits of excellent convergence and quick convergence speed. However, CPSO also has some shortcomings: the particles' initial position is random, easy to fall into a local optimal solution, and slow in convergence speed. Therefore, further research is needed to address these problems.

4.3. Genetic algorithm

A genetic algorithm is a method for global optimisation that was created by mimicking genetic mechanisms used in biological evolution in nature, such as natural selection and gene mutation. Genetic algorithm is essentially an evolutionary computing method, which starts from the characteristics of the problem itself, uses evolutionary rules and algorithms, searches for the optimal solution in the problem solution space, and takes the optimal solution as the final result. Genetic algorithm is an optimization problem based on natural selection, gene mutation and survival of the fittest. It has the characteristics of easy understanding and implementation, good convergence and strong versatility. The advantage of the genetic algorithm is that it can generate a new generation of optimal solutions, which is also a common search strategy in UAV path planning problems. However, because the genetic algorithm is essentially an evolutionary calculation method, when used to design UAV paths, it is simple to fall into a local optimum solution. Common genetic algorithms used to solve the UAV path planning issue include simulation annealing, genetic algorithms, tabu research and more. The search effectiveness and search outcomes of UAV path planning issues can be enhanced by combining these strategies and learning from one another.

4.4. Neural networks

Neural network is a nonlinear processing method that simulates the biological nervous system. It has strong expression ability and learning ability, and can be applied in many fields. In the UAV path planning problem, the neural network can complete complex tasks through learning and memory, and has strong generalization ability. However, the formation of the neuronal network requires an enormous amount of data, and the training result needs to be determined through a large number of samples, resulting in high time and calculation costs. At present, many researchers have proposed UAV path planning methods based on neural networks, but these methods have not studied the core issue in depth, that is, how to apply neural networks to UAV path planning.

5. Conclusion

In this paper, we present a comprehensive examination of path planning methods for Unmanned Aerial Vehicles (UAVs), specifically concentrating on a diverse set of algorithms including random search methods, particle swarm algorithms, genetic algorithms, and A* algorithms. To provide a structured overview, we categorize these methods based on several key factors: spatial dimensions, planning steps, and planning maps. Moreover, we delve into the subject of trajectory optimization, distinguishing between hard and soft constraints. Our findings reveal that the area of pre-flight path planning has reached a certain level of maturity. However, it is important to note that significant gaps remain in the domain of real-time obstacle avoidance and optimal path planning, especially when operating within intricate 3D environments. Consequently, the implications of this study are pivotal for augmenting both the effectiveness and safety of UAV operations. With the aim of optimizing task execution, our research underscores the importance of reducing flight time, energy consumption, and inherent risks. This optimization is not merely beneficial but also critical for the advancement of autonomous flight, intelligent applications, and comprehensive safety management protocols. While this study offers valuable insights, it also identifies certain limitations within current algorithms. Specifically, it highlights that some algorithms prioritize finding the optimal path at the expense of efficiency, often resulting in protracted planning times. Additionally, we observe that the objective functions employed in trajectory optimization are frequently complex, which contributes to slow convergence speeds.

Given these challenges and limitations, the paper strongly advocates for more focused research on the integration of neural networks into UAV path planning algorithms. Although neural networks possess robust expressive and learning capabilities, their application is constrained by their computationally intensive nature. In conclusion, by furnishing a thorough review and pinpointing avenues for future research, this study makes a substantive contribution to the rapidly evolving field of UAV path planning. In doing so, it accentuates the pressing need for the development of more efficient algorithms and real-time planning capabilities.

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