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SURVEY

A Survey of Indoor UAV Obstacle Avoidance Research

JUNLIN LI, XINGZHONG XIONG, YUEHAO YAN, AND YUNHONG YANG
School of Automation and Information Engineering, Sichuan University of Science and Engineering, Yibin 644000, China
Artificial Intelligence Key Laboratory of Sichuan Province, Yibin 644000, China

Corresponding author: Xingzhong Xiong (xzxiong@suse.edu.cn)

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ABSTRACT UAV obstacle avoidance technology is one of the key factors to realize UAV autonomous flight, efficient and accurate obstacle avoidance is significant to complete the UAV autonomous flight task. In contrast, the dynamic, real-time and uncertainty of the environment in which the UAV is located makes the problem very tricky, especially in the indoor environment. At present, a large number of scholars have shown strong interest in the indoor UAV obstacle avoidance problem. With the rapid development of computer technology and hardware devices, many intelligent algorithms have been proposed to solve the obstacle avoidance problem. However, the research on indoor UAV obstacle avoidance technology is not comprehensive enough, and there is a lack of summarization of the research results in recent years. This paper introduces the sensor modules commonly used for indoor UAV environment sensing, related obstacle avoidance methods based on sensory detection. Classifies and composes the commonly used UAV path planning obstacle avoidance algorithms, and gives several representative UAV flight control research methods. This paper summarizes the advantages and disadvantages of different perception modules and detection methods applied to UAV obstacle avoidance tasks, and compares various current path planning methods. Finally, the critical difficulties and challenges faced in the field of indoor UAV obstacle avoidance are discussed, and future research in the field of UAV obstacle avoidance has prospected.

INDEX TERMS UAV, indoor obstacle avoidance, perception, obstacle detection, path planning, control.

I. INTRODUCTION

With the rapid development of technology and the high degree of informationization in society, UAVs have been widely used in many fields. According to the ''White Paper on UAS Development (2018)'' released by the Aviation Industry Corporation of China, the current investment scale of the global UAS industry has increased 30 times compared to 20 years ago. This growth is expected to remain at more than 20% in the next decade, with the cumulative value of output will exceed $400 billion. According to the ''General Aviation Industry Development White Paper (2022)'', the global civil drone market size is growing at a rapid pace and is expected to reach 500 billion yuan in 2025. Civilian drones are ushering in an up-and-coming development space, in which the quadcopter drones as the representative of the rotor drones due to the simple structure, small size, flexibility and other characteristics, compared with other drones, highlight the vast advantages.

In recent years, quadrotor UAVs have been more widely used in indoor reconnaissance [1], forest fire prevention [2], agricultural irrigation [3], emergency rescue [4], express delivery [5], environmental monitoring [6], and other fields. Figure 1 lists six application scenarios for quadrotor UAVs. These application scenarios have dense and numerous obstacles, which put forward higher requirements on the safety and intelligence of UAV flight.

From 2012 to 2022, the overall UAV-related research literature shows a gradual upward trend, and the related literature published in 2022 reaches a calendar year peak. The amount of drone-related publications is shown in Figure 2. (Data source: CNKI)

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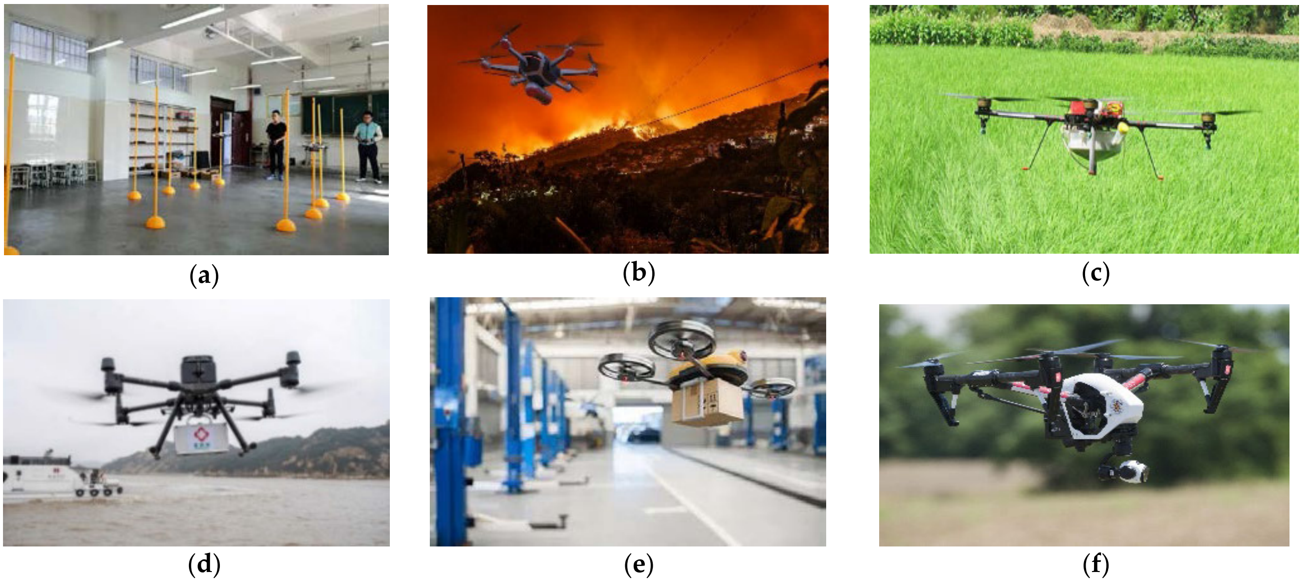

FIGURE 1. Examples of quadrotor UAV application areas. (a) Indoor obstacle avoidance, (b) Forest outfire, (c) Agricultural irrigation, (d) Medicine delivery, (e) Cargo storage, (6) Environmental exploration.

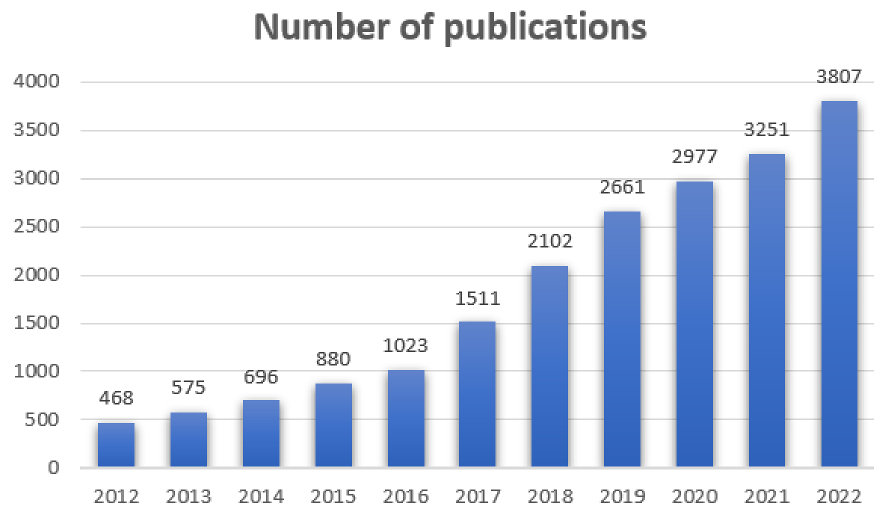

FIGURE 2. Published literature related to drones from 2012-2022.

A large number of researchers have been working on UAV and obstacle avoidance problems in a wide range of disciplines. Figure 3 shows the distribution of UAV-related research in the ten major disciplinary areas. According to the distribution diagram of UAV research by various disciplines, aeronautics and astronautics science and engineering accounted for the highest proportion, reaching 64.34%, automation technology and computer software and application of computer accounted for 12.40% and 9.3%, respectively; electric power industry and agricultural engineering have 6.72% and 2.58% respectively. There are also researches on UAV in telecom technology, plant protection, mining engineering, highway and waterway transportation, and mathematics.

The study of UAV obstacle avoidance problem mainly refers to the use of airborne sensors to obtain information about the environment in which the UAV is located, combining path planning algorithms and flight control methods to guide the UAV to avoid static or dynamic obstacles so as to finally reach the target point safely and without errors [7].

In outdoor scenarios, the drone is often combined with GPS to obtain its location, but when it flies in a tight interior or cave, GPS cannot locate it accurately. In this context, how to make quadrotors have efficient obstacle avoidance capability, find the best flight path and reach the target safely has become a new research hotspot [8].

Therefore, the evolving obstacle avoidance technology has become the key to realize the autonomous indoor application

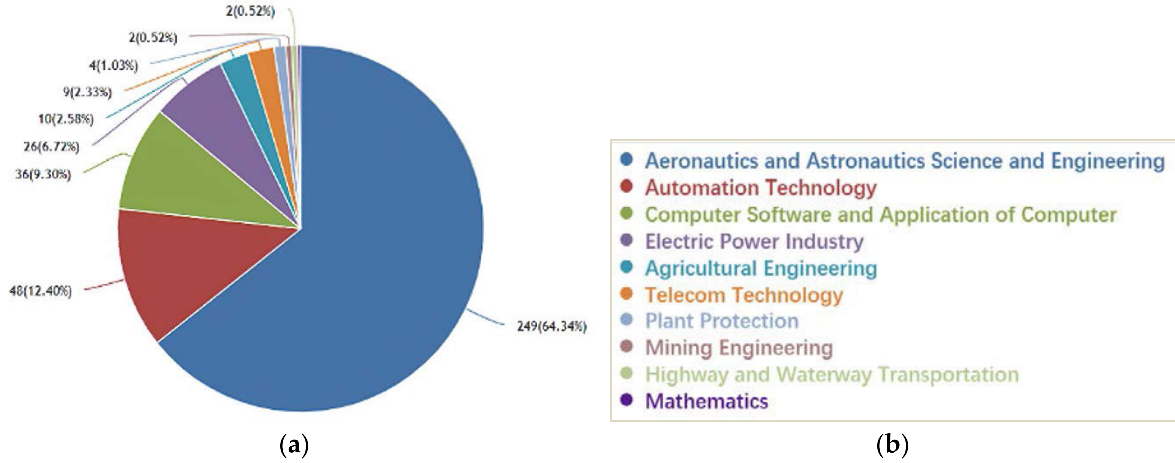

FIGURE 3. Top 10 UAV-related subject areas. (a) Academic field distribution histogram, (b) Names of the top ten subject areas.

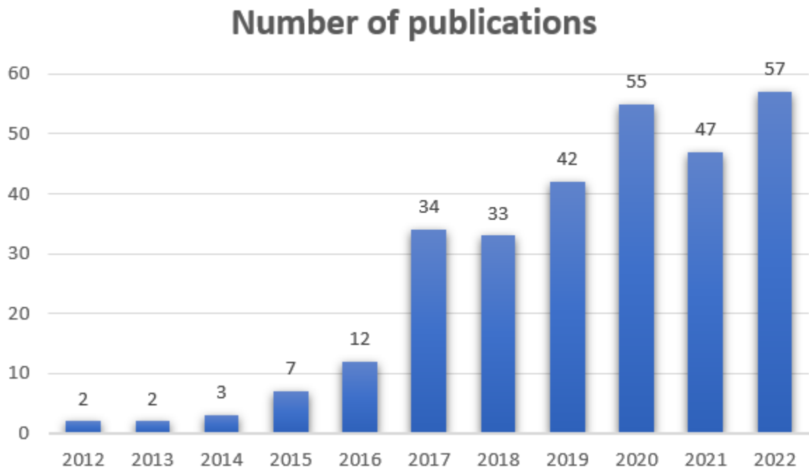

FIGURE 4. Number of publications related to UAV obstacle avoidance.

of UAVs. Meanwhile, rotary-wing UAVs suitable for indoor confined spaces have also been favored by researchers for their outstanding features, and a lot of research has been conducted on their obstacle avoidance-related fields. The number of related literature publications is shown in Figure 4. (Data source: China Knowledge Network) Based on the principle of UAV obstacle avoidance technology, the UAV obstacle avoidance process can be divided into four stages: environment perception, obstacle detection, path planning and flight control. When facing obstacles, the UAV first uses a series of sensors loaded to sense the environment and obtain the position of the body, then detects the orientation and distance information between the body and the obstacles; after that, it continuously searches for feasible obstacle avoidance paths according to the path planning algorithm to obtain the optimal or sub-optimal obstacle avoidance paths; and finally combines the flight control method to control the UAV's attitude transformation for obstacle avoidance and safely reaches the target point. The drone obstacle avoidance process is shown in Figure 5.

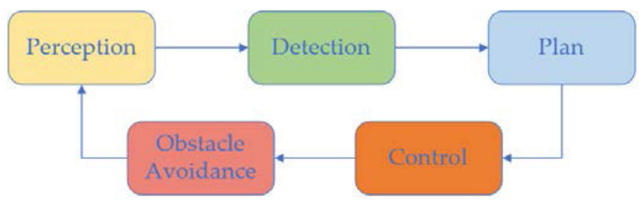

FIGURE 5. Drone obstacle avoidance flow chart.

According to the four stages of UAV obstacle avoidance, this paper firstly introduces the sensor modules commonly used for indoor UAV environment sensing, secondly introduces the development and application of sensory detection technology on UAV obstacle detection, then classifies and composes the typical UAV path planning obstacle avoidance algorithms and introduces the research on UAV flight control methods. In addition, the advantages and disadvantages of different perception modules and detection methods applied to UAV obstacle avoidance tasks are summarized, a comparative analysis of various types of representative obstacle

FIGURE 6. Chapter structure of this article.

avoidance algorithms is presented, at last, the challenges faced by indoor UAV obstacle avoidance are discussed, and the future development of the UAV obstacle avoidance field is foreseen.

