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Collision avoidance control for Unmanned Autonomous Vehicles (UAV): Recent advancements and future prospects

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The recent advances in collision avoidance technologies for unmanned vehicles such as UAVs, AUVs, AGVs, and USVs have greatly advanced the industry. Their lower cost and acceptability of high-risk missions have enabled the development of collision avoidance controllers for autonomous vehicles. These low-maintenance gadgets are also portable, need low maintenance, and enable continuous monitoring to occur near real-time. This may be said; however it would be incorrect, because collision avoidance controllers have been related with compromises that affect data dependability. Research on collision avoidance controls is quickly developing; therefore it is distributed throughout multiple papers, projects, and grey literature. This report critically reviews the recent relevant research on creating collision avoidance systems for autonomous vehicles. Typically, the assessment measures are dependent on the algorithm's use case and the platform's capabilities. The full evaluation of the benefits and drawbacks of the most prevalent approaches in the present state of the art is provided based on 7 metrics which are complexity, communication dependence, pre-mission planning, robustness, 3D compatibility, real-time performance and escape trajectories.

[**Keywords**: Collision avoidance control; Performance comparison, Recent advancements, Unmanned autonomous vehicle]

Introduction

Unmanned Autonomous Vehicles (UAVs) are increasingly used in military and civilian applications due to their increased capabilities and reduced labor[1]. These include search and rescue, weather forecasting, border patrol, firefighting, disaster response, precision farming and commercial fisheries as well as scientific study and aerial photography[2]. The proliferation of UAVs, particularly in civilian uses, has raised worries about their safe integration into national airspace. The ability to avoid emergency circumstances is critical to UAV safety and reliability. However, present methods cannot appropriately combine high-level controls with low-level directives, resulting in mission failure. Reducing the risk of failure and catastrophe by solving high-level problems in a systematic way[3]. Furthermore, four main UAVs kinds exist: Automatic Guided Vehicle (AGV), Unmanned Aerial Vehicle (UAV), Autonomous Underwater Vehicle (AUV), Unmanned Surface Vehicle (USV), as shown in Figure 1.

It is one of the major technologies in the marine vessel intelligence research. After decades of research and development, USV intelligent obstacle avoidance has advanced. Wang *et al.*[4] developed a global path planning algorithm for USVs that reduces planning time and improves planning precision. Campbell *et al*.[5] explored unmanned ship course planning using COLREGS. Tong *et al.*[6] proposed a dynamic obstacle avoidance approach for USVs based on the speed obstacle concept. A dynamic USV collision avoidance approach based on speed adjustment was developed[7].

Decentralization in AGV control architectures has been pioneered recently by Monostori *et al.*[8], Baffo *et al.*[9] and Esmaeilian *et al.*[10]. Future manufacturing systems may use holonic, fractal, and random, biological, and multi-agent techniques to create more decentralized control architecture. Ma *et al.*[11] propose 'Anarchic Manufacturing' based on distributed control. This is an extreme kind of decentralization where all decision-making authority and autonomy is delegated to system parts at the lowest level[11]. Some of these methods can be used to specific domains like self-driving cars, unmanned aerial vehicles, and automated guided vehicles.

Modern Autonomous Underwater Vehicle (AUV) real-time obstacle avoidance systems incorporate clever obstacle avoidance algorithms. AUV intelligent obstacle avoidance algorithms use fuzzy logic, neural networks, and reinforcement learning. The fuzzy logic approach accepts as inputs the distance and orientation of obstacles relative to the AUV[12]. Li *et al.*[13] suggested a three-input fuzzy logic technique to avoid AUV-moving obstacle collisions. The method uses the AUV-obstacle distance change as input and achieves dynamic obstacle avoidance in two dimensions[13]. However, this strategy assumes the AUV and obstacle velocities remain constant. Fuzzy logic-based reactive obstacle avoidance system proposed by Galarza *et al.*[14]. The system uses the AUV's real forward speed as an input and outputs forward speed and yaw angle. It reduces the impact of AUV speed on obstacle avoidance while increasing calculation volume and complexity[14].

