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Research on the Development of Obstacle Avoidance Control Technology for Unmanned Aerial Vehicles

Jie Xu

School of Communication and Electronic Information Engineering, Shanghai University, Shanghai, China

caomeishayu@shu.edu.cn

Abstract. This systematic literature review sorts out the existing research achievements in the field of unmanned aerial vehicle (UAV) control and path planning. The research content includes the analysis of the control system of individual UAVs, various innovative fusion algorithms, as well as the latest achievements introduced in the control framework and intelligent decision-making algorithms for UAV swarm coordination. This review provides a detailed analysis of the core development trends, existing challenges and technological advancements in the field of UAV control and path planning. It also delves deeply into the improvement of algorithms based on traditional PID control, represented by natural heuristic algorithms, as well as the enhancement of algorithms by multi-modal fusion algorithms and the multi-terminal introduction of decision-making systems. Furthermore, this paper further combines the current hot topic of coordinated obstacle avoidance in UAV swarms, identifies the challenges faced by UAV swarms and the directions for technological breakthroughs, and then focuses on analyzing the methods that intelligent decision-making algorithms can adopt in a series of different application scenarios and environments. This systematic literature review not only comprehensively presents the structural framework and research status of obstacle avoidance control and path planning for individual UAVs and UAV swarms, but also clearly follows up on the ideas and characteristics of various innovative algorithms, providing a reference for future research and development in this field.

Keywords: Unmanned aerial vehicle, multi-modal fusion algorithm, drone control

1. Introduction

In recent years, the drone industry has witnessed vigorous development. As drones are widely used in various industries such as industrial inspection, agricultural irrigation, logistics distribution, aerial photography, land surveying and mapping, and military strikes [1], their unique functionality and low price have made drones widely favored by people. According to data from the Federal Aviation Administration (FAA) of the United States, the number of registered drones in the United States is expected to increase to 955,000 by 2027. Meanwhile, the reform of low-altitude airspace in China this year has also driven drones from single isolated airspace to low-altitude integrated airspace.

Among the various technologies applied in unmanned aerial vehicles (UAVs), the most crucial ones are the algorithmic path planning and the active obstacle avoidance control system. These two

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can be regarded as the cornerstones of the UAV field. The path planning and obstacle avoidance system of UAVs ensures that unmanned aircraft can efficiently and autonomously complete flight tasks in complex terrain and climate environments. Its essence is to first perceive the environment, then through path planning, be responsible for finding the optimal travel route for the UAV, while at the same time, the obstacle avoidance system detects in real time the existing or potential collision dangers on the path and avoids them promptly. At the same time, it is fed back to the path planning to make better decisions in real time [2].

Over the past decade or so, the UAV control system has undergone multiple updates and iterations. Overall, it has evolved from the traditional PID (Proportional-Integral-Derivative) control to the combination of intelligent algorithms represented by machine learning or reinforcement learning with PID. From end-to-end applications of individual machines to the collaborative cooperation among drone swarms, its application scope has also expanded from outdoor open scenarios to indoor restricted scenarios or the collaborative obstacle avoidance of drone swarms in low-altitude integrated airspace. Early path planning was based on classical optimization algorithms. Graph search methods such as Dijkstra's algorithm and A * algorithm achieved the retrieval of the shortest path in a simple static environment through raster modeling [3,4]. However, due to their overly idealized models, this often leads to a sudden increase in computational complexity for drones in complex environments and dynamic spaces, thereby affecting their actual performance. However, potential field methods such as the artificial potential field method (APF) and the velocity obstacle method (VO) achieve real-time obstacle avoidance by simulating the gravity-repulsive force mechanism [2]. In most cases, this is superior to relying solely on image algorithms, as it can make the path smoother. Nevertheless, the local optimal solution trap and the problem. As the application of UAVs becomes increasingly widespread, the requirements for obstacle avoidance and path planning in their application environments are growing day by day. Traditional algorithms are gradually struggling with handling dynamic obstacles, complex environments, and real-time response issues. Therefore, emerging methods such as intelligent optimization and machine learning are gradually being attempted. In addition, with the innovation of sensor technology in recent years, the combined application of sensors such as LiDAR, RGB-D cameras, binocular vision, and MIMO radar also provide hardware support for high-dimensional environment modeling and multi-source information fusion, building a more reliable perception foundation [5]. In the past two years, with the advent of the AI era, the explosion of artificial intelligence and machine learning technologies has also brought revolutionary changes to the path planning and obstacle avoidance of drones. Deep reinforcement learning achieves autonomous decision-making and strategy optimization of the system in a dynamic environment through the interaction and trial and error between intelligence and the environment. Large models represented by convolutional neural networks can detect and identify obstacles more accurately, improve the perception accuracy and understanding of UAV agents in complex scenarios, and significantly enhance the robustness of the system [6,7].