Compared with the previous works [9], [10], [11], [12], [13], the contributions of this paper are as follows:

- 1. Divides the indoor UAV obstacle avoidance process into four stages, and each stage of the research is presented in the form of a combination of diagrams so that readers can understand the key indoor UAV obstacle avoidance technologies more intuitively.
- 2. Introducing the characteristics of a variety of commonly used indoor sensors and the latest research results of UAV obstacle avoidance based on perception detection, and classifying the methods of obstacle avoidance based on perception detection according to different working principles.
- 3. Reviewed the latest research results of path planning methods in the field of UAV obstacle avoidance and divided the path planning methods into four categories: based on graph search, based on potential field, based on group intelligence, and based on machine learning. Showed the characteristics and advantages and dis-advantages of different categories of path planning methods through graphical analysis, and gave the breakthrough direction of future path planning.
- 4. Presented the most representative UAV flight control technology research and reviewed the related improvement methods.
- 5. The difficulties and challenges faced in the field of indoor UAV obstacle avoidance are analyzed, and the future UAV development and applications are prospected to provide reference for further research.

The rest of the paper is organized as follows: Section II introduces the sensors commonly used for UAV indoor environment sensing and localization, and clearly shows the advantages, disadvantages, and applicability of each sensor in the form of a table to facilitate the reader to sort out the research. Section III provides an overview of the applications of the above sensors based on indoor UAV obstacle avoidance according to different sensing and detection methods, the achieved results, etc., and a full comparison is made in the form of a table. Section IV introduces various classical path planning methods for UAV obstacle avoidance and their improvements, and summarizes the advantages and disadvantages of the classified path planning methods as well as their application performances. Section V presents a classification of UAV representative flight control technology research. Section VI points out the challenges of current indoor UAV obstacle avoidance research and gives an outlook on future UAV obstacle avoidance research directions. Finally, the contents of this paper are summarized in Section VII. The structural layout of this paper is shown in Figure 6.

II. UAV INDOOR PERCEPTION

Environment perception is the first step to achieve any obstacle avoidance mission. In order to detect obstacles in the environment, UAVs need to be equipped with sensors to collect

FIGURE 7. 20MY14 Monocular camera.

information about the environment they are in. In recent years, smart obstacle avoidance technologies for UAVs have become diversified with the development of sensor technologies, and the selection of sensors is crucial in order to provide real-time detection of the indoor flight environment. This section introduces common sensor devices for indoor UAV sensing and positioning, such as vision sensors, LiDAR and ultrasonic sensors, then compares and analyzes their properties.

A. VISION SENSOR

Vision sensors [14] rely on capturing images of the environment and objects to extract useful information. The principle is that the optical image produced by the object through the lens is projected on a CMOS optoelectronic sensor, which is converted into a digital signal after analogue-to-digital conversion, and then the DSP processes the signal into a specific format before displaying it on the screen. Vision sensors usually include monocular, binocular, and RGB-D cameras.

1) MONOCULAR CAMERA

Monocular cameras [15] perceive and judge the surrounding environment through flat images taken by one camera, and therefore can only obtain two-dimensional information and cannot determine the depth information of the environment they are in. It relies on complex algorithms for ranging, requires a large amount of data, and is constantly updated and maintained, and is highly influenced by the environment and less accurate. The advantages of monocular cameras are lower cost, simple system structure, and easy calibration and identification. Figure 7 shows a picture of a monocular camera.

2) BINOCULAR CAMERA

The binocular camera [16] mimics the human eye function to achieve the perception of obstacle distance and size, and directly obtains the depth information of the scene without detecting the obstacle class by performing parallax and stereo matching calculations on the two images. When the camera parameters are known, the corresponding pixel can be found

FIGURE 8. NVIDIA Jetson nano binocular camera.

FIGURE 9. RealSense D455 camera.

in the camera image to calculate the depth of the corresponding point and reconstruct its 3d position. Nevertheless, its configuration and calibration are more complex and computationally intensive, and the two key factors to be considered are speed and accuracy. Figure 8 shows a picture of the binocular camera.

3) RGB-D CAMERA

The rgb-d camera [17] is different from the binocular camera that calculates depth by the parallax method, which is able to measure the depth information of each pixel directly according to the physical method of structured light or tof (time of fly). Using the structured light method can solve the problems of sensitivity to ambient light and dependence on image texture, improve matching robustness, and support nighttime use; using the tof method can ensure measurement accuracy and is suitable for measuring scenes requiring long distances, but the image resolution is low and the quality of the depth map is not high. Rgb-d cameras can directly perform physical ranging, but the power consumption is high, the cost is high, and they are susceptible to daylight, translucent objects, and mirror-reflecting objects interference, which makes them mainly used in the indoor environment. Figure 9 shows a picture of the rgb-d camera.

B. OPTICAL FLOW SENSOR

The optical flow sensor is used to determine the speed of movement of pixel points relative to the vehicle by detecting the movement of light and dark points in adjacent images. The purpose of studying the optical flow field is to approximate the motion field that cannot be obtained directly from the image sequence. The optical flow algorithm is generally divided into two steps: first, the image is obtained through the downscaled camera, and the frame data at different moments of the image are analyzed to obtain the movement velocity of the pixel; then, the movement velocity of the pixel is converted into the movement velocity of the vehicle.

In [18], the obtained velocity is integrated to obtain the displacement data, and the position information or velocity information returned by the optical flow module is used to

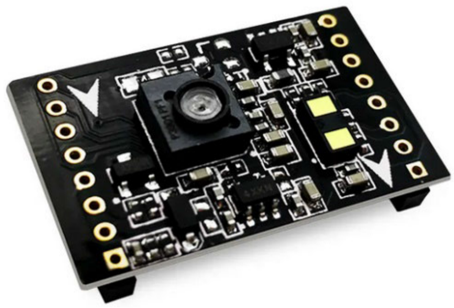

FIGURE 10. PWM3901 Optical Flow Module.

FIGURE 11. RPLidar A2.

achieve the UAV fixation function. The advantages of the optical flow module are its small size, low cost, and simplicity of use. However, a large cumulative error is generated when using optical flow for fixing, and real-time and effectiveness cannot be guaranteed when using optical flow for target detection. Figure 10 shows a picture of the optical flow sensor.

C. LIDAR SENSOR

LIDAR is currently the mainstream sensor of choice for indoor map building and positioning [19], and is divided into two types: single-line and multi-line. Single-line radar can only scan one plane of obstacles and obtains a 2D map; multi-line radar can obtain a rich 3D point cloud of the environment through the combination of multiple scanning surfaces.

LIDAR uses a laser emitting component to emit light into the Field Of View (FOV). After the emitted laser light hits an obstacle, it is reflected by the obstacle and converges to the receiver through the lens set, and using the information related to the emitted and reflected light, information about the detected object can be calculated or deduced.

The advantage of LIDAR is that its detection distance is long and it can accurately obtain three-dimensional information about objects, and its stability is quite high and robust. However, LIDAR is currently costly and cannot detect transparent objects such as glass. A common A2 LIDAR is shown in Figure 11.

D. ULTRASONIC SENSOR

The main component inside the ultrasonic sensor [20] is a piezoelectric chip, which emits ultrasonic waves when stimulated by a voltage and is then received by the receiving

FIGURE 12. HC-SR04 Ultrasonic Sensor.

end. The basic principle of calculating distance by ultrasonic sensors is similar to that of LIDAR, which emits sound waves and measures the time required from the transmission to reception, and calculates the distance to the obstacle based on the time spent.

Compared with LIDAR, ultrasonic sensors are not affected by the transparency of the object, have good directionality and penetration ability, and ultrasonic sensors are very low cost; however, because the speed of sound depends on temperature and humidity, environmental conditions can easily affect the accuracy of its measurement, and if the object reflects sound waves in a direction different from that of the receiver, or its material has the property of absorbing sound, the data information collected by the acoustic wave sensor will be inaccurate. Figure 12 shows a picture of the Ultrasonic Sensor.

E. INDOOR SENSOR COMPARISON

Table 1 lists a comparison of some attributes of commonly used sensors for UAV indoor environment sensing, where factors such as light intensity and weather changes have a significant impact on vision sensors, which also makes vision sensors work only in specific environments and are suitable for indoor environment sensing; LIDAR and ultrasonic sensors, on the other hand, are not sensitive to light and weather factors, which makes them very suitable for working indoors without light or in low-light environments. Table 1 shows that each sensor has its own advantages and characteristics. Thus, when UAVs perform environmental sensing tasks, multi-sensor information fusion can be considered, and the advantages of each sensor can be utilized comprehensively to achieve accurate acquisition of environmental information, which is also an essential direction in UAV obstacle avoidance research.

III. RESEARCH BASED ON PERCEPTION DETECTION

Although there are many methods for sensing the environment, it is impossible to use large sensing and positioning systems such as GPS and radar for accurate positioning and sensing of UAVs in small spaces such as indoors or caves, and the target detection task in UAV environment sensing has high requirements for real-time. Therefore, this paper divides the obstacle avoidance research related to indoor UAV perception and detection into three categories, which

TABLE 1. Comparison of common sensor attributes for UAV indoor environment sensing. (here i stands for indoor and O stands for outdoor).

Sensor Type	Robust	Calculation	Light Impact	Field	Weather Impact	Advantage	Drawback
Monocular camera	Low	High	High	I/O	Large	Low Cost	Poor robustness
Binocular camera	High	High	High	I/O	Large	Low cost + high precision	High complexity
RGB-D Camera	High	Low	High	I	Large	Low Cost	Poor robustness
LIDAR	high	High	None	I/O	Small	high precision	High power consumption
Ultrasound	Medium	Low	None	I	Small	Low Cost	Poor robustness
Optical flow	Low	Low	High	I/O	Small	Low Cost	Cumulative error

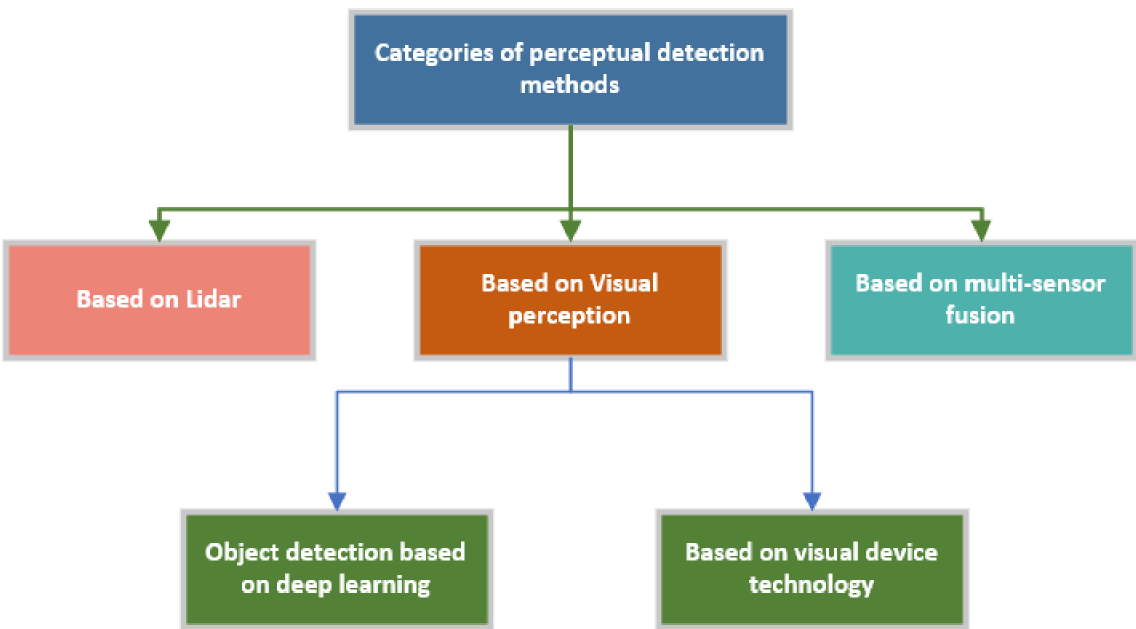

FIGURE 13. Perceptual testing chapter framework diagram.

are vision-based obstacle avoidance research, LIDAR-based obstacle avoidance research, and multi-sensor fusion-based obstacle avoidance research. The framework of this chapter is shown in Figure 13.

A. VISION-BASED OBSTACLE AVOIDANCE

The visual target detection task of the UAV is to obtain the position of the target obstacle in the image from the video or image information captured in real time on the on-board

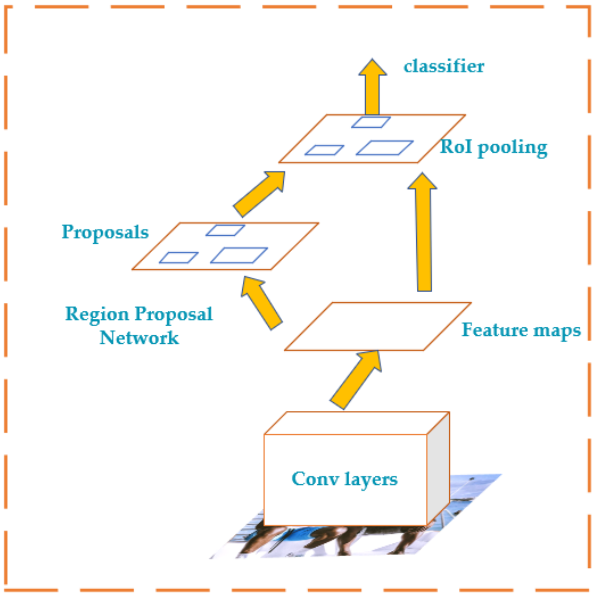

FIGURE 14. Faster R-CNN training framework diagram.

camera, or identify the category of the obstacle so that the UAV can perform the optimal obstacle avoidance maneuver according to the different obstacle categories.