UAVs' current and future interest and autonomy are steadily increasing as part of the IR 4.0. An aerial vehicle which is capable of prolonged flight by a pilot from a distance is considered to be a UAV[15]. In addition, because of the vast range of drones, the low maintenance cost, quick deployment, high portability, and ability to hover, UAVs are both military and civilian/commercial[16]. The usage of UAVs for border security surveillance, reconnaissance, and target removal may be seen in the military. Also, civilian and business purposes such as search and rescue, parcel delivery, precision horticulture, and pharmaceutical transfer all employ unmanned aerial vehicles. Furthermore, four main drone kinds exist: multi-rotor drones, fixed-wing drones, single-rotor helicopters, and fixed-wing VTOLs.

This document summarizes current collision avoidance research in autonomous systems. Collision avoidance concepts are summarized and classified into various approaches. Figure 2 depicts two basic classifications: hardware device and action. In Figure 2, collision avoidance is implemented from top to bottom, first the hardware, then the movement. The hardware device is the first step in any collision avoidance system, especially UAV obstacle detection. During this phase, the UAV design contains sensors capable of identifying obstacles. Based on performance, unmanned aerial vehicles (UAVs) can be categorized as AGV, UAV, AUV and USV. Collision avoidance comprises seven broad strategies that all aim to avoid collisions: a) Sense and avoid[17-19]; b) Conflict resolution[20-22]; c) Model predictive control[23-25]; d) Artificial neural network[26-28]; e) Potential field

