Proceedings of the 7th International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/2027.38472

Autonomous Obstacle Avoidance for UAVs: Algorithms and In-Depth Case Studies

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Abstract. Autonomous obstacle avoidance is crucial for safe and efficient UAVs (unmanned aerial vehicles) operation in complex low-altitude environments in a wide range of applications, including logistics, infrastructure inspection, agriculture and emergency response. In this paper, some of the prominent UAV obstacle avoidance methods such as A* and D* search algorithms, artificial potential field methods, deep reinforcement learning and multi-sensor fusion are reviewed. Their fundamental concepts, common enhancements, advantages and disadvantages and use cases are contrasted. Search-based methods are good at giving an explanation for the planning process and the plans are reliable globally, but they can be computationally expensive and do not perform well in real time. Artificial potential field methods are efficient in computation but the problems of local minima and unreachable target exist. Deep reinforcement learning is good at adapting to changing environments, but has problems with sample efficiency and generalization. Multi-sensor fusion provides complementary information for perception, localization and mapping that increases robustness. Future research should focus on the integration of the models and data, lightweight multimodal perception, and safe and efficient cooperative obstacle avoidance for multiple UAVs. These achievements are likely to make these systems more robust to uncertainty and facilitate wider deployment in the real world.

Keywords: Unmanned aerial vehicle (UAV), Autonomous obstacle avoidance, Path planning, Deep reinforcement learning, Multi-sensor fusion

1. Introduction

Unmanned Aerial Vehicles (UAVs) used in military reconnaissance have since expanded to serve a variety of civilian purposes such as delivery, power-line inspection, crop protection and disaster response due to their capacity to be maneuverable, affordable, and not requiring direct human in the loop control. UAVs in complex environments (e.g. low altitude flight in urban canyons) are extremely vulnerable to collisions with static and dynamic obstacles such as buildings, trees and power lines within the workspace. As such, autonomous perception, obstacle recognition and flight-path planning in such settings have become key capabilities to guarantee safe and efficient UAV missions.

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DOI: 10.54254/2755-2721/2027.38472

There are various approaches to autonomous obstacle avoidance for UAVs, each having its own unique aspects and functionalities. Initial approaches focused on classical path-planning methods like graph-search algorithms (A*, D*), artificial potential field methods and geometric visibility graph approaches. While these methods show strong performance in relatively well-structured known environments, a major challenge is to achieve a balance between planning quality and real-time responsiveness in unknown and/or complex 3-D environments. Due to the progress of this field, some heuristic search algorithms, which include evolutionary computation and ant colony optimization, have been added which provide a good global optimization in complex static environment. But these algorithms are computationally expensive and difficult to use directly in the context of dynamic obstacle avoidance [1]. However, with the quickly increased progress in deep learning in recent years, new perspectives have been gained in developing obstacle-avoidance strategies. For instance, end-to-end approach using the Convolutional Neural Network (CNN) is able to directly infer flight actions from on-board stereo images, which is an efficient solution for small UAVs to avoid obstacles [2, 3]. At the same time, deep reinforcement learning can acquire avoidance policies based on the continuous interaction with environments, which makes the autonomous decision-making and adaptability of robots in complex dynamic environments better [4].

Although significant advances have been made in algorithms and sensor fusion, there are still many challenges to be addressed in autonomous obstacle avoidance systems for UAVs. This paper systematically reviews the main algorithms for autonomous UAV obstacle avoidance, analyzes the basic principle, pros, and cons of various technical methods (such as search-based and optimization-based, rule-based and potential-field-based, deep learning-based and reinforcement learning-based, and multi-sensor fusion-based), summarizes their usage, and introduces the innovation of these algorithms in real research scenarios, and finally, provides background references and some insights to guide the future research and development of autonomous UAV obstacle avoidance.

2. Research progress and limitations

2.1. Methods based on search and optimization

These methods first of all discretize the space domain, and then use intelligent searching method to find the best trajectory from the starting point to the target point. This type of trajectories has the best interpretability and is the most developed.