1) TARGET DETECTION BASED ON DEEP LEARNING

With the booming development of computer vision technology, target detection methods based on Deep learning-based target detection methods have made a great splash and have been highly valued in the field of UAV obstacle detection in recent years. The introduction of the RCNN framework in 2014 marked the formal transition from traditional target detection methods to a deep learning-based approach. Deep learning-based target detection algorithms can be classified into two-stage and one-stage approaches by the manner in which detection is achieved [21], with the former focusing on detection accuracy and the latter on detection speed.

a: TWO-STAGE APPROACH

The two-stage approach uses two networks to achieve classification and regression separately, and is also known as a region-based approach. The main steps of this type of algorithm are firstly, generating multiple potential target regions using a heuristic candidate region generation algorithm; then extracting features of the target candidate regions by deep neural networks; and finally using these features to classify and regress the true boundaries of the target at the same time. The representative algorithms are R-CNN, FAST R-CNN, Faster R-CNN, and Mask R-CNN. Figure 14 shows the training framework diagram of the classical two-stage method Faster R-CNN.

For the UAV obstacle avoidance problem, [22] proposed a deep learning based monocular vision obstacle avoidance method for quadrotor UAVs. Firstly, the Faster R-CNN target detection algorithm frames the location of the target human body in the image, and calculates the length of the upper and lower margins of the target selection frame to estimate the distance between the obstacle and the UAV using the similar tri-angle principle; then the on-board computer determines whether to perform obstacle avoidance actions. The experimental results show that the method occupies a small volume, has good robustness, can achieve recognition of people with different attitudes, and achieves obstacle avoidance under low-speed flight conditions, but there is a distance estimation error of ± 0.5 m, and the detection speed is slow.

Influenced by [22], [23] proposed a quadrotor autonomous obstacle avoidance method based on monocular depth estimation and target detection for the indoor UAV obstacle avoidance problem. The Fast-Depth depth estimation model is used to provide the depth information of the obstacle at the pixel level for monocular depth estimation, and the NanoDet target detection model provides the position information of the obstacle. The depth map of a single image and the target detection result are obtained by the convolutional neural network; the region division of the image is based on the target detection result, and the region depth is calculated based on the depth estimation result; the obstacle avoidance planning algorithm calculates the linear and angular velocities of the UAV based on the region depth and the region division result, so as to realize the autonomous obstacle avoidance of the UAV. The results of real-world experiments show that the proposed algorithm can be used for indoor low-speed autonomous obstacle avoidance of quadrotor UAVs, but the problems of monocular depth estimation accuracy and stability still need to be solved.

Reference [24] proposed a new method for autonomous UAV navigation in a planted forest environment. A pre-trained model, Faster R-CNN, is chosen as the convolutional basis, and the detection model uses the image heights of detected trees to indicate their distance from the UAV and the image widths between trees to find the widest unobstructed space. Compared to Resnet-50, this model is the best detection model for this application in terms of average accuracy and processing cycles. The capability and performance of the UAV's autonomous navigation system in a planted forest were verified in real flight tests at two different locations.

Reference [25] used MASK RCNN to detect and classify targets in video images captured by Tello UAVs, and the relatively small number of training cycles hinders the detection accuracy due to the large amount of processing required by MASK RCNN. However, the authors obtained the best detection accuracy of 99% in the final experiment, with an average accuracy of 95.6%. Future work will be to control the UAV by gestures with the help of the MASK RCNN neural network and to perform attitude estimation.

b: ONE-STAGE APPROACH

The emergence of YOLO algorithm in 2016 became the pioneer of the one-stage algorithm. Unlike the above two-stage algorithm, which solves target detection as a classification problem, it treats target detection as a regression-based detection problem and completes the localization and classification from image input to object directly in a separate network. Its detection speed is greatly accelerated with the help of regression ideas, but the accuracy is less satisfactory. Subsequently, the YOLO series algorithm keeps making improvements and has become more and more popular in the field of UAV obstacle detection with its advantages of gradually balancing detection speed and accuracy.

Reference [26] proposed the use of deep learning-based distance estimation to detect mobile UAVs using YOLOv3 to detect, classify and localize target objects in images; then DNN and CNN were applied to check the performance in distance estimation. The proposed model is evaluated using real flight videos and the results show that the results are satisfactory for aerial obstacle avoidance of small UAVs. However, the model is unable to estimate targets at long distances.

To address the problem that small target detection is not good, a deep learning method for distance estimation is also proposed in [27], where a CNN feature extraction network is first trained to extract the UAV features detected by YOLO v3, and then these features are applied to a DNN distance network to estimate the distance of the target. However, the model structure needs to be changed to improve the performance of the long-range estimation.

Reference [28] proposed an unsupervised monocular depth estimation model for autonomous UAV flight to address the problems of the high cost of binocular vision depth estimation and the need for a large number of depth maps for training. Validation results on the KITTI dataset show that the monocular depth estimation method has higher accuracy and real-time performance.

Reference [29] proposed a monocular vision-based UAV obstacle avoidance response planner with the YOLO algorithm for object detection and classification; in addition, YOLO was combined with a Kalman filter to achieve target tracking. The results of both the simulation environment in Gazebo and the real-world tests in Parrot Bebop2 show that both UAVs successfully avoid collisions with pedestrians based on the generated heading commands.

Reference [30] introduced a new strategy using the advantages of the YOLOV3 target detection algorithm and depth cameras, a scheme that allows the UAV to perceive not only the presence of obstacles but also their attributes such as class, contour and spatial location. The experimental results show that the errors of depth data, width and height are -0.53m, -0.26m and -0.24m, which can significantly improve the UAV environment perception and obstacle avoidance ability. Reference [31] used the YOLOv3 algorithm to detect the category information of obstacles in the process of obstacle avoidance and flight path planning for the UAV. However, the method cannot accurately detect all obstacle classes when the UAV is in a complex indoor environment.

Reference [32] used the single-stage algorithm YOLO V3 combined with a distance estimation method for obstacle detection, and the pre-trained network can accurately detect obstacles and estimate distances in three different scenarios. To achieve more accurate grazing management and control, [33] combined the improved YOLOv5 with an extended dataset to effectively achieve individual identification and localization of cattle on the fly in practice. Experimental results show that the improved YOLOv5 model has excellent detection speed and detection accuracy.

Although the detection accuracy of the two-stage method is improving, the detection speed of this type of algorithm is still difficult to meet the demand for real-time obstacle detection tasks in the UAV field. In future research, this type of algorithm should try to reduce the model parameters and improve the detection speed. While the accuracy of the one-stage class algorithm is lower than that of the two-stage algorithm, the detection speed has been greatly improved, and with the development of deep learning technology, the optimal balance between detection accuracy and speed is being gradu-ally achieved. As a result, more and more lightweight algorithms are being applied to UAV target detection, which further enhances the effect of UAV perception of obstacles. Table 2 conducts a comparison of research on UAV target detection techniques based on deep learning and gives future development trends.

2) OBSTACLE AVOIDANCE BASED ON VISUAL EQUIPMENT

Compared with other sensors, vision cameras have the advantages of small size, light weight, low power consumption, flexibility, and the ability to provide richer environmental image information; this has led to strong interest among researchers in using vision camera-related technologies for UAV indoor obstacle avoidance research.

Reference [34] proposed a method for detecting approaching obstacle states using a single camera for the real-time obstacle avoidance problem. The method first detects the feature points of the obstacles and then extracts the obstacles that are likely to be approaching. Finally, obstacle avoidance actions are taken based on the 2D position of the obstacle and combined with the tracked waypoints. Experiments show that obstacle avoidance accuracy exceeds 92.5% [35] designed a hardware system for indoor detection and obstacle avoidance of mini-UAV based on binocular vision sensors for the needs of small indoor UAV obstacle avoidance system. The visual image is processed by FPGA combined with a binocular vision algorithm to obtain the current 3D environment information effectively. The method takes up less storage space and has high measurement accuracy.

Reference [36] proposed a simple and fast vanishing point estimation method and an obstacle avoidance algorithm based on scale-invariant features using only videos extracted from the front-facing camera. The scheme has been tested in different corridor environments, and experiments show that it is very robust in terms of collision-free rate, full flight rate and obstacle avoidance rate. Reference [37] investigated the problem of obstacle avoidance and path planning using a binocular vision system. During the flight of the UAV, binocular vision sensors acquire local environmental information

TABLE 2. Comparison of UAV target detection techniques based on deep learning.

Target detection classification	Reference	Model	Performance	Development Trend
Two-stage Algorithm	[22]	Faster RCNN	High accuracy and robustness.	(1) Reduce model parameters. (2) Increase the detection speed.
	[24]	Faster RCNN	Improved average accuracy and processing cycles compared to Resnet-50.	
	[25]	MASK RCNN	Best detection accuracy of 99%, average accuracy of 95.6%.	
One-stage Algorithm	[29]	YOLO	● Combined with Kalman filter for target tracking ● Successfully avoided collision with pedestrians	(1) Balance detection accuracy speed. (2) Improve the effect of small target detection. (3) Lightweight module.
	[26]	YOLOv3	Aerial obstacle avoidance using deep learning-based distance estimation.	
	[27]		● Solve the problem of poor detection of small targets ● Improving the performance of long-range estimation	
	[30]		Designed a new strategy for sensing obstacle properties to generate optimal obstacle avoidance flight paths.	
	[31]		Use YOLOv3 algorithm to detect the category of obstacles.	
	[32]		YOLO V3 combines distance estimation methods to accurately detect obstacles and estimate distances in three different scenarios.	
	[22]	NanoDet	● Segmentation of images with target detection results ● Indoor obstacle avoidance based on segmentation results.	
	[33]	YOLOv5	● Realize the identification and positioning of cattle in actual flight ● Excellent detection speed and accuracy	

in real time and analyze the distribution of obstacles in the environment by depth images. A series of experiments were conducted on the DJIM 100 platform, and the experimental results demonstrated the effectiveness of the method.

A collision avoidance trajectory planning algorithm based on the backward horizon is proposed in [38]. Simulation results show that the algorithm proposed in this paper is capable of avoiding both static and dynamic obstacles, but the authors only consider trajectory planning in two dimensions. Reference [39] conducted a real-time obstacle avoidance study on visual target tracking of UAVs, and proposed a UAV obstacle avoidance method based on binocular vision and

TABLE 3. Comparison of UAV obstacle avoidance research based on vision devices. (here OA means obstacle avoidance).

Task	Reference	Vision Equipment	Performance	Static	Dynamic
Real-time OA	[34]	Monocular camera	Over 92.5% accuracy in OA	Yes	Yes
Corridor OA	[36]		• Obstacle avoidance method based on scale invariant features • Robustness	Yes	No
OA Planning	[38]		Realizing OA Planning Based on Backward Horizon	Yes	Yes
Obstacle recognition	[40]		Obstacle recognition model based on feature points	Yes	No
Indoor positioning	[42]		• Feature point method + direct method + depth estimation • Positioning accuracy up to 0.04 m	Yes	No
Indoor OA	[35]	Binocular camera	Small storage space and high accuracy.	Yes	No
OA Planning	[37]		Depth Image + Dynamic Window	Yes	No
Real-time OA	[39]		Real-time and Robustness	Yes	Yes
Obstacle detection	[41]		Low Cost and Robustness	Yes	No

optical flow with good real-time and robustness, but sensor data fusion was not involved in this study.

Reference [40] proposed an obstacle recognition model based on monocular visual feature points and then designed an obstacle avoidance method (PLDOMD) to calculate a safe path for UAV flight based on the obstacle boundaries extracted from the recognition model. The algorithm proves its effectiveness on the DJI M100-based platform. Reference [41] proposed a vision-based optical flow obstacle detection technique and used the proposed algorithm for online real-time processing. However, in the current system, the presence of moving obstacles is not considered. Reference [42] proposed a monocular vision-based UAV indoor localization algorithm for the problem that UAVs cannot be localized in indoor environments where GPS signals are absent. Simulation results show that the proposed method can obtain good performance in indoor environments with a positioning accuracy of 0.04 m.

A comparative summary of UAV obstacle avoidance research based on vision devices is carried out in Table 3.

Research on vision-based obstacle avoidance can take advantage of the small size and low power consumption of cameras, and combined with deep learning and target detection technologies, it can make full use of environmental image information to obtain broader and richer real-world information than other sensors; however, the high sensitivity to conditions such as light and weather makes it susceptible to interference resulting in poor obstacle avoidance and high training costs.

B. LIDAR-BASED OBSTACLE AVOIDANCE

Compared with cameras, which require complex processing to obtain depth information, LiDAR can quickly and directly obtain depth-of-field information about the surrounding environment from the acquired point cloud information. Because it can meet the real-time requirements of indoor UAV obstacle avoidance, research on indoor navigation obstacle avoidance based on Lidar has become a hot topic.

Reference [43] proposed an obstacle detection system consisting of LIDAR and Raspberry Pi. The experimental results show that the method can correct the offset of the point cloud, effectively clusters the point cloud with uneven density, and has a good effect on obstacle detection.