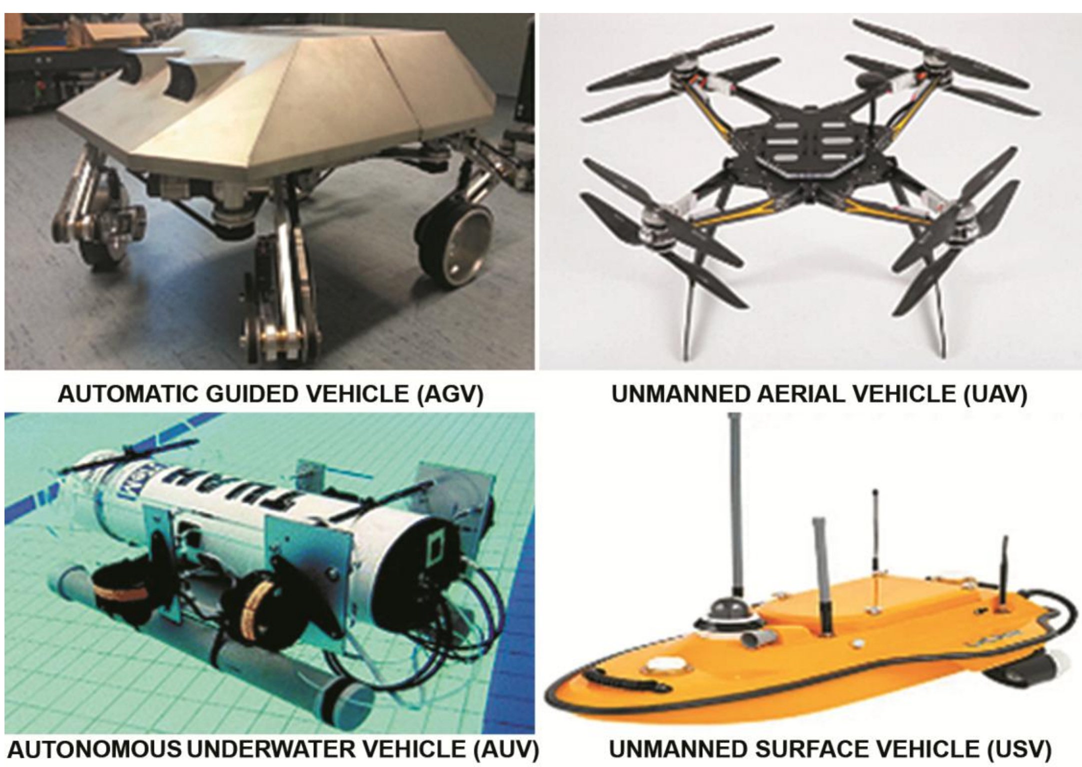

Fig. 1 — Types of autonomous vehicle

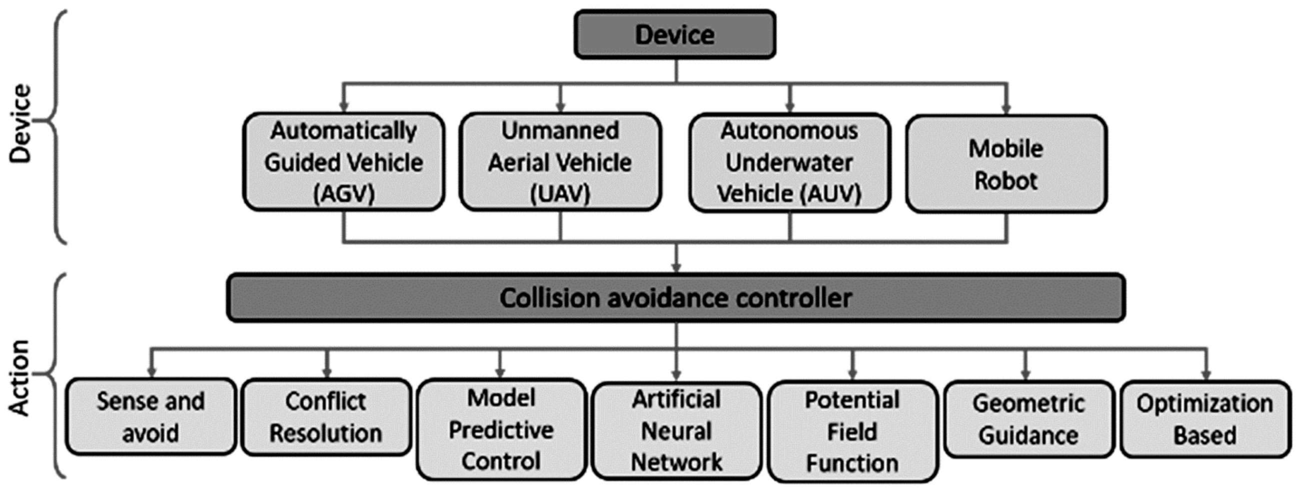

Fig. 2 — Collision avoidance controller modules

function[29-31]; f) Geometric guidance[32-34]; and g) Optimization based[35-37]. These controller comparisons are based on the 7 metrics which are complexity, communication dependence, pre-mission planning, robustness, 3D compatibility, real-time performance and escape trajectories.

From alerting the driver via collision avoidance systems by Huang *et al.*[38], the author using fully or partially guiding the system to avoid a collision. Actuators can apply brakes or direct the car when steering clear of obstacles. Initially, field study focused on roadways built on ground vehicles (a suitable foundation for other vehicles like aircraft and ground), which eventually influenced ground vehicles[39,40]. Mujumdar & Padhi[41] described defining collision avoidance as a global or local path planning problem. Traditional path planning responds to changes in the environment, whereas global path planning considers the totality. When no collisions are expected, avoidance manoeuvres are performed to restore the vehicle to its original course[41].

These systems are required for completely autonomous navigation and obstacle detection[42]. UAV swarms are gaining popularity due to their ability to work together. Multiple UAVs outperform single UAV systems. This device is in demand in many industries, including military, commercial, search and rescue, traffic monitoring, border security, and atmospheric research[43-45]. In a dynamic environment, UAVs struggle to accomplish tasks due to limited on-board payload (sensors, batteries), poor visibility (rain, dust), and challenges in remote monitoring. To ensure the robots' performance and safety, robotics experts are searching for technologies that are more suitable for the environments in which they will operate[46,47]. It is crucial for autonomous vehicles to recognise and avoid barriers in dynamic situations with many UAVs and moving impediments[38,48-50].