In addition, with the upgrading of application demands, the performance of individual UAVs has gradually reached a bottleneck. Driven by technological revolution and the market, the common and collaborative use of multiple UAVs has become a hot topic. This has also led to research on the collaborative path planning and obstacle avoidance of UAV swarms, distributed control, consensus algorithms, and multi-agent collaboration technologies in the task allocation of UAVs. It has played a significant role in breaking through problems such as trajectory planning and collision avoidance, greatly enhancing the execution efficiency of complex tasks [3,8].

This paper will draw on the existing research achievements. In Section 2.1, it will systematically review the development history, core technologies and application scenarios of traditional UAV path

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planning and obstacle avoidance control systems in the past. In Section 2.2, it will focus on introducing the innovative development of UAV path planning and obstacle avoidance control systems based on artificial intelligence and machine learning technologies after the introduction of multi-sensor combinations. In Section 3, the technologies currently applied in the cooperative control of UAV swarms, as well as the possible bottlenecks and future research directions that the current technologies may face, are explored to provide references for promoting the progress and continuous innovation of UAV obstacle avoidance control technology.

2. Analysis of the control system of rotor craft unmanned aerial vehicles

After more than a decade of vigorous development, unmanned aerial vehicles, especially rotary-wing drones, have developed a wide variety of obstacle avoidance control systems and algorithms to deal with various situations. This section will be divided into two parts for analysis: traditional control systems and multi-modal fusion algorithms, and multi-terminal introduction of decision-making systems. Among them, the traditional control system mainly consists of improved algorithms based on PID control and potential field methods. The multi-terminal introduction of multimodal fusion algorithms and decision-making systems mainly focuses on the application of multi-sensors and machine learning.

2.1. Analysis of traditional control systems

PID control corrects system errors through the coordinated operation of three parameters: proportional (Kp), integral (Ki), and differential (Kd). To meet the dynamic requirements of different UAV application scenarios, related research has achieved performance upgrades of PID control by integrating feedforward terms, intelligent optimization algorithms, observers, fuzzy control and other technologies and logics.

The innovative fusion feedforward method (FF-PID) proposed by Saman Yazdannik et al. achieves real-time quality fluctuations by adding feedforward terms and calculating the control input in advance based on the derivatives of the expected position/attitude variables. The core part of its PID control utilizes the rotational speed/attitude information of the propeller to ensure the stability of the foundation. This method consists of two modules: attitude control and position control. The former adjusts the roll angle, pitch amplitude and yaw angle through the Kp-Kd division law, while the latter calculates the command acceleration through PID feedback, thereby achieving more precise maintenance of three-dimensional position and heading angle [9].

Intelligent optimization algorithms are often developed to adapt to a specific scenario, specifically designed to enhance performance within that scenario. The following text takes two natural heuristic meta-heuristic algorithms, namely the African Vulture Optimized PID Control Algorithm (AVOA) developed for the UAV wind power generation inspection system and the Particle Swarm Optimization Algorithm (PSO) developed for multi-waypoint trajectory tracking, complex route flight (such as obstacle avoidance and formation flight), and multi-UAV cooperative navigation, as examples to explore [10,11].

The PSO proposed by Eric X. Rodriguez et al. to simulate the foraging behavior of bird flocks takes "individual optimum (Pbest) + global optimum (Gbest)" as the core logic and updates the particle position through the velocity-position iterative formula. The exploration and development are balanced by relying on inertia weight (w), cognitive weight (c1), and social weight (c2), optimizing 12 parameters of 4 types of PID controllers including thrust, yaw, and x/y position. The fitness function integrates overshoot, adjustment time, and trajectory error. It is suitable for general