Reference [44] proposed a new low-complexity target detector to improve the performance of LIDAR in performing indoor UAV obstacle avoidance. The results show that the proposed detector outperforms OS-CFAR (the standard detector used in automotive systems) in a specific indoor UAV navigation scenario.

Reference [45] developed a new LIDAR SLAM approach for small autonomous vehicles deployed to operate in unknown or updated indoor environments. A LiDAR odometer, loop closure and full 3-degree-of-freedom planar primitives are combined in a graph-based structure. The accuracy of their method was experimentally evaluated using high-resolution LiDAR, and the method was shown to operate on low computational resources.

Reference [46] proposed an airborne radar-based collision detection and avoidance system for UAVs, aiming to detect aircraft flying at a constant speed within the collision avoidance threshold and feed the generated trajectories as recommendations to the control system. Since the reactive collision avoidance algorithm is prone to fall into local minima, the study makes the proposed 3D collision cone method a focus of future research.

Research on lidar-based obstacle avoidance has the advantages of fast detection speed, good robustness and high data accuracy. Because lighting conditions have no effect on it, it is very suitable for indoor environment, but three-dimensional lidar is expensive, large volume, and can not detect glass and other transparent objects, so it needs to be combined with other sensors to achieve better obstacle avoidance effect.

C. MULTI-SENSOR-BASED OBSTACLE AVOIDANCE

Multi-sensor fusion-based obstacle avoidance methods focus on reducing the detection time and increasing the detection range. Many studies have been conducted by equipping quadrotor UAVs with different types of sensors, such as LIDAR, vision cameras, ultrasound, etc., to quickly respond to obstacles within the detection range.

Reference [47] addressed the obstacle avoidance problem of UAVs, increased the number of ultrasonic waves based on the traditional ultrasonic obstacle avoidance scheme, and fused the information of multiple ultrasonic sensors to solve the problem that quadrotor UAVs cannot avoid obstacles in multiple directions when using ultrasonic waves, and realized the obstacle avoidance flight of multi-rotor UAVs.

Reference [48] built a 3D detection device with ultrasonic sensing to detect obstacles in order to achieve all-around obstacle avoidance planning for quadrotor UAVs in indoor environments, preventing the effect of visible light while reducing the system cost. MATLAB simulations verified the effectiveness of the obstacle avoidance decision, but the authors did not perform physical tests.

Reference [49] proposed an autonomous obstacle avoidance scheme based on millimeter wave radar and monocular camera fusion. Obstacles are first detected by vision, then Extended Kalman Filter (EKF) data fusion is used to establish the 3D coordinates of the obstacles, and finally, a path planning algorithm is used to obtain a path to avoid the obstacles. However, the positioning process of the obstacle avoidance scheme described in this paper still requires the use of GPS and cannot be applied to indoor environments.

Millimeter wave radar and monocular camera data fusion are used to acquire obstacle information in [50]. During the obstacle avoidance flight, the minimum error between the actual flight path and the planned path is 0.1m, and the maximum error is 1.4m.

To enable UAVs to fly autonomously and avoid obstacles in environments without GPS or weak GPS signals, such as indoor and dense forests, a UAV autonomous flight and obstacle avoidance system based on monocular cameras and sensors such as IMU and DJIGuidance is designed in [51], and a trace-free Kalman filter is used to fuse multi-sensor information to realize UAVs to distinguish, recognize and detect information about the surrounding environment. Recognition and detection. After AirSim simulation and physical verification, the system can precisely avoid obstacles and steadily complete flight tasks such as crossing the designated obstacle circle, target identification, scene search, and autonomous takeoff and landing.

Reference [52] proposed an intelligent sensing and obstacle avoidance control system in order to overcome the defects of inaccurate obstacle positioning caused by a single sensor. Ultrasonic sensors, infrared sensors, and LIDAR are used to detect the surrounding environment in real time, and then the detection information is calculated by the data analysis and processing module, and finally, the hardware driver and software operation are used to avoid obstacles effectively, which improves the reliability and safety and shortens the detection cycle. A comparative summary of multi-sensor-based UAV obstacle avoidance research is carried out in Table 4.

Research on multi-sensor-based obstacle avoidance combine different sensors so as to quickly achieve environmental sensing and detection tasks. Such methods can fully utilize the advantageous characteristics of different sensors and are suitable for both indoor static obstacle avoidance and indoor dynamic environments. However, different sensor errors and multi-source information fusion techniques are difficult points that affect the effectiveness of multi-sensor obstacle avoidance.

IV. RESEARCH BASED ON PATH PLANNING

Obstacle detection and avoidance capabilities of UAVs are crucial for autonomous flight. Along with the rapid growth of UAV applications in the civil sector, the obstacle avoidance problem has become one of the key research objects in UAV autonomous flight technology, and the obstacle avoidance task aims to achieve the generation of collision-free paths while significantly improving the autonomy of UAVs.

After detecting and identifying obstacles, UAVs need to independently plan feasible obstacle avoidance paths by

TABLE 4. Comparison of UAV obstacle avoidance research based on multi-sensor. (here OA means obstacle avoidance).

Task	Reference	Equipment	Performance	Indoor	Outdoor
Autonomous OA	[49]	Millimeter wave radar + monocular camera	● Successfully avoiding obstacles ● But not for indoor	Yes	No
OA Planning	[50]	Millimeter wave radar + monocular camera	Minimum error from expected 0.1m.	Yes	No
Obstacle detection	[43]	LiDAR + Raspberry Pi	Clustering of point clouds, good detection effect.	No	Yes
Indoor OA	[47]	Multiple ultrasound	Multi-directional OA.	No	Yes
Autonomous OA	[51]	Monocular camera +IMU+DJIGuidance	● fusing multi-sensor information. ● Precise OA	Yes	Yes
Indoor OA	[44]	Low-complexity target detector	● Better than OS-CFAR with more than 19% higher PD ● Lower computational complexity	No	Yes
Indoor SLAM	[45]	LIDAR	● Low computing costs ● High Resolution	No	Yes
Indoor OA	[48]	Multiple ultrasound	● Low Cost ● Resolving Fuzzy Decision Conflicts	No	Yes
Obstacle detection	[52]	Ultrasonic+Infrared+ LIDAR	Reliability and safety,Shorten the testing cycle	No	Yes

combining the results of environmental perception; the path planning obstacle avoidance algorithms developed so far have been widely used for autonomous UAV flights. The path planning problem belongs to the NP puzzle, and in fact, various algorithms can be used to optimize and thus find the global optimal path. There are various obstacle avoidance methods for UAV path planning. In this paper, according to different optimization models established in path planning, they are divided into the following four categories: graph search-based methods, potential field-based methods, population intelligence-based methods, and machine learning-based methods.

It is necessary to note that these obstacle avoidance schemes do not give strict di-vision boundaries, and this paper only provides a classification idea. Each class of methods will be elaborated on later. A classification diagram of the UAV path planning methods described in this paper is given in Figure 15.

A. METHODS BASED ON GRAPH SEARCH

The graph-based search obstacle avoidance method first models the environment through a rasterization method and then generates the obstacle avoidance path using a search algorithm. The graph search methods applied to UAV obstacle avoidance usually include the Voronoi graph, Dijkstra, A*, D*, RRT, PRM and their improvements. The graph-based search algorithm development timeline is shown in Figure 16.

1) VORONOI DIAGRAM

A Voronoi diagram consists of a set of continuous polygons formed by the perpendicular bisector of a line connecting two neighboring points. To address the drawback that

FIGURE 15. Classification chart of UAV path planning methods.

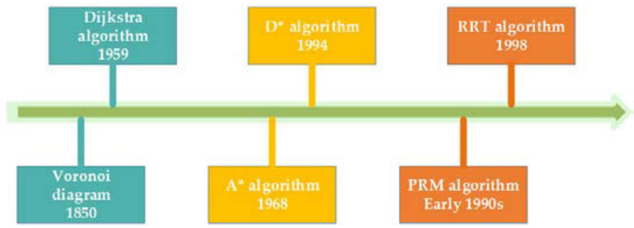

FIGURE 16. Graph-based search algorithm development timeline.

Voronoi diagrams cannot generate optimal path maps, [53] solved this problem by combining it with a node-based algorithm. In [54], the researchers used two-dimensional Voronoi diagrams to divide the target space into several parts to construct the connectivity network graph. Reference [55] combines Voronoi with navigation functions to achieve a global collision-free path. Reference [56] combined Voronoi diagrams and an improved Dijkstra algorithm to reduce the time for path planning in dynamic environments.

2) DIJKSTRA ALGORITHM

The Dijkstra algorithm is proposed by Edsger Wybe Dijkstra in 1956 to find the shortest path between nodes in a graph. As a classical graph search algorithm, it has excellent search efficiency in solving shortest-circuit problems.

Reference [57] constructed the set of possible flight paths for UAVs based on the threat distribution and used the Dijkstra algorithm to search the threat distribution graph represented by the Voronoi diagram to solve for the rough shortest path. Reference [58] construct a UAV trajectory planning model under multiple constraints for the UAV optimal trajectory fast planning problem. By calculating the residual error and the constrained flight distance, the basic Dijkstra algorithm is improved to make it better adaptable in solving the trajectory planning problem under multiple constraints.

3) A* ALGORITHM

As the research problem progresses, the obstacles faced by UAVs in the actual scenario are not regular and cannot be simply reflected in the form of nodes and line segments, and the increase in the map with the number of nodes leads to inefficient execution of the algorithm for solving the shortest route. Therefore, in order to weigh the relevant constraints and route quality and find a relatively better solution, Dutch scientists Dijkstra et al. optimized Dijkstra's algorithm and proposed the A* algorithm.

The A* algorithm was first proposed by Dutch scientists Dijkstra et al. in 1968 in the literature [59] and has since become a popular method for UAV path planning. The A* algorithm is a classical search algorithm for finding the optimal path in a static connected graph based on the evaluation function. The drone searches for the best evaluated new position at the beginning of the movement and continues the search from the new position until it reaches the target point. A two-dimensional real-time UAV path planning process based on the A* algorithm is shown in Figure 17.

Reference [60] proposed an improved A* algorithm for solving the problem that the paths generated by the traditional A* algorithm are not the shortest under certain conditions, and the simulation results proved that the paths planned by this algorithm are shorter than the original ones.

Reference [61] applied the A* algorithm to the path planning of UAVs in battlefield environments with the constraints of minimum hazard exposure and minimum fuel consumption. Experimental results show that the method can solve the UAV two-dimensional path planning problem under multiple constraints.

Reference [62] proposed a memoryless regression A* algorithm based on a highly degraded spatial environment model for the dynamic path planning problem of multi-rotor UAVs in indoor complex environments, and the simulation results showed that the path planning time and path planning length of the proposed method were shorter than those of the memoryless A* algorithm in the specified environment.

Reference [63] improved the A* algorithm for the problems of difficult constraint of UAV 3D path planning, complex search space, existence of critical steering angle, and redundant nodes. The simulation results show that the

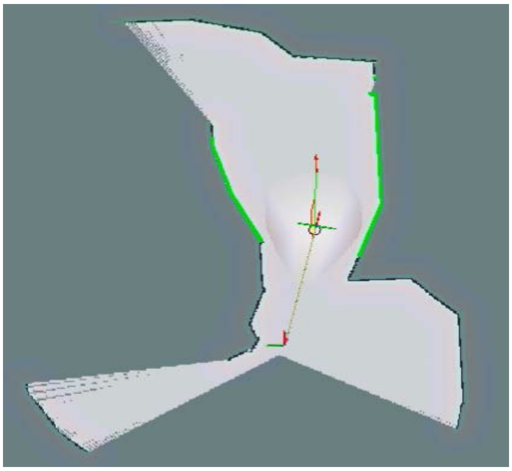

FIGURE 17. UAV path planning process based on A* algorithm.

improved algorithm can effectively improve the flight efficiency of the UAV.

Reference [64] improved the A* algorithm to solve the obstacle avoidance path planning problem in the case of the coexistence of circular and polygonal no-fly zones, which is more practical than the problem with only a single type of no-fly zone, and the obtained routes are closer to the optimum. However, it does not consider the real-time obstacle avoidance path planning means when dealing with unexpected threats.

For the problem of low planning efficiency of traditional A* algorithm in large indoor scenes, an improved A* algorithm based on a topological map is proposed in [65]. Experiments show that the improved algorithm can quickly plan paths in large indoor scenes. Compared with the original A-star algorithm, the algorithm shortens the time cost, reduces the computation and improves the planning efficiency of the algorithm.

4) D* ALGORITHM

Since the traditional A* can only be used for static environment planning, many scholars have improved it. D* algorithm was proposed by Stentz at Carnegie Mellon Robotics Center in 1994 and is mainly used for robotic pathfinding. The difference between the D* algorithm and the A* algorithm is that when the UAV detects a change in information about the surrounding environment, the path generation value is updated accordingly.

For the problems of lag and excessive computation in current motion target route planning, the Kalman filter algorithm is used to predict the position of the target in [66], and then the D* algorithm is used for path planning. Simulation results effectively shorten the path length and reduce the time for the UAV to reach the target position with strong real-time performance.

Reference [67] proposed a path planning method for mobile robots based on partially known indoor environments. For the problem that the search space of the D* algorithm is large, the idea of abstract layering is introduced and the key nodes are reasonably set to reduce the search space of the D* algorithm; for the problem that the path obtained by D* algorithm has multiple turns in a small area, the heuristic function of D* algorithm is improved to effectively reduce the time and fuel cost of the path.