2.1.1. The A* algorithm principle and its improvements

A* algorithm is one of the most popular heuristic search algorithms in UAV path planning for global path planning. Its essence is the generation of a cost evaluation function to direct the search direction, and efficiently search the shortest path between the start and end in the static road network [5-8]. The expression in the canonical form is:

$$f(n) = g(n) + h(n) \tag{1}$$

In this expression, denotes the total estimated cost from the start point, passing through the current node n, to the destination; refers to the actual path cost from the start point to the current node n; and is the estimated cost from the current node n to the endpoint, i.e., the heuristic function [5]. It is precisely the introduction of this heuristic function that provides the A* algorithm with

DOI: 10.54254/2755-2721/2027.38472

directional guidance during search, ensuring both the optimal path can be found and greatly reducing computational load [9].

But for UAV obstacle avoidance, there are several problems when using the standard A* algorithm. For instance, it usually expands node in a fixed eight-neighbor or four-neighbor search pattern, producing a lot of redundant nodes which are not useful in the final path [5, 8]. Furthermore, the type of paths it is planning is usually a polyline constructed by connecting the center of a grid, and the turns are abrupt, the smoothness is not enough, which cannot directly meet the physical requirements of the trajectory curvature and flight attitude of the UAV during flight [5, 8]. Also, its heuristic function is constant, and its adaptability and efficiency of search significantly decreases as the environment becomes more complex and the number of obstacles increases.

In order to solve the above problem, researchers have made improvements to the A* algorithm from different angles, and can more smoothly and intelligently find the obstacle avoidance route in three-dimensional space.

(1) expanded constraints - improvement of the heuristic function.

Conventional heuristic estimates typically rely solely on Manhattan or Euclidean distance for . The simplistic estimation often leads to suboptimal navigation in complex environments. Zhan Weiwei et al. proposed incorporating auxiliary data—such as the UAV's flight altitude, probability of detection, and flight distance—into the evaluation function via cost weights [6]. This enables the A* search to perform a more holistic assessment, yielding trajectories with higher survivability and reduced total cost. Qin Yalong et al. employed a comparable methodology. In dense urban scenarios featuring tall structures, meteorological risk zones, and dynamic no-fly regions, they further refine the heuristic by introducing differentiated penalties for terrain, weather, and no-fly zones, enabling UAVs to exhibit greater adaptability to complex urban low-altitude environments [7].

(2) Search strategy optimisation to make the search more efficient.

In order to reduce too many node explorations and low efficiency of the A* in large scale maps, Li Xiaohui et al. suggested to use the obstacle vertices (both circular or polygonal) as expansion nodes instead of all of grid points [9]. This pruning focuses the expansion effort on the most important points that have the greatest potential to allow obstacles to be circumvented and eliminates many paths that would otherwise be explored. A path-repair mechanism was developed to reduce the number of intermediate points between two adjacent nodes in the resultant plan, so as to avoid combinatorial explosion, which will occur for considering all obstacle vertices. The trajectory that is produced is able to avoid no fly zones while keeping the computation efficient and safe.

(3) Smoothing to make the trajectories implementable.

Since the path generated by the A* based on the grid is not directly executable by UAV, Liu Ying proposed an enhanced Floyd algorithm and cubic B-spline interpolation method [8]. The improved Floyd algorithm first eliminates redundant waypoints that occur on straight sections or on sections where the turning angle is negligible to obtain a smaller set of critical turning waypoints. These points are then smoothed using Cubic B-spline interpolation which generates a trajectory with continuous first and second derivatives that satisfy the kinematic constraints of the UAV.

(4) Expansion to 3D and coordination of multiple UAVs.

As the scenarios become more complex, such as UAVs operating in urban air mobility (UAM), the cooperative operation of multiple UAVs is becoming a must-have. Based on heuristic optimization, Qin Yalong et al. put forward a distributed multi-UAV collision avoidance strategy, which adds a collision-penalty term into the evaluation function: When collision with other UAVs occurs, the subject UAV autonomously detours to complete its task, thus realizing distributed and centerless collision avoidance of multi-UAVs. To improve the sensitivity of the height changes, Liu

DOI: 10.54254/2755-2721/2027.38472

Ying proposed an A* algorithm based on three dimensional space with dynamic adjustment of the heuristic weight; at the same time, Bezier curve smoothing was used to smooth the changes of pitch angle in the three-dimensional trajectory, significantly improving the mission efficiency and the success rate of searching while maintaining the quality of the trajectory.