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scenarios with "position control priority" such as hovering, complex route flight and multi-aircraft cooperative navigation.The core of the order-optimised PID method proposed by Zaidan Zyadat et al. lies in capturing in real time the external disturbances and actuator faults that the PID is difficult to adapt to through the observer, and integrating the estimated values as compensation terms into the control input to reduce the error correction burden of the PID, thereby improving the control accuracy and robustness. The main problem it targets is the core limitations of the PID controller, such as the lack of sufficient active adaptability to unknown disturbances like wind force and actuator failures, such as those of elevators. By predicting these interference terms in advance and directly counteracting their influence through feedforward compensation, the PID can be made to focus more on the core position. The correction of attitude errors, rather than being distracted by countering external disturbances and faults [12]. The core of the hybrid fuzzy PID control proposed by Sairoel Amertet et al. is to adopt the nested structure of "outer loop fuzzy decision + inner loop PID execution", and to dynamically adjust the proportional (Kp), integral (Ki), and differential (Kd) parameters of the PID controller in real time through fuzzy rules. This can thus solve the pain points of traditional PID, such as fixed parameters and poor adaptability to nonlinear systems and dynamic disturbances [13].

The above are four currently mature and common improvement schemes that rely on traditional PID control methods based on their respective requirements. In addition, there is also the predictive artificial potential field method proposed based on the potential field method. Its core lies in the integration of future state prediction and the trajectory generation logic of traditional artificial potential fields (APF). By predicting the future trajectory of the unmanned aerial vehicle and the movement trend of obstacles, generate smooth obstacle avoidance trajectories in advance, thereby solving problems such as obstacle avoidance delay, trajectory oscillation, and local minima in traditional artificial potential fields.

In a nutshell, the main idea is to dynamically change the originally fixed parameters through various means, making the movement trajectory of the unmanned aerial vehicle more flexible and smoother, enabling it to complete tasks more efficiently and reduce the safety risks caused by collisions. However, all these schemes have more or less flaws. FF-PID does not consider sudden disturbance situations and has insufficient adaptability to uncontrolled load scenarios. At the same time, when confronted with multi-processor failures and strong turbulence coupling, it often fails to handle them correctly. The core issues can actually be summarized into three points: First, the limitations of a single sensor in data detection; second, the limitations of fixed algorithms in terms of parameter adjustment capabilities; third, the insufficiency of computing power caused by the simultaneous influx of a large amount of data. Therefore. With the innovation of sensor types and technologies in the past two years and the maturity of machine learning technology, multi-modal fusion algorithms and multi-terminal introduction analysis of decision-making systems have been introduced into the obstacle avoidance control system of unmanned aerial vehicles.

2.2. Multi-modal algorithm and multi-terminal analysis of decision system

With the development of intelligent perception and edge computing technologies, the core architecture of "multimodal sensor fusion perception + machine learning-driven multi-terminal decision-making" has emerged. This model, through complementary perception capabilities and autonomous learning decision-making logic, can significantly enhance the system's adaptive ability and security reliability in complex and harsh environments. This further resolves the predicaments faced under the previous traditional optimization approach.

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Firstly, at the sensor level, due to the fact that a single sensor may be affected by the environment, have detection blind spots, or be disturbed, resulting in insufficient ranging accuracy. At the same time, in the case of identifying complex objects, the modeling of a single sensor may also have significant deviations, thereby triggering obstacle avoidance safety risks. Therefore, with the improvement of computing power, multi-sensor fusion has become a very good improvement solution.

Secondly, machine learning drives multi-terminal decision-making through mechanisms such as model optimization, multi-terminal collaboration, and environment adaptation. The cloud utilizes sufficient computing power to complete the pre-training of general models and environment modeling. Edge servers accelerate model training in complex environments through parallel computing and task splitting. Airborne edge devices achieve low-latency real-time obstacle avoidance decision-making by leveraging lightweight models and reasoning optimization techniques. This multi-terminal collaborative mode breaks through the computing power and latency limitations caused by relying on a single device, and can also adapt to the corresponding scenarios by relying on the generalization ability of the model, matching the core demand of unmanned aerial vehicles' autonomous obstacle avoidance in complex environments. However, the introduction of machine learning has indeed brought about some new problems, such as long training time and high inference latency.