Reference [68] proposed an improved D* algorithm for the indoor path planning problem of multi-rotor aircraft, which keeps the UAV at a certain safe distance from obstacles after introducing the obstacle factor on the traditional algorithm, and takes only the starting point of the linear path by slope judgment, thus realizing the autonomous navigation and obstacle avoidance of the aircraft indoors and improving the UAV flight efficiency.

5) PRM ALGORITHM

In the early 1990s M.H. Overmars et al. proposed the probabilistic roadmap (PRM) algorithm, which is a graph search-based algorithm that converts continuous state spaces into discrete state spaces and improves search efficiency. The basic PRM algorithm is probabilistically complete but cannot generate optimal paths.

Reference [69] proposed an improved PRM algorithm in order to address the shortcomings of the traditional PRM algorithm in dealing with the narrow channel problem. Simulation results show that it can improve the roadmap construction efficiency and solve the narrow-channel problem, and it also performs better under the burst threat condition.

Reference [70] proposed a real-time path planning algorithm for UAVs in complex 3D environments. The environment in question is divided into regions with different bounding boxes, and the PRM is improved by selecting nodes in the bounding boxes to ensure a more uniform distribution in 3D space; the A* algorithm is used to search for paths in the roadmap. Test results show that the algorithm can create collision-free paths in real time.

Reference [71] addressed the problem of a few UAV path planning constraints that could not meet the actual flight demand, first modeled the different constraints separately, and then proposed the grid PRM algorithm to achieve fast path planning in 3D space. However, the proposed method is not capable of handling dynamic environmental information.

Reference [72] introduced obstacle boundaries as definite sampling points based on the traditional PRM algorithm to reduce the dispersion of random sampling points of the traditional PRM algorithm and make the path search definite. MATLAB simulation results show that in 3D space, the improved PRM algorithm reduces the track planning time by 2.469% to 5.721% compared to the traditional PRM algorithm and the track length by 0.89% to 1.54%.

6) RRT ALGORITHM

RRT (Rapid Exploration Random Tree) algorithm was proposed by Professor Steven M. LaValle in 1998. The algorithm can easily handle scenarios containing obstacles and

TABLE 5. Comparison of UAV path planning algorithms based on graph search. (here s/d means static/ dynamic, I/O means indoor/ outdoor).

Type	Reference	Basic Algorithm	Task	Performance	Advantage	Drawback	S/D	I/O
Based on Graph Search	[53-56]	Voronoi	Path Planning	● Reduce time ● Secure Path	Far from obstacles, high security.	Not applicable to high-dimensional, high cost	S+D	I+O
	[57]58]	Dijkstra	Shortest path	● Reduce time ● Shortest path	Robustness and fast computation	Inefficient planning	S+D	I+O
	[59][60]	A*	Path finding	Preferred path	Low complexity, short path	High computational effort, many inflection points	S	I+O
	[61] [64]		Multiple constraints	Preferred path			S	I+O
	[63][65]		Improve efficiency	3D fast planning	Low cost and high efficiency	Static environment only	S	I+O
	[62]		Indoor dynamic path planning	Shorter path lengths	Dynamic planning and high efficiency	High calculation volume	S+D	I
Based on Graph Search	[67][68]	D*	Indoor dynamic path planning	● Reduced path cost, ● indoor obstacle avoidance	Safe distance, short path	High calculation volume and many inflection points	S+D	I
	[70]	PRM	Narrow access problem	Improve composition efficiency	Applicable to higher dimensional spaces	Not suitable for real time planning	S	I+O
	[71-73]		Path planning for complex 3D environments	● Collision-free paths, ● reduced path cost	Applicable to higher dimensional spaces		S	I+O
	[75][77]	RRT	Multi-constraint path planning	Effectively improve route planning efficiency	Fast speed and short path	Not suitable for real-time planning	S	O
	[76]		Threat area detection	Avoid threat areas	Fast and effective	Search Node Multi	S	O
	[78-80]		Path planning for complex 3D environments	● Optimized path, ● adaptive sampling	Applicable to high-dimensional space, dynamic obstacle avoidance	——	S+D	I+O

differential motion constraints and is widely used in motion planning for various robots. RRT algorithm is applicable to high-dimensional space and can effectively solve the path planning problem in high-dimensional space and complex

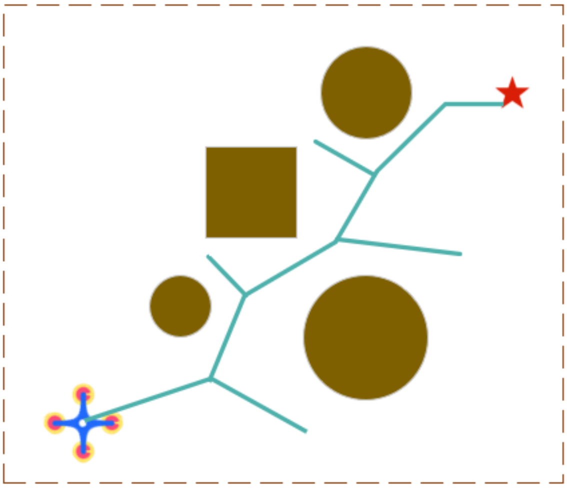

FIGURE 18. **UAV path planning process based on A* algorithm.**

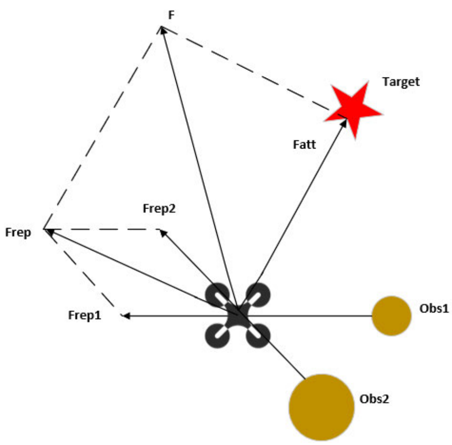

FIGURE 19. **Force analysis diagram of the drone in the potential field.**

constraints by performing collision detection on sampled points in the state space and avoiding the modeling of the environment space. Figure 18 illustrates the sampling process of an RRT algorithm.

Reference [73] proposed an improved bidirectional RRT algorithm to solve the path replanning problem in a dynamic environment. Simulation results show that the method can meet the requirements of path planning in dynamic environments. Reference [74] proposed a multi-constraint RRT algorithm to solve the path planning problem of UAVs in the 3D environment. Four sets of comparative simulation results show the effectiveness of the developed RRT algorithm.

UAV path planning in complex environments usually does not distinguish between unknown threats and obstacles, [75] studied a UAV path planning method based on a hybrid strategy of RRT and APF. Potential fields with different characteristics are used to distinguish between threats and obstacles in the environment. Simulation results show that the algorithm is able to avoid threat areas quickly and effectively.

Reference [76] proposed an improved RRT* algorithm for UAV path planning to address the problems of large randomness, slow convergence speed, and many search nodes of the RRT algorithm. Simulation results show that the improved algorithm improves the convergence speed and reduces the path length compared with RRT*.

In [77], considering the high urgency of high-rise indoor fire rescue tasks, the RRT forest algorithm was proposed for the problems of restricted RRT search area, long time consumption and poor feasibility of results. The efficiency of UAV path planning in complex indoor environments is significantly improved. Future work can be devoted to im-prove the ability of cooperative path planning for multiple UAVs in complex indoor environments.

Reference [78] proposed a heuristic bidirectional objective RRT fusion A* algorithm for the problems of blind search, long paths and zigzag paths in 3D spatial environment path planning.

Reference [79] proposed a UAV path planning algorithm ADRRT*-Connect for dynamic obstacles in 3D environments. To avoid dynamic obstacles, a pruning reconnection mechanism is introduced to repair the path when a new obstacle appears. Simulations show that the proposed algorithm requires only 3.5% of new nodes to repair the paths in replanning, saving the path planning cost.

A comparative summary of UAV path planning algorithms based on graph search is carried out in Table 5.

B. METHODS BASED ON POTENTIAL FIELD

The potential field-based method models the planning space as a kind of region with different potential fields of high and low, and the basic principle is to construct a suitable potential field to drive the UAV movement through the combined force. It has the characteristics of simple model, great real-time performance and smoother path, etc. The representative algorithms have artificial potential field method (APF).

APF introduces the concept of repulsive or attractive forces to repel the UAV away from an obstacle or to attract it to a designated target. The forces on the UAV in the potential field are shown in Figure 19.

Classical APF algorithms are limited to single UAV trajectory planning, which usually cannot guarantee obstacle avoidance. Reference [80] proposed an optimized post-APF algorithm with a distance factor and a jump strategy to address UAV obstacle avoidance and collaborative trajectory planning for multiple UAVs. Simulations show that the method can provide safe and smooth trajectories for UAVs to perform their missions efficiently.

Reference [81] proposed a collision avoidance protocol based on magnetic gravity and repulsion. The protocol was validated for two typical scenarios, achieved good collision avoidance results. Reference [82] determines the presence of narrow channels by setting the detection window. Simulation experiments show that the improved method can perform path planning more effectively, but the authors do not solve the local optimum problem.

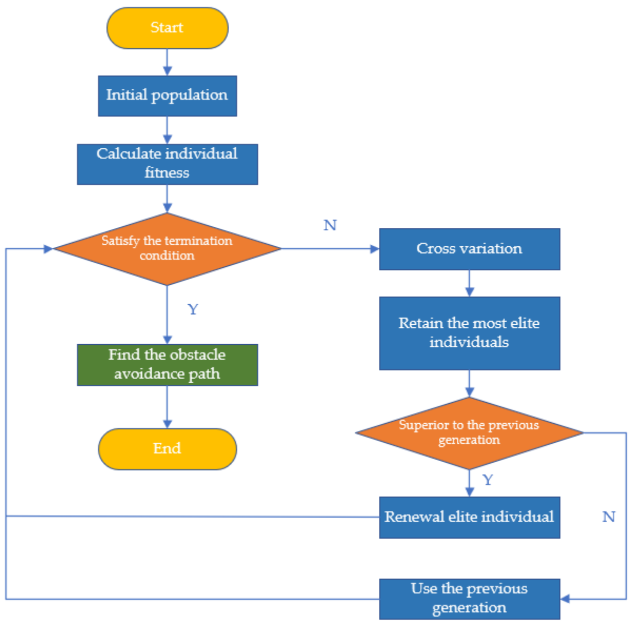

FIGURE 20. Genetic algorithm flow chart.

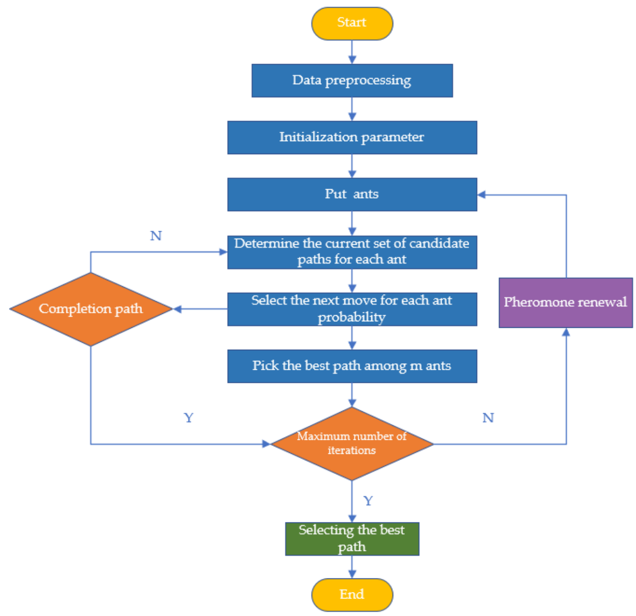

FIGURE 21. Ant colony algorithm flow chart.

The traditional artificial potential field method treats UAVs as mass points for path planning, but the indoor space is small and the size of the UAV needs to be considered during the actual flight. Reference [83] The path planning based on the traditional artificial potential field method ignores the shape or influence range of obstacles, and the path planning results are difficult to be applied in practice. A path planning model based on an improved artificial potential field method is proposed to solve the path planning problem when considering the shape of obstacles. However, this paper considers only a simple two-dimensional path planning problem and does not consider the change in the environment.

Reference [84] applied the improved artificial potential field method to the UAV indoor autonomous obstacle avoidance considering the size of the UAV motion space. By designing an obstacle avoidance prevention detection strategy, the UAV flight direction is corrected in real time. The improved artificial potential field method enables the UAV to escape from local minimal points, avoid obstacles, and reach the target point smoothly.

Reference [85] proposed an improved artificial potential field method for the indoor complex environment, which is easy to fall into local optimum in the obstacle avoidance process leading to the target unreachability problem. The innovative design of the threshold to determine whether to fall into local minima and the introduction of an adaptive escape step factor to quickly escape local minima. The simulation results verify the effectiveness of the algorithm and provide some theoretical basis for the application of UAVs in real indoor environments.

Reference [86] proposed an improved algorithm for UAV obstacle avoidance path planning based on the traditional artificial potential field method in order to solve the problems of un-reachable targets, local minima traps and long path lengths of the artificial potential field method. Reduce the path length by 9% to 15%. It improves UAV safety and has practical application value in UAV obstacle avoidance path planning.

Although the artificial potential field method is computationally small and solves in real time, it requires artificially set force field function and has the disadvantages of easily falling into the local optimal solution and oscillating near the target point. Considering the constraints such as the shape and influence range of obstacles in the indoor environment, the design of the obstacle avoidance scheme should focus on how to solve the local optimal solution problem.

A comparative summary of UAV path planning algorithms based on APF is carried out in Table 6.

C. METHODS BASED ON SWARM INTELLIGENCE

Traditional path planning algorithms have huge complexity in time and space, which can easily lead to unsatisfactory practical results. To solve the complex operations of traditional algorithms, many intelligent path optimization methods have been developed. Swarm intelligence algorithms originate from mimicking the behavior of biological groups to deal with problems. This class of methods omits the process of constructing complex environment models and proposes strong search methods that converge to the target stably.

This paper mainly introduces the three representative swarm intelligence methods of genetic algorithm, ant colony algorithm and particle swarm algorithm. The methods based on swarm intelligence also include the gray wolf algorithm, firefly algorithm, aspen whisker algorithm, pigeon swarm algorithm, cuckoo algorithm, etc.

TABLE 6. Comparison of UAV path planning algorithms based on apf. (here S/D means static/ dynamic, I/O means indoor/ outdoor).

Type	Reference	Basic Algorithm	Task	Performance	Advantage	Drawback	S/D	I/O
Based on Potential Field	[81]	Artificial potential field	Cooperative OA	Secure Path	Fast planning	Local Minimal Value	S	O
	[82]		OA	Shared Routes	Dynamic OA	Oscillation	D	O
	[83]		Path planning	Solving oscillation and target unreachability problems	Improve planning efficiency	Local Minimal Value	S	I+O
	[84]		Indoor OA	Propose a path planning model considering obstacles	Practical applicability	Not applicable to high-dimensional	S	I
	[85]		Indoor OA	Resolving local minima	Real-time reorientation	——	S+D	I
	[86]		Indoor OA	Escape local minimum strategy	Improve the success rate of OA	——	S	I
	[87]		Path planning	Path reduction of 9%~15%	Improve planning efficiency	Lack of physical verification	S	I+O

1) GENETIC ALGORITHM

Originating from Darwin's theory of evolution, the genetic algorithm is an intelligent optimization algorithm with powerful global search capability by simulating the natural selection, crossover and variation of organisms in nature. Genetic algorithms are now widely used to solve UAV path planning tasks. The algorithm flow is shown in Figure 20.

Reference [87] used a genetic algorithm to generate the best path for the UAV to avoid obstacles along the way. However, the generated paths are sharp and tortuous, and further path optimization needs to be made. Reference [88] used an improved genetic algorithm to obtain trajectories that simultaneously satisfy two metrics of sufficient distance from the obstacle and short flight distance by designing an adaptation function after the population initialization operation is completed. Experimental results show that this method can generate a safer and shorter traveled smooth feasible trajectory.

Reference [89] proposed a new nonlinear adaptive adjustment method for the problems of poor local search ability and low planning efficiency of traditional genetic algorithm. Simulation results show that the method enhances the local search ability of the genetic algorithm, but does not consider the trajectory planning problem of UAV dynamics.

Reference [90] used the optimal solution obtained by the genetic algorithm to initialize the ant colony pheromone matrix in order to improve the convergence speed of UAV trajectory planning. Reference [91] proposed a genetic algorithm capable of generating waypoints and achieving obstacle avoidance considering the minimum turning radius.

Reference [92] designed an improved genetic algorithm to ensure that UAVs can select the most efficient and reliable flight path in complex environments. The algorithm uses the objective function as the fitness function to find the optimal trajectory and considers the selection strategy of multiple landing points under different conditions.

Reference [93] proposed a ColorUAV genetic algorithm that considers both obstacle and communication constraints for the UAV path planning problem under multiple constraints. The algorithm can produce near-optimal results using only local range information but still needs to be tested for real-world effects.

2) ANT COLONY ALGORITHM

The ant colony algorithm was proposed by the Italian scholar Marco Dorigo in 1992 and was inspired by the pheromone selection mechanism released by ants when foraging for food. Ant colony algorithm is famous for its distributed computing, positive feedback mechanism and robustness, and has been widely used in the field of UAV path planning and obstacle avoidance. In the UAV path search task, ants usually represent UAVs and the probability of moving from one point to the next depends in part on the concentration of map pheromones. The ant colony algorithm flow is shown in Figure 21.

In [94], the authors use a minimum time search algorithm with ant colony optimization to ensure the successful computation of collision-free search paths for UAVs under communication-related constraints.

Reference [95] proposed a UAV indoor path planning method based on ant colony optimization. The problems of

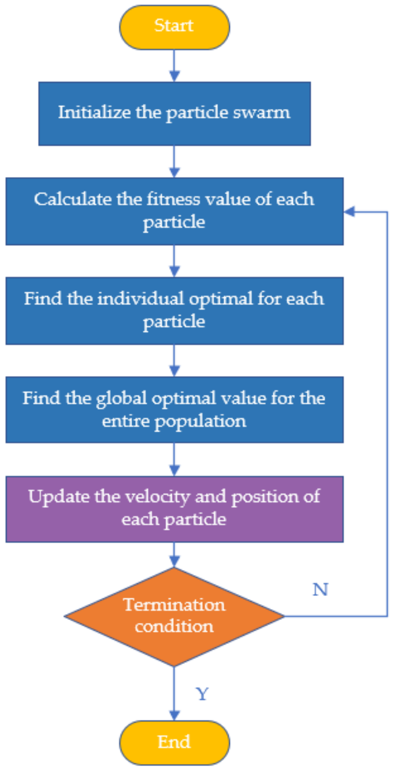

FIGURE 22. **Particle swarm algorithm flow chart.**

premature convergence and inefficiency of the traditional ant colony algorithm are solved with the help of a 3D grid and the weights of the climbing height. Simulation results show that the proposed algorithm can generate the optimal solution in a shorter time.

Reference [96] investigated the path planning problem of searching multiple targets by UAV in an environment with irregular obstacles. An improved geometric algorithm was first used to find an accessible path between any two targets, and then an ant colony system (ACS)-based search strategy was proposed to find the search sequence with the shortest flight distance. The effectiveness of the algorithm is experimentally demonstrated, but further research is needed to solve the large-scale problem as the number of targets increases.

Reference [97] improved the basic ant colony algorithm in terms of both guidance factors and node pheromone updates. Simulation results show that the improved ant colony algorithm improves the flight path optimization of the UAV. Reference [98] proposed an improved ant colony algorithm for the problems of slow convergence and easy to fall into local optimum when the traditional ant colony algorithm is used for 3D path planning. By adjusting the pheromone update strategy and the design of the heuristic function, the directionality and robustness of the search are improved, thus shortening the overall search distance.

Due to the complexity of indoor UAV navigation, [99] proposed an improved ant colony algorithm for indoor UAV 3D trajectory planning for the problems of early blind search, easy to fall into local optimum and slow convergence of traditional ant colony algorithm. The initial pheromone adjustment factor is improved to enhance the directionality of the ant colony search; the heuristic probability function is designed to improve the state transfer rule to effectively improve the visibility accuracy of the ant colony; the pheromone update rule is improved to add the dynamic adjustment strategy of pheromone volatility, thus speeding up the convergence iteration of the algorithm. Simulation results show that the improved ant colony algorithm effectively improves the global search capability, reduces the number of convergence iterations, and obtains an optimal path length that is 38.6% shorter and takes 3.8% less time on average than the traditional ant colony algorithm, which significantly improves the adaptability of the ant colony optimization algorithm.

3) PARTICLE SWARM ALGORITHM

The concept of particle swarm algorithm (PSO) originates from the foraging behavior of birds in nature. It was proposed by Eberhart and Kennedy in 1995 and is based on the sharing of information within a group to guide the group toward a target with high efficiency in a search space of a certain size. To implement the particle swarm optimization algorithm, a set of particles is first randomly generated, and each particle is treated as a feasible solution. The particles are guided by the individual fit-ness value and the global optimum value to update their position and velocity for the next action to obtain the solution of the problem. The algorithm flow is shown in Figure 22.

Reference [100] proposed a three-dimensional spatial path planning method based on con-centric spherical coordinates and an improved particle swarm optimization algorithm. The combination of constraints and the improved particle swarm optimization algorithm makes the path search more efficient. Simulation results show that the improved method can generate 3D paths satisfying different constraints.

The convergence and migration operations of the bacterial foraging algorithm BFO are introduced into the PSO algorithm to improve its merit-seeking ability in [101]. MATLAB simulation experiments show that the hybrid algorithm effectively improves the defects of the particle swarm algorithm, and the merit-seeking accuracy and stability are significantly improved compared with the traditional PSO algorithm.

Reference [102] proposed an adaptive Cauchy variant particle swarm (ACMPSO) based UAV 3D trajectory planning algorithm in order to solve the difficult problem that PSO is easy to fall into local extremes and slow convergence speed in UAV trajectory planning. Simulation results show that the ACMPSO algorithm is stable, can effectively avoid obstacles and threats, and can search the optimal trajectory faster.

Reference [103] proposed an improved particle swarm algorithm combined with the aspen whisker search (BAS) algorithm for the disadvantage that PSO converges quickly in the early stage and easily falls into local optimum in the later stage. Taking advantage of the individual aspen, it has its own

TABLE 7. Comparison of path planning algorithms based on swarm intelligence. (here S/D means static/ dynamic, I/O means indoor/ outdoor).

Type	Reference	Basic Algorithm	Task	Performance	Advantage	Drawback	S/D	I/O
Based on Swarm Intelligence	[89][92-94]	Genetic Algorithm	Multi-constraint path planning	Path security smoothing	Low cost	——	S+D	I+O
	[90]		Path planning	Astringency	Enhanced Local Search	Consider only static	S	I+O
	[91]		Path planning	Overcoming local minima	Fast speed	——	S	I+O
	[96]	Ant colony algorithm	Indoor Planning	Solving the problem of premature convergence	Short time	Obstacle effects not considered	S	I+O
	[97]		Multi-objective planning	Planning for Success in Irregular Barrier Environments	Shortest flight distance	Large-scale	S	I+O
	[99]		3D Planning	Shorten the search distance	Directionality, Robustness	Consider only static	S	O
	[100]		Indoor Planning	38.6% reduction in path length	Convergence, adaptability	Consider only static	S	I
	[101]	Particle Swarm Algorithm	3D Planning	3D paths satisfying constraints	More efficient path search	Local Optimal	S	O
	[102-104][106-107]		Path planning	Shorten the path	High accuracy and robustness	Complexity	S+D	I+O
	[105]		Autonomous Planning	Effective planning	Few parameters	——	S+D	I+O

judgment of the environment space in each iteration, which makes the path more reasonable and the search more efficient. Simulation results show that the improved algorithm has better convergence, avoids falling into local optimum, and effectively shortens the path length.

Reference [104] improved the overall weights and learning factors of the particle swarm, and the proposed new algorithm can autonomously and efficiently plan the path of the UAV. The advantages of the proposed PSO improvement algorithm are the relatively small number of parameters compared to various other algorithms and the ease of adjusting the weights and improving the learning factor.

Reference [105] proposed an improved particle swarm optimization (FPSO) algorithm that focuses particles on different optimization-seeking tasks according to the fitness value, and proposed an improved strategy incorporating genetic algorithms based on this improved direction. The simulation results show that the FPSO algorithm has better global search ability and local convergence speed compared with PSO and GA algorithms.

In [106], the authors used the TFmini laser sensor to detect the direction and distance of obstacles near the airframe, and after modeling the environment, they used Dijkstra's algorithm to search for feasible paths for the UAV, and finally proposed an improvement on the PSO algorithm, which was used to obtain the globally optimal path. The simulation results show the effectiveness of the proposed obstacle avoidance strategy, but the locally optimal path for the unknown environment is not studied and discussed.

A comparative summary of UAV path planning algorithms based on swarm intelligence is carried out in Table 7.

D. METHODS BASED ON MACHINE LEARNING

Machine learning-based algorithms are intelligent optimization algorithms that have been very hot in recent years. Machine learning based techniques are very useful when dynamic obstacles are present, as the UAV can make decisions based on real-time data captured from the surrounding environment. Drones use three common techniques when doing obstacle avoidance research using machine learning techniques: neural networks, reinforcement learning, and deep reinforcement learning.

1) METHOD BASED ON NEURAL NETWORK

Inspired by the nervous system of the human brain, early scientists constructed a mathematical model that mimics the

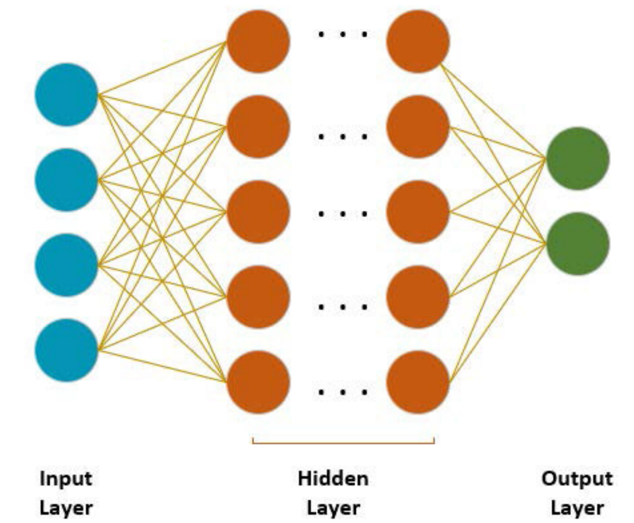

FIGURE 23. BP neural network structure diagram.

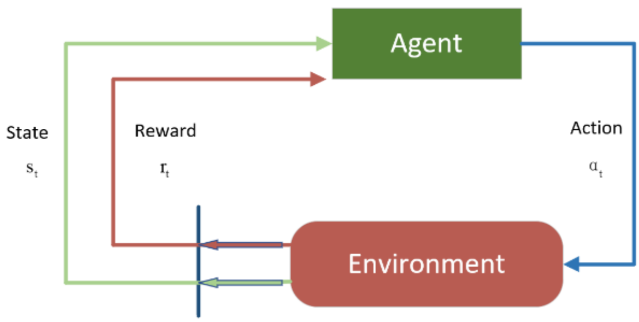

FIGURE 24. Flow Chart of RL.

nervous system of the human brain, called an artificial neural network, or neural network for short. In the field of machine learning, a neural network is a model of network structure composed of many artificial neurons. Perceptrons were the first neural networks with machine learning ideas. Until around 1980, the emergence of the back propagation (BP) algorithm became the most popular neural network learning algorithm.

BP neural networks are divided into three main components: the input layer, hidden layer, and output layer. A typical BP neural network structure is shown in Figure 23. With the rapid development of artificial intelligence and hardware performance, more and more researchers are using neural network algorithms for UAVs to solve their path planning and obstacle avoidance problems.

The author of [107] realized the globally optimal path of the robot with the aid of neural network algorithm. But when implemented in a 3D environment, neighbor neurons will explode [108] proposed a UAV path planning method based on genetic algorithm and artificial neural network, which uses the output of the genetic algorithm to train the artificial neural network and can plan the path faster and better compared to the traditional genetic algorithm and avoid the obstacles effectively.

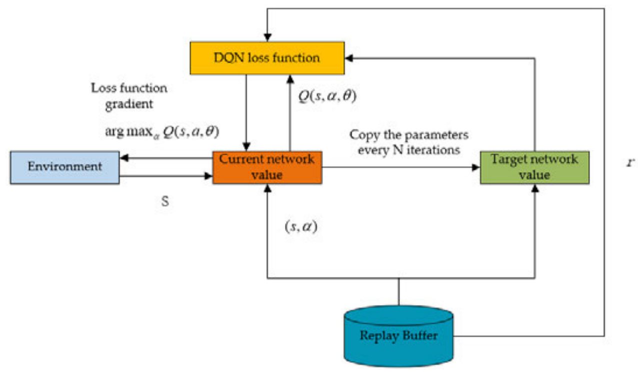

FIGURE 25. Flow Chart of DQN.

Reference [109] proposed a UAV path planning method based on the fusion of the Sparrow Search Algorithm (SSA) and Bionic Neural Network (BINN). The fusion algorithm combines SSA, improved BINN and B spline curves to generate safe, smooth and short paths for UAVs with radar threats, mountain threats and dynamic obstacles in mountainous environments. Experimental results in different static and dynamic environments show that the proposed fusion algorithm can effectively solve the path planning problem of UAVs in complex environments.

Reference [110] addressed the obstacle avoidance problem of UAVs in 3D complex dynamic environments, and for the first time combined the advantages of interference fluid dynamics system (IFDS) obstacle avoidance technology and neural network with strong adaptive learning capability to effectively solve the UAV real-time dynamic obstacle avoidance problem.

Reference [111] proposed a real-time UAV obstacle avoidance algorithm based on fuzzy neural network to address the problem that fuzzy control obstacle avoidance algorithm is difficult to effectively avoid "concave polygon" obstacles. Simulations show that the fuzzy neural network algorithm is more adaptable and has a higher success rate in obstacle avoidance in unknown environments.

To solve the indoor UAV navigation and obstacle avoidance problem, deep neural network-based image processing was used to provide support for UAV navigation indoors in [112]; in addition, hyperparameter rectification of CNNs was implemented using genetic algorithms. The comparison found that the algorithm in this paper has better results than the other 11 state-of-the-art peer-to-peer deep neural networks.

2) METHOD BASED ON REINFORCEMENT LEARNING

The reinforcement learning (RL) problem can be described as an intelligent body continuously learning knowledge from its interaction with the environment to accomplish a specific goal. Since reinforcement learning does not require a large number of a priori training samples, in which case the UAV always learns path planning from the environment; it is therefore attractive to implement the idea of RL in an unknown

TABLE 8. Comparison of UAV path planning algorithms based on machine learning. (here S/D means static/ dynamic, I/O means indoor/ outdoor, nn means neural network, rl means reinforcement learning, drl means deep reinforcement learning).

Type	Reference	Basic Algorithm	Task	Performance	Advantage	Drawback	S/D	I/O
Based on machine learning	[110]	NN	Path planning for complex environments	Secure Smooth Path	Consider multiple constraints	High complexity	S+D	O
	[111]		3D dynamic OA	Effective OA	Dynamic OA	——	S+D	I+O
	[112]		Real-time OA	High success rate of OA	Highly adaptable	Long training time	S+D	I+O
	[113]		Indoor OA	Enabling indoor navigation and OA	High real-time	Multiple parameters	S+D	I
	[114] [117] [118]	RL	Path planning and OA	Improve planning efficiency and successful OA	Fewer parameters	Slow convergence	S+D	I+O
	[115]		3D dynamic OA	High success rate of OA	High real-time	——	S+D	I+O
	[116]		Path planning	81% success rate	Low complexity	only static	S	I+O
	[119]	DRL	Indoor OA	Indoor unknown environment OA	Low cost	Insufficient convergence	S	I+O
	[120]		Indoor dynamic OA	Indoor OA with pedestrians	Achieving Transfer Learning	——	S+D	I
	[121]		Autonomous OA	Better learning efficiency and performance	Suitable for 3D	Local Optimal	S	I+O
	[122]		Complex environment OA	Rapid obstacle avoidance in complex environments	High real-time	Long training time	S+D	I+O

environment to support UAV tasks. The reinforcement learning thought process is shown in Figure 24.

Reference [113] designed a UAV path learning and obstacle avoidance method based on Q-learning algorithm. On the one hand, a neural network is used to achieve continuous state space fitting, which makes it easier for the UAV to learn a priori knowledge and improve the learning rate. On the other hand, a trap escape strategy is proposed to help UAVs get out of traps when they are in trouble. The method has been validated by simulations on four different maps and the authors are satisfied with the results.

Reference [114] proposed an algorithm for collision avoidance decisions in dynamic scenes of UAV flights. Reinforcement learning is used to solve the UAV obstacle avoidance problem in 3D complex environments. The obstacle avoidance process is modeled as a Markov decision process and a structure consisting of a dual joint neural network estimator is introduced as the decision maker. Simulation results show that the UAV can obtain a higher success rate of obstacle avoidance in environments with dynamic obstacles by reinforcement learning training.

Reference [115] applied reinforcement learning based on a proximal policy optimization algorithm to UAV path planning in open space. Tests of the training model showed that the UAV achieved the goal with an 81% success rate, but the authors only considered environmental spaces where static obstacles were present.

The DQN algorithm is a method of approximating the Q-learning algorithm to a value function through a neural network, and the algorithm flow is shown in Figure 25.

Reference [116] combined global path planning and local obstacle avoidance methods, first using Q-learning algorithms to find paths and then applying the local obstacle avoidance system to UAV training by deep Q-learning algorithms in an AirSim simulation environment. The simulation results demonstrate that the weights obtained after training using the DQN algorithm are effective for obstacle avoidance in the simulated environment.

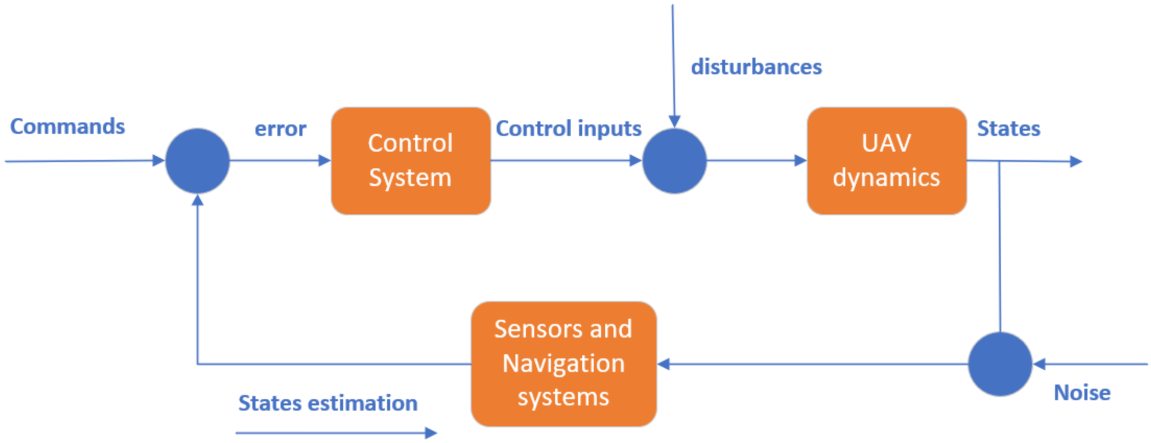

FIGURE 26. UAV control system architecture diagram.

Reference [117] proposed a Q-learning-based planning algorithm to improve the efficiency of single UAV path planning in dense obstacle environments. By constructing a spatial action state offline learning planning architecture, the method achieves fast UAV path planning and solves the highly time-consuming problem of reinforcement learning online path planning. Simulation results show that the path planning time based on the trained Q-table can be reduced from seconds to milliseconds compared with the classical A* algorithm, which significantly improves the efficiency of path planning.

3) METHOD BASED ON DEEP REINFORCEMENT LEARNING

Another class of path planning methods derived from the RL algorithm is the Deep reinforcement learning algorithm, which is currently used extensively for intelligent body path planning. DRL makes full use of the perceptual capability of deep learning and the decision-making capability of reinforcement learning, and makes the system more intelligent in decision- making and control through the process of continuous trial and error in the interaction between the robot and the environment, combined with the evaluative feedback from the environment, to help mobile robots achieve a certain degree of autonomy and intelligence in certain complex and unknown environments.

Reference [118] proposed a deep reinforcement learning-based obstacle avoidance method for UAVs, and designed and analyzed the performance of a deep recursive Q-network with temporal attention, enabling a quadrotor UAV equipped with a monocular camera to autonomously avoid obstacles in unstructured and unknown indoor environments. The key idea of the method is partial observability and how the UAV retains information about the environmental structure to make better navigation decisions. The next extension preparation can integrate SLAM with the proposed OA approach.

Reference [119] proposed a cross-sensor migration learning method based on an asynchronous deep neural network structure to address the difficulty of migration of reinforcement learning strategies from a simulation environment to the real world. A stable primary obstacle avoidance strategy is first trained in a simulation environment by a deep deterministic policy gradient (DDPG) based deep reinforcement learning method; Secondly Enabling cross-sensor migration learning from virtual LiDAR to real monocular vision; Finally, YOLOV3-tiny network and Resnet18 network are introduced to form an asynchronous deep neural network structure. The experimental results show that the method in this paper can effectively improve obstacle avoidance performance in indoor scenes with pedestrians.

A framework based on D3RQN was proposed in [120]. It can guide a quadrotor to achieve autonomous obstacle avoidance on images captured by a monocular camera only. Training and testing results show that D3RQN has better learning efficiency and testing performance compared to other methods such as dual DQN, D3QN and dual DRQN, which need to take moving obstacles into account in the future. Reference [121] proposed a UAV reactive obstacle avoidance method based on LSTM-DDPG for the problem that traditional obstacle avoidance methods are difficult to be applied to complex and uncertain environments with multiple obstacles. The rapid obstacle avoidance of UAV in different complex environments is achieved. However, this paper only discusses UAV reactive obstacle avoidance in two-dimensional space, and designing UAV reactive obstacle avoidance algorithm in three-dimensional space and significantly reducing the training time of neural network will be the direction of subsequent research.

A comparative summary of UAV path planning algorithms based on machine learning is carried out in Table 8.

V. RESEARCH BASED ON FLIGHT CONTROL

After getting the obstacle avoidance path, the UAV needs to rely on the flight control method for the next action. The flight control technique is to generate commands to control the UAV to make various obstacle avoidance maneuvers based on the current UAV's state and the planned obstacle avoidance path. UAVs are subject to interference during the flight from conditions such as sensor noise and drift, strong winds and turbulent air currents, load changes and excessive inclination, all of which can seriously affect the flight quality of the UAV.

Therefore, it is important to study the control techniques of UAVs for the development of the UAV obstacle avoidance field. The goal of the controller should be to minimize the error between the desired state and the estimated state. The current typical flight control methods for multi-rotor UAVs include PID control, LQR control, sliding mode control, and backstepping control. Figure 26 shows the architecture of the UAV control system.

A. RESEARCH ON PID CONTROL

PID control is a traditional control method, which is one of the most successful and widely used control methods. Its control method is simple, requires no preliminary modeling work, and has a clear physical meaning of parameters, which is the main-stream control method for quadrotor UAV applications. The disadvantage of the PID controller is that it is not optimal enough to control more complex objects with large inertia and hysteresis.

A method for autonomous flight in partially unknown indoor environments is presented in [122]. An optimal PID controller based on the proposed multi-objective particle swarm optimization (MOPSO) and accelerated update method is designed and implemented. This accelerated update method allows the use of cascade control methods for path-tracking tasks. However, its effectiveness in dynamic environments is yet to be verified.