2.1.2. D* algorithm principle and its improvement

In some cases, such as indoors, UAV operations face with unknown environmental information in a GPS-denied environment. Thus, a dynamic path planning algorithm that is able to detect the obstacles in real time and adjust the path on-the-fly in the presence of unrecognized obstacles is needed. The D* algorithm was explicitly devised for such tasks.

Dynamic A* is the complete name of the D* algorithm. It is an offshoot of the A* algorithm with dynamism as the fundamental capability. The main difference between D* and A* is the direction of search: D* treats the goal node as the origin node and does an outward circular evaluation from the goal node, calculating the cost from each node on the map to the goal node [3] while A* treats the origin node as the start node. No matter where the UAV is located in space, there is an existing path cost in the grid cell it is in to the goal. It has to move in the direction of the steepest cost decrease to get to the destination.

The D* algorithm's main equation is very similar to the A* algorithm's, except that the meaning of the variables is different:

$$f(n) = g(n) + h(n) \tag{2}$$

In D*, denotes the actual cost of moving from the goal to the current node n. represents the estimated cost from node n to the start position (i.e., the UAV's current position). Following Zhang Fei et al., the Manhattan distance is used to estimate this value, namely:

$$h(n) = max(|x_{start} - x_i|, |y_{start} - y_i|) \tag{3}$$

This expression is easy to compute and it matches the properties of the indoor gridded maps.

The algorithm can be divided into two phases. Phase I precedes takeoff. The D* algorithm initially assumes an obstacle-free map, performs a complete reverse search from the goal, computes the value for each grid cell under this assumption, and stores it in the map [3]. Phase II is the actual flight. The UAV proceeds according to the pre-stored cost map. When onboard sensors detect newly encountered obstacles, some of the previously computed values become invalid. Unlike the A* algorithm, which requires full re-computation, D* selectively selects the nodes affected by the new obstacles, reinserts them into the open list for re-evaluation, updates their values, and then propagates the recalculated cost changes to neighboring nodes [1]. By adopting a local, "small patch-up" correction strategy, the D* algorithm achieves substantially higher computational efficiency than A* in real-time, dynamically changing environments.

However, when the classic D* algorithm is directly used on real UAVs, there are two main challenges. The first is safety - paths generated by D* on the grid map can hug against the edges of cells in the obstacle map. This does not create any issues in simulation where the actual volume and vibrations of the aircraft are negligible, but this is not the case with real aircrafts where the volume and vibrations of the motors are not negligible and the pose estimation errors are finite. Swallowing such border-laying corridors is very dangerous from the perspective of collision risk [10]. Second is efficiency. As with A*, the planned paths of the D* algorithm are polylines that are constructed by

DOI: 10.54254/2755-2721/2027.38472

sequencing the centers of the grid cells. There are multiple redundant path points on the same straight line. The UAV has to slow down, stop and hover, and then realign with the next point at each one of these.

2.2. Rule- and potential field–based methods

In addition to graph-search and dynamic-search path planning algorithms, Artificial Potential Field (APF) is a popular method used for multi-UAV cooperative collision avoidance and local obstacle avoidance with its simple mathematical formulation, good real-time performance and capability of path smoothing.

2.2.1. Core principles of the conventional artificial potential field method

The underlying idea of the Artificial Potential Field method is the modelling of the UAV motion in the environment as a force-based navigation in a virtual potential field. This field is created by the combination of two factors - one of attractiveness from the goal and one of repulsiveness from obstacles.

The attractive field is used for attracting UAV towards the goal point. It is usually characterized by having a potential function in the form of a parabola:

$$U_{att}(\xi_i) = \frac{1}{2} k_{att} \rho^2(\xi_i - \xi_{goal}) \tag{4}$$

Where is the attractive gain, and are the position vectors of the UAV's current state and the target, respectively, and denotes the Euclidean distance between them. By taking the negative gradient of this potential, the attractive force is obtained:

$$F_{att}(\xi_i) = -\nabla U_{att} = k_{att}(\xi_{goal} - \xi_i) \tag{5}$$

It can be seen from the expression that the direction of the attraction force is always from the UAV to the target, and the attraction force is proportional to the distance from the UAV to the target.

