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Path planning method for unmanned aerial vehicles

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Abstract. Unmanned aerial vehicles, commonly known as drones, have seen tremendous growth and wide-spread use in the last ten years, largely because of unheard-of technological improvements. It is currently one of the most significant study subjects since it involves many different areas of robotics and control systems. This study aims to thoroughly assess the most popular approaches for unmanned aerial vehicle path planning, while also outlining their benefits, drawbacks, potential uses, and overall effectiveness. The objective is to present the academic community with a summary of the existing environment and the development direction of future unmanned aerial vehicle path planning algorithms to encourage more research for quickly evolving planning of intelligent systems.

Keywords: Unmanned Aerial Vehicles (UAVs), path planning, RRT.

1. Introduction

Unmanned Aerial Vehicles (also known as UAVs) have seen explosive expansion and widespread use over the past decade, thanks in large part to the advent of previously unimaginable technological advancements. UAVs are now being used in a wide variety of civilian applications, including firefighting, agricultural activities, weather forecasting, package delivery, and many more of these and other types of jobs. Previously, UAVs were only used in military operations. Because of the wide variety of uses for unmanned aerial vehicles (UAVs), there has unavoidably been an uptick in interest in efficient path planning methodologies that assure the smooth, risk-free, and most effective operation of UAVs. Calculating an optimal trajectory from a starting point to an endpoint while taking into consideration certain constraints, such as avoiding obstacles and using the least amount of fuel possible, is essentially what path planning is all about. This is a subject with many facets, and it involves many different parts of robotics and control systems. Because of this, it is currently one of the most important research areas.

Evidently, the one-of-a-kind nature of each application calls for distinctive requirements and difficulties, both of which have been major contributors to the growth and development of a wide variety of path planning strategies. Despite the substantial progress that has been made, insurmountable difficulties still exist as a result of the complications presented by real-world limits such as dynamic environments, computational efficiencies, and the physical constraints of the UAVs themselves. As a result, the purpose of this study is to provide a comprehensive evaluation of the key available path planning methods for UAVs, while also casting light on their benefits, drawbacks, application scenarios, and overall performance. The goal is to provide academics with an overview of the existing environment and future directions in UAV route planning methodologies, with the hope that this will encourage further developments in this rapidly advancing subject.

In the following section, the fundamentals of several distinct approaches to path planning for unmanned aerial vehicles will be discussed. In the next section, it will talk about the current state of path planning for unmanned aerial vehicles, and then it will conclude by providing a summary of the current position as well as the challenges that are currently being faced.

2. Background

The traditional path planning methods for unmanned aerial vehicles mainly include the following: graph search-based path planning: abstracting a map into a graph, and transforming the path planning problem of unmanned aerial vehicles into the problem of searching for the optimal path on the graph. Common graph search algorithms include Depth-first search (DFS), Breadth-first search (BFS) and A * algorithm. Path planning based on heuristic search: By introducing heuristic functions to guide the search process and reduce search space. The commonly used heuristic search algorithms include Dijkstra algorithm and A * algorithm. Path planning based on genetic algorithm: The path planning problem is regarded as an optimization problem, and the optimal solution is searched by simulating gene crossover and mutation in the process of biological evolution. Genetic algorithm has good performance in solving complex path planning problems. Path planning based on planning algorithm: use planning algorithms, such as Linear programming, integer planning and mixed integer planning, to transform the path planning problem into an optimization problem, and obtain the optimal path by solving the optimization problem. Path planning based on Simulated annealing algorithm: Simulated annealing algorithm searches the optimal solution by simulating the atomic movement in the process of metal annealing. In path planning, simulated annealing algorithm can be used to search the global optimal solution. To sum up, the traditional path planning methods of UAV include graph-based search, heuristic search, genetic algorithm, planning algorithm and simulated annealing algorithm. These methods have their own characteristics and are suitable for different path planning problems.