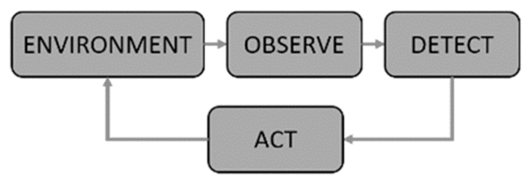

Fig. 3 — Reactive collision avoidance

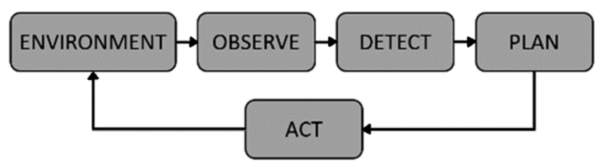

Fig. 4 — Deliberative collision avoidance

Collision avoidance control

Collision avoidance control systems use reactive and deliberate planning. It gathers information about its environment from onboard sensors and acts accordingly. This approach enables for fast environmental changes. However, reactive control might become imprisoned, needing a new type of navigation as in Figure 3. An environmental map can be used to experience and update the environment, as seen in Figure 4. The map is updated first, followed by a goal-oriented trip plan. An accurate map of the surroundings is essential for the operation. The method fails in dynamic situations where variables change often. Especially using a hybrid technique that can adjust to the environment's needs.

Collision avoidance algorithms can be categorized into seven methods already listed in introduction and summarized in Figure 2. These methods will be further elaborated in the following subsections.

A. Sense and avoid

Most sense-and-avoid approaches employ simpler methods, such as short response times, to limit the computing resources required to accomplish collision avoidance, as well as improving drone stability by using individual detection and avoidance of objects to steer the swarm. Formations contain set locations for each drone, and an avoidance procedure incorporates individual path planning to steer clear of both drone-to-drone collisions and collisions with exterior obstructions. Rapid collision avoidance, which responds rapidly to oncoming objects, is a suitable approach for dynamic situations. In this method, a robot or agent has sensors such as sonar, radar, and LiDAR.

2D LiDAR-based approach, Zheng *et al.*[17] proposed utilized RPLIDAR A2 to locate the UAV's position through the scanning of the point cloud. RPLIDAR A2 has a detection range of 8 m, a weight of 190 g, a scanning frequency of 10 Hz, a resolution angle of 1°, and produces a scan sequence that has 360 points. In order to determine the LiDAR's position while it scans each point, a polynomial-based velocity estimation approach is applied to determine the position of the LiDAR after it corrects the distorted point cloud. To achieve better results using clusters, a method based on relative distance and density (CBRDD) is applied. The experimental findings suggest that the strategy proposed in this study can address the offset of the point cloud and ensuring even distribution in point cloud clusters. A lightweight and inexpensive obstacle detection system has been proven to have a good effect on UAVs.

The work proposed by Ma *et al.*[18], which brings together an unmanned two-wheeled robot with a laser-based avoidance system, is all about laser-based avoidance for autonomous guided vehicles. This system can swiftly collect obstacle information and use it to avoid barriers and afterwards choose a new path.

By using a 2D laser, Faria et al.[19] was able to achieve 3D exploration with reduced cost and weight. In order to put the sensor optimally, exploration must find the Next Best View (NBV) solution. The author devised a modular design that employs both local and global levels of the frontier algorithm, broadening the concept of a frontier surface to include a surface neighborhood. The Lazy Theta* method generates safe routes during the mission by utilizing the popular A* algorithm. The UAV can cover 93 % of the search environment within 30 minutes, exploring and constructing a path that adjusts to varying spaces, which include indoor locations, irregular structures, and barriers that are not completely flat.

B. Conflict resolution

The purpose of the conflict resolution system is to anticipate conflict in the future, notify an operator of the dispute, and aid in conflict resolution as appropriate. It is possible to structure these three primary processes into multiple stages or constituent pieces. Involving dangers other than another aircraft in a decision-making process can be simplified to the same basic process.