The repulsive field serves to push the UAV away from obstacles or other UAVs. The conventional repulsive field is typically defined within a finite obstacle influence radius :

$$U_{obs}(\xi_i) = \begin{cases} \frac{1}{2} k_{rep}\left(\frac{1}{\rho(\xi_i, \xi_{obs})} - \frac{1}{\rho_0}\right)^2 & , \rho(\xi_i, \xi_{obs}) \le \rho_0 \\ 0 & , \rho(\xi_i, \xi_{obs}) > \rho_0 \end{cases} \tag{6}$$

where is the repulsive gain, and is the distance from the UAV to the obstacle. By taking the negative gradient of the repulsive field, the repulsive force is obtained. The magnitude of the repulsive force is inversely related to the distance to the obstacle, and its direction points from the obstacle toward the UAV.

The motion of the UAV in space is governed by the global resultant potential field , formed by the superposition of the attractive and repulsive fields. The resultant force it experiences, , drives it to move along the negative gradient direction of the resultant potential field — that is, from high-potential regions to low-potential regions — until it reaches the target point.

DOI: 10.54254/2755-2721/2027.38472

2.2.2. Analysis of collaborative obstacle avoidance strategy based on improved artificial potential field method

In highly dynamic and complex conflict situations with multiple unmanned aerial vehicles (UAVs), the conventional artificial potential field (APF) method has some difficulties. In particular, in the case of obstacles being close to the destination of the UAV, the "unreachable target" situation can occur, where the repulsive force may dominate the attractive force so the UAV hovers close to the target [11]. Moreover, when the obstacles are closely spaced or very complex in shape, the attractive and repulsive forces may balance out at a non-target position, causing a "local minimum" state and making it difficult for further flight, significantly reducing flight efficiency.

To mitigate these deficiencies, Zou Jie et al. proposed a comprehensive enhancement strategy predicated on the reformulation of the repulsive force field to address the inherent limitations of the classical APF method. This improved methodology integrates an adaptive coefficient, , modulated by conflict urgency, enabling dynamic recalibration of the force field response. In parallel, Shah et al. focused on augmenting the reliability of the environmental perception model by leveraging multi-sensor data (stereo vision, laser scanner, ultrasonic) to enhance the precision of the potential field method. For instance, the fusion of ultrasonic data facilitates the specific detection of transparent obstacles such as glass [12]. These two distinct approaches represent the predominant evolutionary trajectories for the APF method: one prioritizes perceptual refinement, while the other emphasizes decision-making enhancements.

2.3. Learning-based methods

2.3.1. Obstacle avoidance decision-making methods based on deep reinforcement learning

Most of the traditional obstacle avoidance algorithms, such as artificial potential field method, D* algorithm and A* algorithm have achieved good results in specific situations and require accurate model of the environment or artificially established rules. However they do not work well in dynamic, complex and uncharted environments. On the other hand, the obstacle avoidance strategy based on deep reinforcement learning (DRL) allows for making decisions dynamically in complex environments, which can optimize the trajectory of obstacle avoidance.

DRL obstacle avoidance algorithms are broadly categorized based on their optimization objectives. The first category encompasses value-function-based methods, exemplified by Deep Q-Networks (DQN). This approach employs a deep neural network to approximate the state-action value function, ,which quantifies the expected long-term reward for executing a specific action within a given state. The fundamental update mechanism is rooted in temporal difference learning:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_{t+1} + \gamma Q(s_{t+1}, a) - Q(s_t, a_t)] \tag{7}$$

Here, denotes the learning rate, and represents the discount factor.

The second category comprises policy-gradient-based methods, such as the Proximal Policy Optimization (PPO) algorithm. In contrast to value-function methods, these approaches eschew indirect value estimation and instead directly optimize a parameterized policy, . The policy network is updated by computing the gradient of the expected cumulative reward with respect to the policy parameters, [13]. The Actor-Critic architecture synergistically integrates the strengths of both paradigms. It comprises an Actor network responsible for action execution and a Critic network

DOI: 10.54254/2755-2721/2027.38472

tasked with evaluating the quality of these actions, thereby offering robust policy expressiveness alongside improved sample efficiency and training stability.