3. Related method

3.1. RRT

Rapid exploration random trees (RRTs) are the focus of this section.

The exploratory activity of many animals served as the impetus for the development of the Rapidly exploring Random Trees (RRT) algorithm [1]. The RRT makes use of random sampling technology in order to rapidly grow the structure tree and connect these nodes to their parent nodes. This is done in the context of drone path planning. Because it can adjust the search path on the fly to navigate around both static and moving obstructions, this technique is well suited for dealing with path planning issues in situations that are particularly complicated [2].

The RRT approach makes use of the nearest neighbour search to locate the existing node that is the closest to each newly created node. This information then acts as the foundation for steering the expansion tree. However, there is a possibility that this approach can sometimes become stuck in a "closed area," and as a result, it will use an excessive number of computational resources to identify locations that are closer to the target location. This is also a potential avenue for improvement.

3.2. A algorithm*

An example of a heuristic search algorithm that also takes priority is the A-star algorithm. The total cost function, which is comprised of the sum of the current cumulative cost (referred to as g-cost) and the predicted remaining cost (referred to as h-cost), is what decides the search order. If the point has a lower total cost function, there is a larger chance that it will be chosen. Selecting the heuristic function h in a strategic manner can not only guarantee path optimization but also control the amount of time spent searching.

The A* algorithm can be applied to many kinds of networks, including geographic, grid, and graphical networks, among others. When trying to find the quickest route from one point to another, it is simple to use and straightforward to put into action using this method. Since the A* algorithm is a Greedy algorithm, there is a possibility that it will result in a local optimal solution rather than a global optimal solution. Because of this, it is important to apply it with caution [3].

3.3. Random with a bias

A method known as biased random sampling is one that can be used to improve the effectiveness of path planning searches. The utilization of a higher sampling density in areas that are either important or possible is the primary distinction between it and more traditional methods of random sampling. This indicates that after taking topography or previously obtained information into account, it has a tendency to sample particular locations, which ultimately results in more samples being generated in places that need more in-depth research. Biased sampling, on the other hand, might lead to an unequal spatial distribution of the search and is quite sensitive to the parameters that are chosen [4].

3.4. One location at a time sampling

This approach begins by randomly generating several candidate spots on the map before sorting through them according to a set of criteria that has been established in order to find the most efficient route. Even though it is straightforward and easy to comprehend, it may result in a huge increase in the amount of computing overhead, particularly for activities that require a high level of precision and scale. In addition to this, its performance is constrained by stochastic processes, and therefore, the outcomes may not correspond to the best possible approach [5].

3.5. Optimal control theory

The differential equations that are used to describe the motion of unmanned aerial vehicles are established with the help of the optimal control theory of dynamic systems, which is used by the optimal control theory model. By working out these equations, one may determine the best path for the drone to take in order to either reduce or optimize several different performance metrics, such as the amount of time spent or the amount of energy consumed, for example [6].

These kinds of models, together with radio theory, Hamilton Jacobi Bellman, and a variety of other theories, are merged in accordance with the parameters that have been determined. However, because determining the optimal path requires a significant amount of computing, this approach is probably not the best choice for solving path planning problems that call for an immediate solution [7].

3.6. Genetic algorithm

Genetic algorithms interpret difficulties with path planning as optimization challenges, encode potential solutions in the form of genetic codes, and use fitness functions to rank and choose among a variety of potential solutions. Applying operations such as crossover, mutation, and selection based on fitness values, followed by iterating several times, will finally lead to the discovery of the path that has the highest fitness [8].

In its most basic form, the genetic algorithm searches for the best possible answer all around the world by applying the concept of natural selection. The selection of parameters for genetic algorithms is notoriously complex and prone to error, even though in certain contexts, genetic algorithms are superior to other approaches in terms of their ability to produce optimal solutions. Nevertheless, genetic algorithms continue to be used in these contexts.