The approach developed by Zhao & Wang[20] is applicable to the collision avoidance problem with static and dynamic impediments in fixed-wing AUVs. An emergency control algorithm is created to ensure that the UAVs can be operated in a hazardous environment without jeopardizing their safe return to a safe place. In order to prevent frequent state switches in which the UAV enters “safe mode” only to instantly exit it, an additional conflict buffer is also implemented for the resolution of conflicts and a seamless transition between the two states. The sufficient criteria apply not just to static and dynamic impediments but also to internal vehicle collisions. The conclusions drawn from these results reveal that UAVs perform better when avoiding both static and dynamic impediments. The three UAVs use relative position speed to select the flight trajectory.

Chauffaut & Burlion[21] suggested a new technique known as the method of Output to Input Saturation Technique (OIST) for MAVs. To assure collision avoidance for a formation of up to three MAVs, this technique is extended. The goal of this technique is to find out if many vehicle operators may be controlled by one operator. In order to be able to effectively focus on the supervision of an unmanned aerial vehicle fleet, it is imperative that both basic formations maintaining procedures and specifically collision avoidance capabilities be available (MAVs). In contrast to previously reported experimental results, the data reveal that the minimum distance between MAVs is respected globally during the formation of the fleet.

Rodionova *et al.*[22] proposed a decentralized, on-demand aerial collision avoidance system for several

UAS was presented in the article, Learning-to-Fly (L2F). Mixed Integer Linear Programming (MILP) is used to address the issue of enabling UAS to avoid collision without impacting the goals of the mission (MILP). However, there is no easy way to tackle this problem on the internet. Rather, we have created L2F, a learning-based approach for making decisions and a distributed, linear programming-based UAS control system. Through extensive simulations, we demonstrate that our method is completely real-time, offering 6000 fewer simulation cycles than the MILP approach and resolving 100 % of collisions even given abundant space for movement. As well, we exhibit an implementation on quad-rotor robots when comparing L2F to two other approaches.

C. Model predictive control

MPC is a novel way to controlling processes. Power system balancing models and power electronics are current examples. Model predictive controllers use dynamic models, such as linear empirical models developed from system identification. Using the MPC algorithm allows us to alter the current time slot while considering future time slots. The Linear-Quadratic Regulator is attained by carefully considering a limited time horizon, then implementing a time slot and fine-tuning again (LQR). MPC can also predict future events and implement appropriate management actions. PID controllers cannot provide accurate predictions. Most MPC systems are digital, however some analogue hardware has been built for faster response.

Kamel *et al.*[23] proposes a nonlinear model predictive control for multi-MAV collision avoidance. A decentralized system of trajectory monitoring and collision avoidance was employed to optimize movement. The global planner's trajectory does not need to be modified before sending it to the tracking controller; the local avoidance controller must deliver it there. The prediction horizon propagates the state estimator's uncertainty, reducing collisions. If the prediction horizon is long enough, a stringent distance constraint between agents ensures collision-free navigation. This method has been tested with six simulated MAVs and two real-world MAVs. This study demonstrated how to perform quick and dynamic avoidance maneuvers while maintaining system stability at a low cost.

Lindqvist *et al.*[24] developed a revolutionary path-planning and obstacle avoidance system in which they used a Novel Nonlinear Model Predictive Control (NMPC) architecture that is capable of handling dynamic obstacles. A system for classifying different kinds of trajectories was also used to anticipate future obstacle positions. The findings demonstrate that for the two oncoming obstacles, the distance between the avoiding UAV and the approaching UAV is 0.45 m, and that of the obstacles, 0.42 m. Like the single-obstacle example, the avoidance maneuver starts as soon as the obstacle-UAV starts moving, and solver time is 35 ms, peaking at that point.