2.3.2. Enhanced methods based on value functions and application analysis

Among value-function–based approaches, Mou Zhiyu and colleagues proposed a hierarchical reinforcement learning algorithm, option-DQN, for UAV-assisted sensor data collection, enabling joint optimization of the UAV's flight path and charging process. The core innovation is the introduction of "options." This hierarchical framework decomposes the decision problem of a semi-Markov decision process into two levels: a high-level policy selects which option to execute, while a low-level policy within each option executes the specific sequence of primitive actions until its termination condition is satisfied [14]. Simulations show that, compared with traditional DQN, which selects primitive actions at each step and switches frequently, option-DQN yields a more coherent and efficient task execution strategy, with faster reward growth and shorter path lengths, avoiding the UAV's inefficient back-and-forth flights between sensors.

Zhang Shichong proposed an APF-DQN–based path-planning model to address rendezvous and task allocation among multiple UAVs in unknown environments. Drawing on the artificial potential field concept, he designed a set of dense guiding reward functions. At each step, the UAV receives an immediate reward composed of multiple weighted components:

$$r_{sum} = w_1 r_{arrive} + w_2 r_{target} + w_3 r_{obs} + w_4 r_{away} + w_5 r_{collision} \tag{8}$$

where rewards approaching the target point, penalizes approaching an obstacle after entering its influence range, and is a penalty term addressing the "wandering but unreachable" problem near the target in the traditional artificial potential field method, which penalizes movement away from the target point [15, 16]. Experiments show that, compared with the original DQN using sparse rewards, APF-DQN converges faster during training, and the average path length of the planned routes approaches the ideal shortest path, achieving a task completion rate over 97% under varying obstacle densities [17].

2.4. Multi-sensor fusion methods

2.4.1. UAV obstacle avoidance methods based on multi-sensor fusion

In complex and dynamic flight environments, UAVs have to rely on a single sensor (such as monocular camera or LiDAR) to complete environmental perception and obstacle avoidance decision making, which is often difficult. The multi-sensor fusion fuses data from different types of sensors to produce the UAVs with reliable and comprehensive information about the environment, and then to make more accurate obstacle avoidance decisions.

2.4.2. Core principles of multi-sensor fusion for localization and mapping

Consequently, the main idea of obstacle-avoidance schemes based on multi-sensor fusion is to combine various types of sensors like an inertial measurement unit, a vision sensor, and LiDAR to compensate for each sensor's limitations in accuracy and robustness and to obtain better estimates of the environment and of a vehicle's pose [16, 3]. Some of the important technologies include intrinsic and extrinsic parameter calibration, temporal synchronization and spatial alignment of data of diverse nature, and filtering or optimization based data fusion.

DOI: 10.54254/2755-2721/2027.38472

In Wang Chao's research, the combination of vision cameras, IMUs, and wheel odometry provides a fused localization system which can be used for ground platforms as well as aerial ones [17]. The main novelty is the design of different fused odometry strategies depending on the motion state of the UAV: a visual–inertial–wheel odometry fusion using an error-state Kalman filter, where the wheel odometry is used to constrain the drift of the IMU with visual data; and a visual–inertial odometry fusion using an improved Kalman filter. The strategy is to set up a joint optimization which minimizes the reprojection errors of the visual images and the kinematic residuals of the IMU:

$$\theta^* = argmin(\sum E_{visual}(k,j) + \sum E_{imu}(i,j)) \tag{9}$$

where denotes the visual reprojection error and the IMU pre-integration residual. This tightly coupled formulation fully exploits sensor complementarity, substantially improving positioning accuracy and robustness.

During the process of map construction, Yang Jiaheng etc. used binocular vision, IMU and GNSS to establish a multi-sensor fusion UAV pose-tracking system [18]. Overall, the system consists of two working modules: GNSS–IMU module and GNSS–IMU–Stereo Visual module. The GNSS–IMU module provides initial value or constraints to the optimization based on the GNSS information, and performs tightly coupled optimization using the information from both sensors, providing more accurate six-degree-of-freedom pose trajectories, while the GNSS–IMU module performs the loosely coupled using an extended Kalman filter and provides initial value or constraints to the optimization based on GNSS information [18]. Based on this, Yang Jiaheng used the combined filtering and redundancy-removal stitching approach to generate three-dimensional environmental maps, used voxel filtering and statistical filtering to denoise the original point cloud data, and used octree to encode three-dimensional grid maps of the environment.