PATRICK McENROE et al. achieved knowledge reuse by proposing transfer learning (TL). The basic logic is to first train the basic model in a general environment (Env0) to obtain general feature extraction capabilities, such as convolutional layer weights. When fine-tuning the target environment (Env1), freeze the core feature extraction layers, such as the first two convolutional layers, and only update the fully connected layers to avoid training the model from scratch. The advantage of doing so is that it reuses the existing knowledge under the premise that there are common features in multiple environments, significantly reducing repetitive learning, lowering the exploration cost after model initialization, and also improving the generalization ability of the model. The only limitation lies in that this solution can only be used when there are commonalities in the environment. Similarly, TENG Fei et al. achieved an improvement in algorithm efficiency through algorithm structure optimization and modification of the reward mechanism. Firstly, they extracted environmental temporal features by fusing the LSTM network, such as the movement trend of dynamic obstacles, to reduce ineffective exploration and enable the model to capture the optimal strategy pattern more quickly. Then, the Control Obstacle Function (CBF) is introduced to prevent the model from falling into cancelation iterations due to collision penalties through safety constraints, thereby accelerating its convergence speed. This solution is more applicable in a dynamic environment and can significantly enhance the effective learning efficiency of each iteration [14]. More importantly, Patrick McEnroe relies on the establishment of multi-edge servers and a distributed communication architecture. By splitting large and complex environments into multiple small environments and conducting parallel training with multi-edge servers to share the training pressure. It can shorten the overall training time when facing an entire complex task, thereby supporting the rapid deployment of large-scale environments. The goal of task splitting has been achieved [15].

3. Multi-UAV cooperative control system

3.1. Analysis of the control framework

The core objective of a single UAV is to ensure safe path tracking in a dynamic environment. Its obstacle avoidance control mainly adopts a serial architecture of "perception - decision-making - control", and the core of its control logic focuses on the interaction and balance between its own movement trajectory and local obstacle avoidance. The transformation from single-machine control to cluster control mainly manifests in three dimensions: Firstly, the control target dimension has expanded from 1 dimension to N dimension (cluster scale), and cluster control must simultaneously meet global tasks such as individual obstacle avoidance, no collision within the cluster, formation maintenance, collaborative monitoring, and target tracking. Secondly, information interaction has shifted from single-machine autonomy to distributed collaboration. The cluster achieves information sharing through communication networks, enabling information such as location and obstacle detection to form a collaborative perception advantage. In terms of control logic, group decision-making focuses more on the balance between local obstacle avoidance and global formation goals, rather than single-machine decision-making, which only considers its own local environment. This section will discuss the distributed collaborative control framework, the leader-follower control framework, the hierarchical fusion control framework, and the event-triggered control framework.

The fusion algorithm of the improved 3D vector field histogram (3D VFH) and the improved Dynamic Window method (DWA) proposed by Xinhua Wang et al. is a typical representative of the distributed cooperative control framework. Under this algorithm, each unmanned aerial vehicle builds a local 3D environment model through OctoMap. Candidate paths are generated by using the improved DWA, and the optimal path is screened by combining the azimuth and pitch Angle constraints of 3D VFH +. Distributed cooperative obstacle avoidance is achieved through preset formation protocols, such as maintaining relative positions. The advantages of this framework lie in its strong robustness (no single point of failure) and good scalability (no need to reconstruct the framework when adding or removing drones), making it suitable for unknown environments and large-scale clusters. However, the drawback is that it relies on the connectivity of the communication network. When the communication delay is large or the packet loss rate is high, the formation consistency is easily affected [7]. Similarly, the leader adopted by Haonan Li et al. generates the global trajectory based on MPC, and the followers track the leader and avoid obstacles through adaptive APF. The leader adopted by Rui Hao et al. is responsible for path navigation within the tunnel, and the followers achieve a dynamic balance between tracking the leader and avoiding obstacles through dynamic weight distribution. Essentially, they all adopt the Leader-Follower framework. This framework designates one or more leaders, with the rest being followers. The leaders are responsible for overall path planning and obstacle detection, while the followers maintain formation by tracking the positions and postures of the leaders and avoiding local obstacles. Its advantages lie in the simplicity of control logic and good formation consistency, and it performs extremely well in structured environments such as tunnels and flight routes. The drawback is that once the leader malfunctions or fails to sense, the performance of the entire cluster will significantly decline.It is worth mentioning that Rui Hao et al. also introduced the elastic formation deformation coefficient and the leader deceleration adaptation mechanism in the paper. When the followers face obstacles or fall behind, the leaders will appropriately decelerate, and the followers will dynamically adjust the formation position. This greatly improves the fault tolerance and flexibility of the frame [16].