Ille & Namerikawa[25] featured two multi-UAV teams, each starting from a different location and travelling to a different destination. The leaders measure the obstacles positions and use a Kalman Filter model to anticipate their future positions and calculate their movement. To calculate their reference trajectories, each agent knows the positions of the others. The leader estimates a route to transport the troop to the destination. This method tracks each agent's reference trajectory and applies MPC to each individual trajectory. Inability of UAVs to link has led to this method. They can't agree on where to go, therefore they must avoid each other. Both teams move sideways as though colliding. The fact that the formations hold even when the teams deviate from them shows that the teams follow the formation without colliding.

D. Artificial neural network

Artificial Neural Network (ANN) describes a type of simulation that involves creating a computer system that imitates human intelligence, along with human-like behavior. For machines to be considered conscious, they must demonstrate features of human intelligence, including learning and problem solving. Computer vision-based drones are used mostly for AI-based purposes. This technology makes it possible for drones to scan the environment while in flight and to collect data on the ground.

The use of unmanned aerial vehicles has proven beneficial to several plants. Balkanized undeveloped agricultural lands are a major flight safety concern. Wang *et al.*[26] created a Task Control System (TCS) that included object identification and picture processing. A UAV may detect and identify obstacles while also observing depth information including category, shape, and 3D spatial position using the suggested solution's deep learning algorithms. Its obstacle avoidance and ambient sensing skills are tested in experiments. On average, the CNN model detects 75.4 percent of images with a processing time of 53.33 ms. The item's distance from the depth camera is also important. There are 0.53 m errors in depth, breadth, and height. In order to avoid obstacles, the UAV might create a flight route with the shortest distance between waypoints using the RGB-D findings of RGB-fusion.

Bin *et al.*[27] introduced a framework for multi-UAV collision avoidance, known as multi-UAV cooperative collision avoidance, based on multi-UAV cooperative collision avoidance (our elements of state space, action space, the environment model, and returned value). Two collision avoidance control strategies based on UAVs (drone systems) were introduced, after which a matrix for classifying collisions was implemented, and based on a new collision avoidance control strategy using reinforcement learning method, a new cooperative multi-UAV collision avoidance control algorithm was proposed. The experiment showed that the algorithm is capable of effectively utilizing multi-UAV coordination for collision avoidance, resulting in collision avoidance with control decisions completed in 100 milliseconds.

The technique described by Yang *et al.*[28] uses a lightweight probabilistic CNN (pCNN) for real-time monocular depth prediction and obstacle avoidance. The suggested pCNN can forecast the depth map and confidence for each video frame. The proposed pCNN benefits greatly from using visual odometry to assist dense depth and confidence inference. It is then turned into Ego Dynamic Space (EDS) by adding dynamic motion limitations and relative degrees of confidence to the map. EDS uses control inputs to compute automatically traversable waypoints. Extensive testing on public datasets showed that our method achieves 12Hz with a 1050Ti GPU and 45Hz with a TX2 GPU, which is 1.8 – 5.6 times faster than existing techniques and improves depth estimate accuracy.

E. Potential field function

Repelling an agent/robot from an obstruction with the use of a repulsive or attracting force field is known as force-field methods, which is also known as potential field methods. This approach focuses on the motion and geometry of the robot and the obstacles. These characteristics of the obstacles are unknown in advance in dynamic situations.

Sun *et al.*[29] proposed an optimized artificial potential field (APF) algorithm for multi-UAV operation. The APF method has been shown to only be able to support single UAV trajectory planning, and the lack of collision avoidance is a common failure. A solution is proposed with a distance factor and leap strategy to prevent impediments from the UAV from colliding, even unreachable objectives. The method takes into consideration the dynamic impediments presented by UAV companions when preparing for collaborative flight path planning. Dynamic step adjustment is used to mitigate the jitter issue. Several possible resolutions are presented below. Quantitative simulation models showed that the process worked satisfactorily in a simulated metropolitan context.