2.4.3. Environment map construction and path planning based on multi-sensor fusion

After obtaining the precise localization and environment data, the construction of the environment map, which can be used to support obstacle avoidance decision and realize the path planning on the map, is an important task of obstacle avoidance subsystem.

In environmental-map construction, Zhang Honglei et al. proposed an enhanced Bayesian fusion framework that integrates point-cloud information from 2D LiDAR with depth-camera measurements to compensate for the limitation that 2D LiDAR cannot detect obstacles in the vertical direction [19]. The core of this approach lies in augmenting the traditional Bayesian update scheme. For standard Bayesian updating, the posterior probability is computed as:

$$P(E|O) = \frac{P(O|E)P(E)}{P(O|E)P(E)+P(O|\overline{E})P(\overline{E})} \tag{10}$$

To address the issue that 2D LiDAR scans are limited to horizontal planes and yield incomplete perceptual information, the study designed an adaptive likelihood model based on a sigmoid function [19]:

$$P_s = \begin{cases} \frac{2}{1+e^{\frac{-10x_{dist}}{x_{max}}}} - 1 & , \quad x_{dist} < x_{max} \\ 1 & , \quad x_{dist} \geq x_{max} \end{cases} \tag{11}$$

DOI: 10.54254/2755-2721/2027.38472

This function exhibits the following characteristic: when the point-cloud data from the two sensors are spatially close, the information is considered consistent and approaches 0. In this scenario, the fusion result places greater trust in the high-precision data from the 2D LiDAR. As the spatial distance increases, indicating that the LiDAR may not have detected that region, gradually increases toward 1, at which point the fusion result supplements the data with depth-camera information. Experimental results show that the root-mean-square error (RMSE) of the fused point cloud can be constrained within 0.06 m, significantly more accurate than using a single sensor alone [19].

In the field of path planning, Zhang Cheng put forward an improved artificial hummingbird algorithm for the trajectory planning of UAV. The first step is to write in mathematical models the maneuverability constraints of a UAV related to its range, flight altitude, and heading angle as well as the environmental constraints, and second step is to define a total cost function, which is the sum of flight-energy cost and collision-threat cost, as the function to be optimized [16]. To improve the ability to get out of local optima and to accelerate the convergence, the Levy flight strategy is introduced which will enhance the guided-foraging phase of the hummingbird process to make it concurrent, both fine local exploitation and large-scale global exploration. This is still a global-planning algorithm, but it is much more suitable to compute an optimal safe trajectory for a UAV once a macro scale environment map is built by multi-sensor fusion.

3. Summary of principal algorithms and development trends in UAV autonomous obstacle avoidance

This paper systematically reviews the main algorithms for UAV autonomous obstacle avoidance, compares the basic ideas of different algorithms, and analyzes the pros and cons of different solutions as well as their applications in different environments, and summarizes the new directions of multi-sensor fusion and intelligent obstacle avoidance. The most outstanding advantage of A* search is its completeness, in line with the bio-inspired algorithms like ant colony optimization and particle swarm optimization, A* can find the optimal path if there is a feasible path, and the search results of A* have high stability [5, 7]. In cases of dynamic obstacles or ultra-large scale environments, vertex expansion [9] and stepwise smoothing [8] are two possible improvements of A* which demonstrate clear improvements in computation speed and versatility compared to the traditional A*.

In contrast, the Artificial Potential Field (APF) method creates an attractive potential at the goal and a repulsive potential at obstacles, and then takes the resultant force as the UAV's direction to reach local obstacle avoidance. APF has an easy computation, good real-time performance and relative smooth trajectory, and, therefore, it is suitable to the local real-time obstacle avoidance tasks. It has the merits of smooth, continuous trajectories and low computation load, which is beneficial in dynamic, cluttered or partially known environments. But the classical APF is afflicted with three well known flaws. One is the Goal Non-Reachable with Obstacle Nearby (GNWON) problem: if the obstacle is close to the goal, the repulsive field dominates the attractive field and it may not converge to the goal. Second, under complex obstacle configuration (e.g. U shaped traps) it can be stuck in local minima when the resultant force becomes zero and the UAV stalls or oscillates. Third, the use of fixed repulsion coefficients may result in too much maneuvering or unnecessary large avoidance actions, which is worsened in a multi-UAV scenario with different collision urgency and limited adaptive response ability.

Several recent studies have tried to reduce these shortcomings by modifying either the potential function itself, such as adding variable coefficients to the repulsive term that depend on the distance

DOI: 10.54254/2755-2721/2027.38472

to the target, splitting the repulsive force into its components along the different directions, adapting the repulsion gain based on the time to collision or adding additional forces or virtual target points to exit potential wells [12]. Adaptive repulsion is combined with multi-UAV coordination mechanism in a cooperative collision avoidance algorithm [12] which is used to reduce the average path length and increase the rate of target arrival without compromising safety. However, these improved techniques are still mostly parameter dependent and in highly dynamic and uncertain environments, path quality, stability, and robustness may still be limited. Furthermore, these enhancements are usually performed at a heuristic level, depend on the parameters used and do not provide ways to ensure worldwide optimization or reliable performance when the circumstances are highly dynamic and uncertain. On the other hand, most traditional APF formulations are only based on the distance or proximity, and do not fully leverage the rich sensor data like depth maps, semantic labels, and motion predictions, making them difficult to use in real-world complicated situations.

Beyond these two families, deep reinforcement learning provides an intelligent paradigm for UAV obstacle-avoidance decision-making, with methodologies that exhibit both distinctive and complementary characteristics. Value-function–based approaches, such as option-DQN and APF-DQN, derive policies through optimization of , with improvements focusing on designing more effective reward structures and accelerating sequential decision-making, rendering them suitable for scenarios with clear objectives and well-structured tasks. In contrast, policy-based methods, such as MAPPO, address high-dimensional continuous action spaces or stochastic policies by directly learning the policy , and their decentralized execution framework is advantageous for distributed systems with limited communication [13]. Overall, current research indicates a trajectory from single-UAV operation to swarm-scale collaborations and from purely data-driven to data-knowledge-fused strategies. The approaches entail trade-offs across dimensions such as sample efficiency, generalization, optimality guarantees, and computational complexity. Future investigations will emphasize integrating multi-modal perception, offline pre-training with online fine-tuning, and more efficient multi-UAV collaboration mechanisms to realize UAV autonomous obstacle avoidance systems that are more intelligent, robust, and versatile.

Multi-sensor fusion technologies in UAV obstacle avoidance also have made great progress. The fusion based obstacle avoidance systems have a common three stage paradigm – Fusion Positioning, Environment Mapping and Path Planning – and the major difference between them is in the selection of sensors and fusion algorithms. As far as sensor configuration, combining millimeter-wave radar and monocular vision will result in a smaller and simpler solution that could be used on small UAVs with limited payload, and millimeter-wave radar could be used in the event of poor weather such as rain and fog. Several air–ground amphibious configurations aim at combining wheel odometry with global navigation satellite systems for different motion modes, vision–inertial fusion focuses on positioning accuracy, and some studies emphasize redundancy and fault tolerance by providing degradation and compensation techniques when the visual or satellite information is lost. As for fusion algorithms, data-level fusion aims to integrate the point-cloud information of multi-source sensors at the probabilistic-model level to generate more complete and accurate obstacle maps; feature-level or decision-level fusion uses the multi-source sensors' data comprehensively to improve UAV pose estimation or obstacle-avoidance decision. Through empirical results, they have shown that the point cloud fusion significantly reduces the root mean square error as compared to the single sensor and fusing approaches are more effective than pure vision approaches in challenging situations like satellite outages and visual occlusions. In general, obstacle avoidance with multi-sensor fusion is moving from simple sensor-stacking to a more complex system that includes deep perception, intelligent decision making and cooperative control.

DOI: 10.54254/2755-2721/2027.38472

In the future, high-level fusion of new sensors (e.g., LiDAR and event camera) with traditional sensors and the integration of artificial intelligence technologies (e.g., deep reinforcement learning) into the intelligence and adaptability of obstacle-avoidance decision will be emphasized.