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The event-triggered framework is an optimized solution for resource-constrained environments. Rui Hao et al. adopted this framework in their research on the event-triggered pulse formation control of UAV swarm cooperative obstacle avoidance in tunnel environments. Maintaining the current control instructions when there are no events significantly reduces communication and computing overhead. This framework has a high resource utilization rate and is extremely suitable for communication-restricted environments such as tunnels and remote areas [17].

Based on the above framework, it can be seen that the common characteristics of the UAV swarm obstacle avoidance control framework are threefold: The first is multi-objective coupling optimization, that is, it must handle multiple tasks such as obstacle avoidance, formation, and path tracking simultaneously; The second is to take into account the comprehensive impact of constraints from multiple aspects such as movement, communication, and the environment. The third is that they are mostly hybrid architectures, which can simultaneously address the weaknesses of poor scalability of pure centralized architectures and weak consistency of pure distributed architectures. During the development process, it can also be observed that the perception-communication-control of the control framework is gradually moving towards integration, and its adaptability and robustness have also been enhanced.

3.2. Intelligent decision-making algorithms are introduced

In the previous section, we discussed the control framework, and in this section, we will focus on the intelligent decision-making algorithm. The intelligent decision-making algorithm for obstacle avoidance in UAV swarms is the core of the control framework, responsible for generating the optimal path and control instructions in complex environments. Its performance is directly linked to the safety, efficiency and task completion degree of the swarm. In recent years, a series of intelligent decision-making algorithms based on the integration of traditional algorithm improvements, machine learning, and perception-decision-making integration have been proposed around the three major goals of constraint compatibility, dynamic adaptation, and collaborative optimization. This section will review their innovation points, common features, and comparisons of advantages and disadvantages.

Traditional path planning and obstacle avoidance algorithms remain the basis for cluster decision-making due to their clear principles and high computational efficiency. However, through improvements such as cross-algorithm integration, constraint adaptation, and dimension expansion, the collaborative capabilities of the cluster can be better enhanced. Xinhua Wang et al. proposed the "Fusion of 3D VFH + and Improved DWA" algorithm, which solved the dimensional limitations and performance defects of traditional algorithms. The improvement of DWA focuses on the optimization of the evaluation function. By introducing the target distance to correct the azimuth angle, integrating the dynamic weight of A *, and adding a rotation cost function, the problems of weak target guidance, path oscillation, and excessive rotation angle in the standard DWA have been solved. The introduction of 3D VFH + extends two-dimensional obstacle avoidance to three-dimensional space. Combined with OctoMap's three-dimensional environment modeling, it achieves obstacle perception in complex terrains. The integration of the two adopts a distributed architecture, with each unmanned aerial vehicle independently executing algorithms and achieving coordination through preset formation protocols, which takes into account both decision-making efficiency and coordination [8].

Haonan Li et al. integrated Model Predictive Control (MPC) with adaptive APF, leveraging the advantages of MPC in handling multi-constraint optimization and APF in rapid obstacle avoidance: the rolling optimization feature of MPC is adapted to the dynamic environment of the cluster and

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can explicitly handle physical constraints such as speed and overload. Adaptive APF solves the problems that traditional APF is prone to fall into local optimum and saturation of repulsive force near the target point by introducing adjustment factors of target distance and obstacle distance. The algorithm integrates collision avoidance within the cluster and external obstacle avoidance into the cost function of MPC, achieving unified decision-making for trajectory tracking, formation maintenance and obstacle avoidance [16]. Based on the traditional optical flow awareness and pulse control, Rui Hao et al. proposed a special improvement strategy for tunnels: The sectoral optical flow model divides the perception domain into 8 sectors, improving the directionality and accuracy of obstacle recognition in tunnels; The combination of pulse control and event triggering enables rapid response in resource-constrained environments and avoids the high overhead problem of traditional periodic control [17].

In addition to integrating traditional algorithms, the application of machine learning, especially reinforcement learning, is also a very good improvement idea. Reinforcement learning (RL/DRL) has become an important direction for cluster decision-making due to its powerful environmental adaptation and optimization capabilities. Research focuses on aspects such as reward function design, algorithm adaptation, and integration with traditional algorithms.