Zhang *et al.*[30] uses the artificial potential field method to solve the problem of many unmanned aerial vehicles (UAVs) accidentally flying into each other while avoiding an obstacle. This technology allows UAVs to avoid each other in 3-D space. My method depicts the state of the virtual structure in 3-D space and the “leader-follower” control approach for successfully steering a vessel around a barrier. The artificial potential field force is used to guide the three UAVs and the virtual leader in keeping the regular triangle configuration while driving toward the destination. A repulsive artificial potential field can separate the UAVs from each other while still preventing a collision between the UAV and the barrier.

Verginis *et al.*[31] describes the difficulties faced by 2^{nd} order nonlinear multi-agent systems while building a class of such systems in a 3D workspace with obstacles. To complete the problem-solving part of the overall aim, the author proposed a potential function-based decentralized control protocol that can solve a broader class of problems involving multiple rigid bodies subject to Lagrangian dynamics, with guarantees that every instance of a collision is avoided. The strategy assumes that the originally linked agents are guaranteed to remain connected permanently. Also, inter-agent collision avoidance can be performed using particular distance limits. The simulations showed that the goal function decayed toward zero, whereas the obstacle function remained at a positive value.

F. Geometric guidance

The use of geometric techniques uses geometry to ensure that set minimum distances, like UAVs, are not exceeded. This is performed by using the distances between the UAVs and their velocities to compute time to collision.

Seo *et al.*[32] suggested strategies to avoid pop-ups by using line-of-sight vector data to help navigate. It can eliminate the iterative and/or offline method used by each UAV to find the collision avoidance direction by solving this problem. A large UAV formation was formed to avoid obstacles. The proposed collision avoidance guiding legislation was predicted using Lyapunov's theory. The movement of the UAVs was considered in the study of the envelope for collision avoidance. The system will adopt a sense-and-avoid method, which is more suited to drone flying operations where we need to avoid shifting obstacles. Depending on the application, collision avoidance algorithms work with single or several drones. As a result, the approach may benefit actual drone operations.

Behjat *et al.*[33] created a revolutionary concept called TRACE (Training, Risk-Reduction, and Collision-Avoidance Notion for Quadrotor UAVs) to apply this concept. An approach for optimizing mutually coherent (speed or direction change) operations was created to avoid drone collisions (subject to flight-dynamics constraints). An optimal reciprocal action can be learned in seconds rather than minutes. In the end, the more effective DC actions were found to be present across a wider range of angles, but the consumption difference was less than 2.5 %. In 425 unknown cases, the classifier exhibited an error rate of roughly 87.5 % in both training and testing. Additional performance investigation over unexplored scenarios resulted in 95.3 percent successful collision avoidance.

A 3D velocity obstacle technique for multi-UAV systems was developed by Tan *et al.*[34] to avoid collisions with static objects while navigating a dynamic and changeable obstacle environment. So, the multi-UAV system can do its job without interfering with other aircraft or ground impediments. The author is working on a three-dimensional collision avoidance system to keep the vehicles safe. As a result, the author proposed the 3-D VO method for computing 3-D velocity barriers. Also, the suggested collision avoidance algorithm leverages the pyramid cone approach, which works well with static obstructions. So, the UAV achieved its goal and flew around the obstruction. It avoids collisions and achieves its goal effortlessly. As shown in the trajectory, the UAV avoided the static obstacle. The UAV's closest point to an obstacle is 0.3521 meters distant.

G. Optimization based

Geographical information plays a critical role in the determination of the avoidance trajectory in the context of optimization-based approaches. To create an optimized search region, probabilistic search algorithms use ambiguous information to decide where to focus their efforts. Computational complexity of these algorithms presents several optimization challenges, which several optimization approaches are created to address. All these techniques are included here; one should review these examples to gain a better understanding of the field.

Zhang[35] described a method for configuring multiple UAVs' flight and collision avoidance. With UAVs' high speed and unstructured environments, they developed a modified tentacle strategy to reduce the detrimental impact. The modified Tentacle technique reduces calculation time and increases data retrieval accuracy, solving a previously challenging data calculating challenge. