Review of UAV obstacle avoidance planning based on artificial potential field

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Abstract. UAV obstacle avoidance technology is an integral part of intelligent UAV systems. Using sensors to collect data, solve the drone's onboard computing power, and build its environment in simulation space is now a common method used by researchers. Through the perception and processing of the environment, the drone can use a series of algorithms to avoid obstacles in the environment to maximize the safety of the mission route. Researchers have been working on UAV obstacle avoidance algorithms based on the potential field method in recent years, and this paper summarizes and organizes their application, and this paper organizes and summarizes the application and some innovative modifications of potential field method in the field of UAV by different researchers, and puts forward the prospect of the future development direction of potential field method.

Keywords: Artificial potential field method, drone obstacle avoidance, situational awareness, UAV control

1. Introduction

An unmanned aerial vehicle, also called an UAV, is an unpiloted aircraft controlled by radio-controlled devices and self-generated programming systems, which has been widely used in agriculture, logistics, and other fields, and has realized the detection and analysis of aerial perspective in application scenarios.The safety of autonomous unmanned aerial vehicles (UAVs) operating in challenging environments is ensured by their onboard sensors, the computing power of onboard or central clusters, and advanced planning and control algorithms. The obstacle avoidance and path planning are crucial components for UAV automation, which can help UAVs avoid collisions during flight and improve their safety and reliability. After years of development, many UAV obstacle avoidance and planning methods have been produced, among which the artificial potential field is widely used due to its simplicity, high computational effectiveness and ability to be applied to local environments. Proposed by Oussama Khatib in 1986[1], the artificial potential field (APF) method generates a virtual potential field based on the environmental features around the robot and guides the robot to achieve the goal through the effects of attraction and repulsion in the field. The purpose of this paper is to introduce the development of UAV obstacle detection technology, the artificial potential field-based UAV obstacle detection technology, and its advantages and disadvantages, and explore the future development trend of this technology. .

The structure of the article is divided into four parts. The first part introduces technologies on recognition of the UAV environment, the second part outlines the development history of UAV obstacle avoidance technology, the third part focuses on the concept, principle, and process of artificial potential field-based UAV obstacle detection technology, the fourth part analyzes the advantages and disadvantages of this technology and its future development trend, and finally, the conclusion summarizes the content of this paper and discusses future research directions.

2. Automatic recognition of the UAV environment

Recognition of the environment is the first step in obstacle avoidance planning for UAVs. Now researchers in the laboratory often use high-precision sensors to perceive and model the environment, so that environmental data can be used as an important basis for the entire decision-making system[2].

Sensor-based drone obstacle avoidance technology mainly relies on the installation of various sensors to perceive and recognize the surrounding environment, such as LIDAR, ultrasonic sensors, and infrared sensors. Using these sensors, drones acquire environmental data and calculate their flight trajectory in real-time to avoid collisions .A sensor obstacle avoidance system has the advantages of high real-time performance, accuracy, and wide applicability in industrial, agricultural, and firefighting applications[3-4]. Previous research has been conducted on drone obstacle avoidance systems equipped with sensors. Gageik et al. [5] proposed a quadrotor obstacle detection and collision avoidance system based on ultrasonic and infrared ranging sensors. The system fused data from inertial and optical flow sensors to improve distance control accuracy. The system has the advantages of low cost, low computational burden, and no need for simultaneous localization and mapping. Liu [6] introduced a method and technology for using a lightweight fixed-wing medium-range drone (UAV) to perform power line inspection. The drone will be equipped with a combination of obstacle avoidance lidar scanning and infrared thermal imaging camera, which can monitor and analyze power lines in real-time during flight, identify and locate faults, and improve inspection efficiency and safety.

Vision-based UAV obstacle avoidance technology has made significant progress in perceiving and recognizing obstacles, mainly through the use of cameras and image processing algorithms. UAVs equipped with optical cameras have gradually developed in the field of environment reconstruction and target detection and recognition, relying on the development of Simultaneous Localization and Mapping (SLAM) and deep learning. Mount et al. [7] studied the coverage range of the visual sensor equipped on the visual positioning system and proposed a set of automatic methods to determine the trade-off between coverage rate and visual positioning performance, which can identify the minimum visual sensor coverage required to obtain the best positioning performance with minimal computation. In addition, visual sensors have deeper application scenarios. Zhang et al. [8] introduced a novel cooperative visual-inertial dense SLAM system (CVIDS), which can achieve multi-agent system co-localization and dense reconstruction using a single camera kit. As opposed to traditional visual SLAM frameworks that are limited to single-agent systems, CVIDS utilizes a centralized, loosely coupled framework that can be incorporated into any number of systems. The motion-based dense mapping module uses a keyframe depth recovery algorithm to reconstruct the three-dimensional structure and fuse it into the global map.

Deep learning-based UAV obstacle avoidance technology has developed rapidly, mainly achieved through the deployment of deep neural networks to perceive and recognize the surrounding environment, thereby achieving UAV obstacle avoidance decision-making. Deep learning technology has strong learning and adaptive capabilities, can automatically learn environmental features from a large amount of data, and can achieve complex obstacle avoidance decisions. Yang et al. [9] studied the deep reinforcement learning (DRL) method for autonomous UAV obstacle avoidance, and proposed a multi-branch (MB) network structure and a revised Q-value (RQ) algorithm to improve the convergence speed and optimality of the algorithm. The improved algorithm's obstacle avoidance performance was validated in the V-Rep three-dimensional physics simulation environment, with an average round reward increase of 3%. Gageik et al. [10] proposed a Multi-Pool Twin Delayed Deep Deterministic Policy Gradient (MPTD3) algorithm to solve the shortcomings of DRL methods in target tracking tasks andautonomous UAV obstacle avoidance. The algorithm uses a continuous model to describe the UAV's state space and action space, which is more realistic. The algorithm introduces a multi-experience pool mechanism and gradient truncation technology to accelerate the algorithm's convergence process and enhances the algorithm's generalization performance by endowing the UAV with environmental perception capability. Comparative experiments in simulation environments have demonstrated the algorithm's advantages in obstacle avoidance and tracking tasks.

3. UAV Obstacle Avoidance planning based on APF

3.1. Principle of APF

APF is an algorithm commonly used for robot path planning[11]. Its basic principle is to treat targets and obstacles encountered during robot motion as potential fields, and calculate the repulsive and attractive forces exerted on the robot based on the distance and relative direction between the obstacles and the robot , so that the robot can move towards the goal.

In the artificial potential field algorithm, the robot is affected by two types of potential fields: the attractive field of the target point and the repulsive field of the obstacle. The attractive field of the target point makes the robot receive a force towards the target point, while the repulsive field of the obstacle makes the robot receive a force away from the obstacle. Specifically, the potential field that the robot receives can be represented as:

$$U(q) = U_{att}(q) + U_{rep}(q) \qquad (1)$$

where $U(q)$ is the location of the robot, $U_{att}(q)$ is the attraction area of the target point, and $U_{rep}(q)$ is the repulsive field of the obstacle.

The attractive field of the target point can be represented as:

$$U_{att}(q) = \frac{1}{2}\zeta\| q - q_f \|^2 \qquad (2)$$

where ζ is the attractive constant and q_f is the location of the target point.

The repulsive field of the obstacle can be represented as:

$$U_{rep}(q) = \frac{1}{2}\eta\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)^2 \qquad (3)$$

where η is the repulsive constant, q is the position of the obstacle, $\rho(q)$ is the distance between the obstacle and the robot, and ρ_0 is the minimum safety distance.

Based on the potential field forces calculated from the environment, the robot's controller can calculate the direction and speed of movement that the robot should adopt, so that the robot can avoid obstacles and move towards the target point.

3.2. UAV obstacle avoidance detection process based on artificial potential field

3.2.1. Establishing the Environment Model

Firstly, a three-dimensional model of the UAV flight environment needs to be established, including information such as the location of the UAV, the location and size of obstacles, etc. Common modeling methods include laser radar scanning and visual recognition technologies. This data can be input into the obstacle avoidance algorithm.

3.2.2. Computing Artificial Potential Field

In order to calculate the artificial potential field of each point, we must use the environmental model. The artificial potential field consists of two parts: An UAV moves towards the target point through attraction, whereas it avoids obstacles through repulsion. The calculation formulas for attraction and repulsion are usually as follows: Attraction: F_att = k_att * (p_goal - p_now) Repulsion: F_rep = k_rep * (1/d)^2 * n_dir where F_att is the attraction force, F_rep is the repulsion force, k_att and k_rep are constants, p_goal is the position of the target point, p_now is the current position of the UAV, d is the distance between the UAV and the obstacle, and n_dir is the direction vector from the UAV to the obstacle.

3.2.3. Processing the APF Data

Next, the calculated artificial potential field data needs to be processed. Firstly, all attraction and repulsion forces are added together to obtain a total force vector. Then, by decomposing the force vector into horizontal and vertical components, the direction and speed that the UAV needs to follow can be obtained.