Changheng Wang et al. proposed an adaptive weighted path tracking algorithm based on DDPG. The innovation lies in the design of the reward function: this function considers both distance error and speed error simultaneously, and its weight is dynamically adjusted with the distance error: distance optimization is prioritized when the distance error is large, and speed matching is prioritized when the error is small. This reward function resolves the problems of the traditional DRL reward function being single and the difficulty in balancing tracking accuracy and speed stability. The algorithm adopts a strategy of single drone training and multiple drones' reuse. It achieves cluster collaboration through virtual following target (VFT) allocation, eliminating the need for retraining for different cluster sizes and enhancing scalability. They also designed an untrained online obstacle avoidance strategy to avoid the sparse reward problem caused by integrating obstacle avoidance into the DRL reward function. When the obstacle distance is less than the safety threshold, the obstacle avoidance control instruction is directly generated through the repulsive force vector without the need to retrain the model, which reduces the decision-making complexity and improves the dynamic environmental adaptability [18].

Liang Lu et al. reviewed the multimodal perception fusion strategies in non-cooperative environments, providing a perception basis for cluster decision-making: Visual sensing (RGB-D, event camera) has low cost and rich information, but is affected by illumination; LiDAR has high precision and strong anti-interference ability, but it is heavy and consumes a lot of power. Radar and ultrasonic waves are suitable for harsh environments, but their accuracy is limited. In cluster decision-making, the adoption of multimodal fusion can complement each other's advantages, enhance the robustness of obstacle detection, and provide more reliable environmental information for decision-making [19].

Based on the above algorithmic innovations, it can be seen that multi-algorithm integration has become the mainstream. Existing research generally adopts the "traditional algorithm + improvement" or "multi-algorithm hybrid" model, giving full play to the complementary advantages of various algorithms. Meanwhile, due to the high cost and large delay in obtaining global information, cluster decision-making is mostly based on local information collaboration. Global behavior consistency is achieved through consensus mechanisms or preset protocols, avoiding the scalability bottleneck of centralized decision-making. Dynamic adaptability and robustness enhancement: Additionally, algorithms generally introduce adaptive mechanisms to address

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environmental dynamic changes such as movement obstacles, position errors, and communication constraints, thereby improving decision-making reliability in complex environments. Finally, all algorithms prioritize obstacle avoidance and internal collision prevention within the cluster as their top priorities, while also taking into account formation maintenance and path tracking accuracy. As shown in Table 1 below, the characteristics and advantages and disadvantages of intelligent decision-making algorithms can be classified accordingly.

Although intelligent algorithms have undergone considerable research, the existing algorithms still have the following key issues: First, the balance between computational complexity and real-time performance: As the cluster scale expands, the decision space grows exponentially, and the real-time performance of algorithms such as MPC and DRL is difficult to guarantee. Further optimization of algorithm complexity is needed, such as through distributed computing and model simplification. Second, the ability to handle uncertainties is insufficient: The modeling and response to uncertainties such as environmental dynamic changes, Agent state errors, and communication delay, packet loss are still inadequate, which can easily lead to a decline in decision robustness. Third, the contradiction between universality and specificity: Algorithms optimized for specific environments have poor universality, while general algorithms have insufficient performance in complex and specialized environments. It is necessary to develop a universal decision-making framework that adapts to the environment. Fourth, it is difficult to achieve collaboration in large-scale clusters: Most existing algorithms are suitable for small-scale clusters, and the consistency of collaboration and resource overhead in large-scale clusters remains a challenge.

Table 1. Comparison of the advantages and disadvantages of intelligent algorithms

Algorithm Type	Representative Algorithms	Advantages	Disadvantages	Applicable Scenarios
Traditional Algorithm Fusion and Improvement	3D VFH+-Improved DWA	High computational efficiency, good real-time performance, clear principles	Weak global optimization capability, dependent on parameter tuning	Unknown environments, large-scale clusters, real-time obstacle avoidance
	MPC + Adaptive APF	Strong constraint handling capability, smooth trajectory	High computational complexity, real-time performance affected by cluster scale	Structured environments, high-precision trajectory tracking tasks
Reinforcement Learning	DDPG Adaptive Weight Path Tracking	Strong environmental adaptability	High training cost, sparse reward problem	Dynamic environments, complex task scenarios
Perception-Decision Integration	ISAC + Variable Formation Perception	High perception accuracy, low communication overhead	Dependent on dedicated hardware (ISAC), high algorithm complexity	Communication-constrained environments, high-precision obstacle avoidance tasks
Hierarchical/Distributed Decision-Making	NSB Hierarchical, Distributed 3D VFH+	Good multi-objective coordination, strong scalability, high resource utilization	Complex protocol design, additional guarantee required for consistency	Large-scale clusters, multi-task coupling scenarios
Specialized Environment Optimization Algorithm	Tunnel Event-Triggered Impulsive Control	Good adaptability strong robustness	high transplantation cost	Narrow and complex environments,