3.7. Ant colony algorithms

The Ant Colony Optimization (ACO) approach is a heuristic processing method that mimics the way in which ants behave when they are searching for food [9,10]. Pheromone enhancement mechanism is used to encourage ants to travel and seek on shorter paths. This is done by replicating the process of ants looking for food in the environment. At the beginning, a collection of paths is generated at random. Find the solution that is best for the world as a whole [11].

The optimization approach that uses ant colonies considers both global and local search functions. It also ensures that the algorithm is both resilient and parallel. On the other hand, the rate of convergence of this method is typically somewhat sluggish, and complications may arise in contexts with complicated computation. Ant colony optimization methods, to put it succinctly, offer an efficient means of resolving optimization issues by modelling the behaviour of biological colonies of ants.

3.8. Particle swarm optimization

A Swarm intelligence-based optimization system called particle swarm optimization (PSO) mimics the behavior of biotic communities like fish and birds. Everyone (particle) represents a solution and iteratively explores the solution space for the best answer. The main goal of the PSO algorithm is to direct the search process through information exchange, teamwork, and memory of previous effective solutions. Each particle updates according to its own position and speed, and it modifies its direction of motion by interacting with particles around it. The PSO approach, which works well for continuous optimization issues and nonlinear problems, eventually converges to the optimal solution through continuous iteration.

3.9. The grey wolf optimizer

The Grey Wolf Optimizer (GWO) is an optimization method that is based on the group behavior of gray wolves and was motivated by how they cooperated while hunting. The grey wolf algorithm mimics the social behavior of grey wolves to find the best answer. Each gray wolf in the algorithm represents a potential solution, and gray wolves constantly recalculate their positions through actions including chasing, hunting, and cooperative group behavior. By replicating Grey Wolf's benefits and drawbacks, the Grey Wolf algorithm directs the search process as it moves closer to the ideal outcome. The nonlinear and continuous optimization issues are good candidates for the Grey Wolf algorithm. The Grey Wolf algorithm can identify the ideal solution faster than other optimization algorithms because it has better search efficiency and convergence performance.

3.10. Q-learning

Q-learning is a Reinforcement learning-based path planning technique designed to address Markov Decision Process (MDP) issues. By mastering a value function Q, which stands for the expected return on an activity in a particular state, Q-learning directs the path planning process. The path planning method is enhanced by the algorithm by continuously updating and optimizing the Q value. The balance between exploration and use, which entails balancing the investigation of unexplored states with the usage of current information, is a fundamental idea in the Q-learning algorithm. The Q value is zero at the start. The Q value eventually converges to the ideal value as the algorithm iterates and interacts with the environment, resulting in the best path planning approach.

Q-learning is appropriate for path planning issues in discrete states and discrete actions, such as autonomous vehicle navigation and robot navigation, among others. Without requiring an in-depth representation of the environment beforehand, the algorithm discovers the best course of action through interaction with the environment. The advantage of Q-learning is its propensity for generalization and strong convergence performance in complex and dynamic contexts, as well as its capacity for independent learning and adaptation. Q-learning must balance exploration and usage, cope with large-scale state spaces, and make the necessary algorithm and parameter adjustments, among other difficulties. Q-learning offers an excellent solution for autonomous decision-making and path planning in intelligent systems, and has a wide range of potential applications in path planning issues.

4. Discussion

Despite the tremendous advances that have been made in the field of drone path planning research over the course of the past several years, numerous obstacles still exist and require further investigation.

These emerging technological frontiers hold the potential to not only improve the operations of unmanned aerial vehicles (UAVs), but also to widen the uses of drones across a variety of industries.

It is of the utmost importance to ensure a smooth operation that avoids potential conflicts because the number of drones is expected to rise in the years to come. Collaborative efforts between the UAVs are required for completing tasks such as path sharing, task allocation, and the avoidance of obstacles.