3.2.4. Obstacle Avoidance Control Logic

Final step is to implement barrier hedging control logic based on the processed APF data.UAVs generally need to fly according to the calculated direction and speed. There is a threshold distance between the UAV and the obstacle , avoiding obstacles measures need to be taken, such as adjusting the UAV's flight direction or speed to avoid the obstacle.

3.3. Recent progress on APF

The unmanned aerial vehicle obstacle avoidance technology based on the APF method originated from early years, and this rule-based obstacle avoidance algorithm is still active in many robot control algorithm practices today. In practical application scenarios, researchers have made many improvements to the potential field method to adapt to the needs of different tasks.

In the research of unmanned aerial vehicle formation coordination algorithm, many researchers commonly encounter low collaboration and poor unmanned aerial vehicle formation retention. Therefore, researchers attempt to introduce other factors to adjust virtual attraction and virtual repulsion, such as using parameters like velocity, acceleration, and angle to regulate the generation of potential field. Attempts to use velocity obstacle methods combined with potential field methods have made its analysis of dynamic motion more reasonable and improved the accuracy of obstacle avoidance. In addition to algorithmic improvements, the artificial potential field algorithm with novel sensors such as event cameras has also had better results compared to the past, thanks to more reasonable data input and ease of computation.

3.4. Improvement through combination with other methods

The mixed method based on the APF and integrating multiple obstacle avoidance techniques is a method that introduces other obstacle avoidance techniques on the basis of the APF method to improve the performance and efficiency of path planning. Its purpose is to solve the problems of local minimum value, unreachable target, and swinging in the APF method.

The mixed method based on guidance law and artificial potential field method adds guidance law as a virtual force to the APF, enriching the richness of mechanical environmental modeling and making the model less likely to encounter local minimum values. This enables the robot to move along the optimal path and effectively avoid obstacles to rest and movement.

The mixed method based on velocity obstacle method and APF method adds velocity obstacle method as a virtual force to the APF, enabling the robot to adjust its movement direction according to its own speed and surrounding environment. This method can effectively help unmanned aerial vehicles avoid static and dynamic obstacles.

Other methods such as the mixed method of fuzzy logic and artificial potential field method add fuzzy logic as a virtual force to the APF, allowing the robot to process uncertain information according to fuzzy rules, enhancing the robustness of the algorithm.

4. Conclusion

As a classic path planning algorithm, the rule-based artificial potential field method still has extremely common usage scenarios in all applications, despite the inundation of deep learning in all research fields. Its simplicity and effectiveness can often achieve good results in simulation tests with known environment data, and it is still reliable and common in laboratory environments. In field testing environments, after constructing environment models using sensors and SLAM algorithms, the artificial potential field method can still provide sufficient performance for researchers to provide results for comparison in popular and more effective algorithm research.

In terms of real-time performance, the APF method has the advantage of fast response and can establish a virtual environment for analysis using fewer sensors, which is the biggest difference between rule-based path planning algorithms and deep learning. Moreover, the artificial potential field method has strong robustness to noise and errors, mainly due to the virtual potential field model it constructs that can change with environmental changes. Due to its relatively simple computational logic, the computational cost of environment modeling and simulated potential field construction in open scenes is relatively small, leading to faster computation and response speeds.

However, in situations where the environment changes quickly and is complex, the potential field method will be limited by computational logic and exhibit poor response capabilities. This inability to adapt to changing conditions can threaten the accuracy of drone safety and obstacle avoidance In scenarios with large amounts of noise, such as electromagnetic interference and errors, the artificial potential field method, which relies on sensor data acquisition, may face risks in terms of computational quality. Due to its computational logic, situations where multiple obstacles appear in narrow environments can seriously interfere with the output veracity of the potential field method, and in specific environments, the algorithm is prone to falling into local optima. At some special sites, such as when the repulsion field and the attraction field cancel each other out equally, the UAV may become stuck at a zero gradient point and it is difficult to get the target point. Additionally, the high requirements for sensor accuracy and environmental quality also mean that the APF cannot be the optimal solution for UAV obstacle avoidance planning algorithms in all situations.

To improve the performance and applicability of the APF method, future research directions can be explored in the following aspects: (1) improving the design of the potential field function to overcome local minima and non-convergence problems, enabling robots to find global optimal or suboptimal paths; (2) combining with other path planning algorithms to improve the optimization and robustness of the path, enabling robots to cope with uncertainty and complexity; (3) extending to three-dimensional space or dynamic environments, considering the kinematic and dynamic constraints of robots, enabling robots to adapt to various scenarios and tasks; (4) applying to multi-robot collaboration or autonomous driving and other fields, increasing complexity and practicality, enabling robots to achieve higher-level intelligence.

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