4. Conclusion

This paper focuses on the research of obstacle avoidance by UAVs and the collaborative control of multiple UAVs. It systematically discusses the basic applications of traditional control methods and the innovative breakthroughs of modern intelligent algorithms, and constructs a complete technical system from independent obstacle avoidance by a single UAV to collaborative operation by multiple

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UAVs, providing theoretical support and practical reference for the autonomous operation of UAVs in complex scenarios.

Its proportional-integral-differential closed-loop regulation mechanism can quickly counteract minor external disturbances, ensuring flight stability. The artificial potential field rule achieves an intuitive integration of obstacle avoidance and target guidance by simulating the mechanical model of "gravity-repulsive force", with low computational complexity and rapid response. It is suitable for real-time obstacle avoidance in simple, structured scenarios. However, the limitations of both are also quite significant: PID control relies on precise dynamic models, the parameter tuning process is cumbersome, and it has insufficient adaptability when facing dynamic obstacles and complex disturbances. The artificial potential field method is prone to fall into a local optimum due to the superposition of multiple obstacle potential fields, and has weak modeling ability for irregularly shaped obstacles, making it difficult to meet the obstacle avoidance requirements in complex environments. These limitations have driven the iterative upgrade of control algorithms, providing a practical basis for the improvement of traditional methods and the integration of intelligent algorithms.

In response to the performance bottleneck of single UAV obstacle avoidance and the complex requirements of multi-UAV collaborative control, this paper further explores multi-dimensional optimization paths. At the level of traditional algorithm improvement, by integrating fuzzy control, using observers to increase feed forward, simulating the foraging logic of bird flocks and other algorithms, the online dynamic adjustment of PID parameters is achieved, enhancing the system's adaptability to environmental changes. Through the predictive artificial potential field method, the local optimum problem of the artificial potential field method has been solved, and the ability to handle complex obstacles has been enhanced. At the application level of intelligent algorithms, deep reinforcement learning (DRL) has become the core breakthrough point. The algorithm learns the optimal strategy through autonomous interaction with the environment without relying on precise models, effectively addressing the uncertainties of dynamic and unstructured environments. The introduction of technologies such as transfer learning and parallel training with environment splitting has significantly shortened the training cycle of DRL models. Combined with low-latency inference at the edge, it provides the possibility for engineering deployment. At the system architecture level, the integration of perception and decision-making has become a core trend. Multi-modal sensor fusion provides high-precision environmental perception input, while machine learning models achieve end-to-end optimization of perception feature extraction and decision-making instruction generation. It has broken through the traditional modular barrier of "perception - decision-making - control", enhancing the collaborative efficiency and robustness of the system.

In the future, there is still broad room for development in the technology of obstacle avoidance and cooperative control of unmanned aerial vehicles. In terms of algorithm optimization, it is necessary to further enhance the sample efficiency and generalization ability of intelligent algorithms to address the issue of rapid self-adaptation in dynamic and complex environments. In terms of system deployment, efforts should be focused on the design of low-power and lightweight models to achieve efficient adaptation of algorithms to on-board edge devices. In terms of application expansion, it is necessary to enhance the multi-scenario adaptation capability to meet the personalized demands of different scenarios, such as power inspection, emergency rescue, and low-altitude logistics. In terms of technological integration, it is necessary to deepen the collaboration between traditional algorithms and intelligent algorithms, and combine multi-modal perception, edge computing, 5G communication and other technologies to build a more reliable, secure and intelligent UAV control system. With the continuous evolution of technology, UAVs will gradually

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make a leap from "auxiliary operations" to "autonomous operation", providing stronger technical support for the intelligent upgrade of various industries.

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