Therefore, it is highly desirable to see progress made in the areas of multi-drone collaboration and cooperation technologies. The primary focus of researchers should be on developing robust communication frameworks that will enable unmanned aerial vehicles to quickly share crucial information with one another. They might also investigate decentralized control systems, which would pave the path for several drones to collaborate effectively when operating in huge numbers. These advancements are sure to improve the operating efficiency and safety of drones that are working together, opening paths into applications that were previously unreachable due to the limitations imposed by technology.

It is possible that researchers and industry stakeholders will be able to instrumentalize breakthrough advancements within drone route planning technologies if they concentrate their efforts on these dynamic arenas. This will, in the end, reshape the landscape of UAV applications.

This discussion offers a complete summary of the developments that have been made and the strategies that are utilized in drone path planning. It is abundantly evident that these procedures, which have been refined over the years, are of the utmost importance to the successful and productive operation of UAVs. The technology of path planning is the foundation of various applications for drones, the most important of which are the enhancement of job efficiency, the guarantee of operational safety, and the accomplishment of precise control.

It is impossible to exaggerate how important flight path planning is for modern unmanned drone flight. A detailed and accurate mapping of the trajectory offers a variety of advantages. It brings about enhanced performance in mission objectives, increases safety standards by proactively avoiding impediments, and decreases the amount of energy that is consumed by limiting flight lengths and maximizing speed.

5. Conclusion

The progression of technology is unstoppable, and there is an increasing need for a wide variety of uses for unmanned aerial vehicles (UAVs), therefore it seems inevitable that further advances in drone path planning technologies will be made. Not only does each step it takes toward refining these algorithms result in an increase in operational competency, but it also opens the door to the possibility of carrying out missions that were previously not feasible due to their increased level of complexity.

At the same time, each step forward gives rise to new difficulties that demand additional investigation and a solution. These involve concerns like greater environment sensing, computational power, algorithm optimization, enhanced safety measures, and collaborative operations, among other things. In order to address these frontiers, it will need to push the limits of both our understanding and our capabilities, which will force us into new territory.

The symbiotic dance that takes place between the progression of technology and increasingly complex demands is the engine that is propelling the field of drone applications to new heights. With each obstacle it conquers, it can acquire more powerful tools that help us build a stronger basis for the future generation of drone route planning. The future holds a great deal of possibilities for drones. Upcoming breakthroughs are going to drastically change the landscape of what can be accomplished with drones.

References

[1] LaValle, S. M. 1998. Rapidly-exploring random trees: A new tool for path planning. Technical Report, Iowa State University.

[2] Kuffner Jr, J. J., & LaValle, S. M. 2000. RRT-connect: An efficient approach to single-query path planning. In Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference

on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065) (Vol. 2, pp. 995-1001). IEEE.
[3] Hart, P. E., Nilsson, N. J., & Raphael, B. 1968. A formal basis for the heuristic determination of minimum cost paths. IEEE Transactions on Systems Science and Cybernetics, 4(2), 100-107.
[4] Russell, S., & Norvig, P. 2016. Artificial intelligence: a modern approach. Pearson.
[5] Karaman, S., & Frazzoli, E. 2011. Sampling-based algorithms for optimal motion planning. International Journal of Robotics Research, 30(7), 846-894.
[6] Karaman, S., & Frazzoli, E. 2010. Incremental sampling-based algorithms for optimal motion planning. Robotics Science and Systems, 6.
[7] Goldberg, D. E., & Holland, J. H. 1988. Genetic algorithms and machine learning. Machine learning, 3(2), 95-99.
[8] Michalewicz, Z. 1996. Genetic algorithms + data structures = evolution programs. Springer Science & Business Media.
[9] Dorigo, M., & Stützle, T. 2004. Ant colony optimization. MIT press.
[10] Dorigo, M., Maniezzo, V., & Colorni, A. 1996. The ant system: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, 26(1), 29-41.
[11] Karaman, S., & Frazzoli, E. 2011. Sampling-based algorithms for optimal motion planning. International Journal of Robotics Research, 30(7), 846-894.