4. Conclusion

According to the described above analysis, most of the current work about the autonomous obstacle avoidance of UAV has converged to several directions, such as geometric search, force field reaction, learning-driven autonomous obstacle avoidance, multi-source fusion autonomous obstacle avoidance. Both methods have its own pros and cons in terms of optimality, real time performance, environmental adaptability, and robustness. However, previous approaches continue to have trouble in achieving good path planning, real-time performance and generalization of the model in highly dynamic and complex uncertain environments. Moreover, there is a lack of a unified framework that delivers global optimality, real-time responsiveness, and generalization in such conditions. In the future, we will focus on synergistically combining model-driven and data-driven approaches, efficient multi-modal perception processing under limited resources, and safety and mission efficiency in cooperative obstacle avoidance of multi-UAVs. In particular, deeply integrating the model-based priors with data-driven approaches, ensuring multi-modal perception fusion with lightweight computation, and guaranteeing safety and efficiency in multi-UAV collaboration are still open challenges that need to be addressed.

References

[1] He, S. (2016). *Research on UAV autonomous obstacle avoidance based on multi-sensor fusion* [Thesis]. Beijing Institute of Technology. Beijing/

[2] Yang, S., Yu, G., Wang, Z., et al. (2024). UAV autonomous obstacle avoidance path planning based on improved A* algorithm. *Technology and Market, 31*, 83–86.

[3] Chen, H. (2018). *Research on UAV autonomous obstacle avoidance system based on millimeter-wave radar and monocular vision fusion* [Thesis]. Xidian University. Xi'an.

[4] Liu, M., & Shi, H. (2025). Autonomous obstacle avoidance strategy of UAV based on EFRE-SAC. *Computer Systems & Applications, 34*, 53–61.

[5] Wang, X., Zhang, L., Gao, J., & Xu, W. (2023). Obstacle avoidance route planning of UAV based on optimized A* algorithm. *Modern Electronic Technique, 46*, 181–186.

[6] Li, X., Miao, M., Ran, B., Zhao, Y., & Li, G. (2021). UAV obstacle avoidance path planning based on improved A* algorithm. *Computer Systems & Applications, 30*, 255–259.

[7] Qin, Y., Long, Z., Ma, Y., et al. (2026). Research on UAV path planning based on improved A* algorithm. *Unmanned Aerial Vehicles, 6*, 77–79.

[8] Liu, Y. (2026). *Research on UAV path planning algorithm based on improved A* algorithm* [thesis]. Liaoning University of Technology. Jinzhou.

[9] Wang, C., Zhan, W., & Chen, N. (2015). UAV route planning using an improved A* algorithm. *Geomatics and Information Science of Wuhan University, 40*, 315–320.

[10] Bai, W., Qiao, Y., Xing, B., & Zhou, P. (2019). UAV indoor path planning based on improved D* algorithm. *CAAI Transactions on Intelligent Systems, 14*, 662–669.

[11] Shah, S. G. (2012). Research on UAV autonomous obstacle avoidance and navigation technology based on stereo vision and 3D laser scanner [Thesis]. Nanjing University of Aeronautics and Astronautics. Nanjing.

[12] Zou, J., Li, J., & Lei, Z. (2026). UAV negotiating collision avoidance algorithm based on improved artificial potential field method. *Electronics Optics & Control, 33*, 14–19, 54.

[13] Si, P., Wu, B., Yang, R., Li, M., & Sun, Y. (2023). UAV path planning based on multi-agent deep reinforcement learning. *Journal of Beijing University of Technology, 49*, 449–458.

[14] Mou, Z., Zhang, Y., Fan, D., Liu, J., & Gao, F. (2020). Research on UAV data collection and path planning based on deep reinforcement learning. *The Chinese Journal on Internet of Things, 4*, 42–51.

[15] Zhang, S. (2021). *Multi-UAV path planning based on reinforcement learning*. Sichuan University. Chengdu.

DOI: 10.54254/2755-2721/2027.38472

[16] Zhang, C. (2023). Research on UAV mapping and path planning based on multi-sensor fusion [Thesis, Jilin University]. Changchun.
[17] Wang, C. (2023). Research and implementation of air-ground path planning algorithm based on multi-sensor fusion SLAM [Thesis, University of Electronic Science and Technology of China]. Chengdu.
[18] Yang, J. (2019). Multi-sensor fusion based UAV pose tracking and path planning [Thesis, Zhejiang University]. Hangzhou.
[19] Zhang, H., Sheng, Z., Yang, Q., Ye, L., & Fang, Y. (2024). Obstacle avoidance method of UAV based on multi-sensor fusion. *Laser Journal, 45*, 229–235.