Reference [123] addressed the problem that the quadrotor load and its strong coupling characteristics would cause large interference to the flight control performance, a comprehensive analysis of the classical PID system and the fuzzy control PID system was carried out, and the previous method of frequent adjustment of PID parameters was replaced by designing and improving the fuzzy control rule table. MATLAB simulations show that the method can improve the adaptability of PID and reduce the instability of flight attitude control during operation.

Reference [124] proposed a balanced control algorithm combining fuzzy adaptive PID control with expert PID control. Improved balance control of the UAV. Reference [125] In order to improve the obstacle avoidance effect, a PID control algorithm combined with a genetic algorithm is proposed. By establishing the mathematical model of the UAV, the classical PID control algorithm is used to realize the UAV obstacle avoidance, and then the genetic algorithm is used to optimize the control system. The experiment proves that the algorithm has a good obstacle avoidance effect and strong robustness in a low-speed complex environment.

Reference [126] developed trajectory control algorithms using a PID controller that should control the required linear coordinates of the quadrotor UAV over the entire course [127] modeled and simulated the autonomous navigation of a quadrotor system based on obstacle avoidance in Simulink. Two genetic algorithm-based PID controllers were developed for quadrotor altitude and attitude control using integral squared error (ISE) and integral time absolute error (ITAE). Simulations show that the ITAE-based PID controller obtains the best results in terms of altitude control and attitude control.

B. RESEARCH ON LQR CONTROL

LQR, or linear quadratic regulator, is one of the more successful methods being used to control UAVs with a linear system that can be represented by a state space expression, where the objective function is the integral of a quadratic function of the state or control variables. The basic idea is to design the controller according to the corresponding principles while satisfying the constraint that the performance function obtains the optimal value. However, it requires the complete system state and is more computationally intensive than the PID controller.

Reference [128] investigated the design of attitude control loops for small high-speed UAVs in complex flight environments with external disturbances and unmodeled characteristics of the aircraft. A robust servo LQR linear controller is designed for the angular velocity control loop, and then a dynamic inverse PID design is performed based on the angular velocity inner loop. The simulation results prove the effectiveness of the method.

Reference [129] proposed an implementation of an LQR controller and performed experiments in simulation and hardware to demonstrate that the proposed control scheme allows the UAV to accurately reach and track a given trajectory.

Reference [130] implemented three controllers, Smart Flight PID, LQR and State Feedback, the implemented controllers were tested and simulated using NI LabVIEW tools for comparison. While all the implemented controllers gave satisfactory feedback in stabilizing the quadrotor, the comparison showed that the LQR controller had the best performance.

Reference [131] used an LQR controller to control the three attitude angles of a quadrotor UAV for the problem of poor resistance to complex interference problems. The single-loop and multi-loop LQR controllers were tested against wind interference in stage wind and full wind, respectively, to verify the excellent characteristics of the multi-loop LQR controller under complex interference conditions.

C. RESEARCH ON SLIDING MODE CONTROL

Sliding mode control, also known as variable structure control, is a special kind of nonlinear control, the most important feature of which is that the "structure is not fixed". The system performance is completely determined by the sliding mode surface, independent of the object parameters and disturbances of the controlled system. However, the slide control is prone to the problem of control discontinuity and jitter vibration.

Reference [132] proposed a sliding mode control method to design robust flight controllers for small quadrotor UAVs for global stabilization of quadrotor UAVs with uncertain model parameters. Simulation results verified the effectiveness and robustness of the proposed control method, but external disturbances such as wind and collision were not considered.

Reference [133] proposed on the one hand a proportional-integral differential-sliding-mode control (PID-SMC) scheme aiming at finite-time stability and tracking control of a 6-degree-of-freedom UAS in the presence of external disturbances with known boundaries. On the other hand, the upper bound of the external disturbance is considered to be unknown and an adaptive PID-SMC is proposed to estimate the external disturbance. However, the time lag problem of the UAV in the control input is not considered.

Reference [134] proposed a high-precision tracking control algorithm for moving targets in obstacle conditions. The control structure consists of position and attitude controllers, and for position control, a combination of sliding mode control and artificial potential fields is proposed. The simulation results show that the control system has good robustness and tracking performance in the case of motion target tracking and obstacle avoidance.

Reference [135] proposed a neural network-based sliding mode control method for a quad-rotor attitude altitude system. The sliding mode controller is combined with a neural network algorithm to achieve a time-varying sliding surface; the gain is adjusted by back propagation rules. The tracking performance and interference immunity of this method are better than the adaptive sliding mode control only, however, the authors only considered constant disturbances in the quadrotor model, and time-varying disturbances can be considered in the future.

Reference [136] proposed an inner and outer loop control algorithm for the problems of model uncertainty and external wind interference in the attitude control process of quadrotor UAVs. The inner loop is designed as a self-anti-disturbance controller, and the outer loop is designed as a non-singular terminal sliding mode controller to improve the response speed of the system; the simulation results show that the designed controller has high tracking accuracy and good anti-disturbance capability, which can effectively realize the attitude control of quadrotor UAV.

D. RESEARCH ON BACKSTEPPING CONTROL

Backstepping control is one of the most commonly used methods for controller design of nonlinear systems and is more suitable for online control, which can reduce the time of online calculations. The basic idea is to decompose the complex system into multiple subsystems not exceeding the order of the system, and then design partial Lyapunov functions and intermediate virtual control quantities for each subsystem by backward recursion until the entire controller is designed. The backstepping method can handle the effects of a class of nonlinear, uncertain factors and has been shown to have relatively good stability and convergence of errors.

Reference [137] investigated the problem of modeling and attitude stabilization control of a quadrotor UAV, and a nonlinear controller was developed to stabilize the attitude using backstepping control techniques. Future work will emphasize the position or path-tracking control of the quadrotor even in the presence of external disturbances [138] proposed a new stabilization control strategy based on the fractional order theory using the backstepping sliding mode method. The simulation results show that the new control method is robust to different complex trajectories under disturbances.

Reference [139] designed a novel nonlinear robust controller in order to reduce the effect of different external disturbances on quadrotor flight. A quadrotor flight controller was designed using the classical backstepping control (CBC) method, and it was demonstrated using Lyapunov stability theory that the nonlinear system using this controller is asymptotically stable in the absence of external disturbances. The simulation and real flight results show that the proposed strategy has good robustness and has some practical application value.

Reference [140] considered the control problem of quadrotor orientation and position in the presence of parameter uncertainties and external disturbances. A robust ABFTSMC is designed to control the attitude loop by combining backstepping control and fast terminal sliding mode control. By comparing the performance with various methods such as classical sliding mode control, integral backpropagation and second-order sliding mode control, the proposed controller has higher performance and good interference immunity.

VI. DISCUSSION

Although many researches have been conducted to propose solutions to the UAV obstacle avoidance problem, it is worth noting that there are still a large number of unresolved difficulties that require additional considerations and new solutions. This section will provide a discussion and analysis of the different challenges and future directions for the development of UAV indoor obstacle avoidance technology.

A. CHALLENGES OF INDOOR OBSTACLE AVOIDANCE

1) SENSOR ERROR

Autonomous uav control systems should analyze the conditions that ensure obstacle avoidance, especially when dealing with uncertainty, since there are always ac-curacy and velocity errors in the sensors. While some literature has given conditions for collision avoidance, robustness is not discussed and it is important to consider the effect of sensor error on collision avoidance. Thus, The Modeling Of Airborne Sensors Should Be Further Refined In The Future, And Corresponding Obstacle Information Processing Strategies Should Be Designed For Sensors With Different Characteristics.

2) MODEL BUILDING

Most of the existing obstacle avoidance techniques assume a simplified uav and experimental environment, but in real life, the environment and obstacles are very variable. The modeling of complex environments with most u-shaped and irregular obstacles, as well as the dynamics of uavs in confined spaces such as indoors and caves, are also important to be studied.

3) WORST-CASE CONSTRAINTS

Usually, the minimum safe distance is a mandatory constraint in the obstacle avoidance algorithm. this requires the knowledge of the worst-case safety condition, i.e., the uav is able to come to a complete stop before colliding with an obstacle. In addition, distance errors caused by communication delays should be considered within a safe distance, and the obstacle avoidance technique must be able to reprogram the path while detecting sudden obstacles.

4) CONTINUITY CHALLENGE

The battery capacity of a uav is a key factor in achieving online obstacle avoidance tasks. As the battery capacity increases, its weight will increase, which will cause the uav to consume more energy for obstacle avoidance missions. How to develop hybrid batteries to improve the range of uavs for missions is a major challenge that needs to be studied.

5) CONTROL METHOD

The current control methods can be divided into two categories, linear and non-linear, and how to balance the robustness and efficiency of control methods is a key factor worth studying.

6) OPTIMIZATION CHALLENGES

Optimization pursues the goal of optimality or suboptimality, which requires a combination of the uav's constraints and environmental information, and minimizes the cost of the cost.

B. FUTUR PROSPECT

1) MULTI-SENSOR INFORMATION FUSION

Although some scholars have already explored the research of sensor combination for obstacle avoidance, the research of fusion of heterogeneous information from multiple sources is still not deep enough. The Combined Use Of Environmental Information Obtained From Different Sensors Can Greatly Reduce The Environmental Detection Time And Achieve More Comprehensive Perception And Recognition, Thus Improving The Efficiency And Success Rate Of Obstacle Avoidance.

2) HYBRID ALGORITHM OBSTACLE AVOIDANCE

Due to the fact that uav path planning is an np problem, current uav path planning obstacle avoidance algorithms have gradually tended to integrate with other algorithms to achieve optimal path generation by mixing multiple algorithms together. Hybrid Algorithms Can Combine The Advantageous Characteristics Of Different Algorithms And Solve The Problem That Individual Algorithms Usually Cannot Obtain The Best Results Alone.

3) PATH TRACEABILITY

Most of the current path planning obstacle avoidance methods only consider theoretical innovations and advantageous combinations, and not much consideration has been given to whether the planned obstacle avoidance paths can actually be accurately tracked by uavs. Therefore, it is necessary to further consider the uav controller characteristics in path planning in the future, and it is important to improve the uav path tracking accuracy for obstacle avoidance tasks.

4) THREE-DIMENSIONAL OBSTACLE AVOIDANCE

Current obstacle avoidance research has analyzed the 2d collision avoidance problem in depth. however, most of the real application scenarios are in dynamic 3d environments. There is still relatively little exploration of 3d obstacle avoidance path planning methods in complex environments, and the common idea of dimensionality reduction is not flexible enough to cope with complex 3d environments. Hence it is necessary to further develop 3d obstacle avoidance algorithms with higher accuracy and accuracy detection in the future.

5) FORMATION COOPERATION

Single uavs are often unable to efficiently complete obstacle avoidance-related tasks due to their loads and their own characteristics. The introduction of uav formation into the field of indoor obstacle avoidance can fully share information among uavs, play the role of group intelligence, and greatly improve work efficiency.

VII. CONCLUSION

The Obstacle Avoidance Effect Is A Key Indicator Reflecting The Level Of Uav Indoor Autonomous Control As Well As Intelligence, And As The Core Module Of Uav Mission Planning, The Research Of Obstacle Avoidance Technology Has An Irreplaceable Role. In This Paper, By Considering The Uav Obstacle Avoidance Problem, The Process Of Obstacle Avoidance Is Split Into Several Major Steps, And The Different Steps Are Reviewed And Analyzed Respectively.

Since uavs must have the ability to sense their surroundings in order to achieve indoor autonomous flight, this paper first introduces the sensors commonly used for uav indoor environment sensing and their characteristics. Secondly, the perception detection obstacle avoidance methods are classified into three major types based on vision, lidar and multi-sensor fusion according to their working principles and their characteristics are compared. Then this paper reviews the classical path planning obstacle avoidance methods and their improvements in the uav field, and classifies them into four main categories according to the different principles of the methods. After that, the development and improvement of the current representative uav control technologies are reviewed.

In addition, this paper critically analyzes the challenges faced in the development and application of indoor uav obstacle avoidance techniques and suggests possible future research directions and development prospects. We hope that this review will be helpful to those studying uavs, especially those interested in uav obstacle avoidance tasks. we believe that with the innovation of various theories and the iterative development of technologies, uav obstacle avoidance technologies and applications will rise to a new level.

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JUNLIN LI received the B.S. degree in Internet of Things engineering from the Sichuan University of Arts and Science, Dazhou, China, in 2020. He is currently pursuing the M.S. degree with the Sichuan University of Science and Engineering, Yibin, China. His research interests include UAV path planning and obstacle avoidance.

XINGZHONG XIONG received the B.S. degree in communication engineering from the Sichuan University of Science and Engineering (SUSE), Zigong, China, in 1996, and the M.S. and Ph.D. degrees in communication and information system from the University of Electronic Science and Technology of China (UESTC), in 2006 and 2009, respectively.

He is currently a Professor with the School of Automation and Electronic Information, SUSE. His research interests include artificial intelligence, wireless communications, and intelligent signal processing.

YUEHAO YAN received the B.S. and M.S. degrees in computer science and software engineering from the University of Electronic Science and Technology of China (UESTC), in 2001 and 2008, respectively, and the Ph.D. degree in advanced manufacturing (aviation) from Northwestern Polytechnical University, China, in 2022.

He is currently a Professor with the School of Automation and Electronic Information, Sichuan University of Science and Engineering. His research interests include UAV obstacle and UAV navigation and control.

YUNHONG YANG received the B.S. degree in communication engineering from the Sichuan University of Science and Engineering, Yibin, China, in 2021, where he is currently pursuing the M.S. degree. His research interests include UAV formation and path planning.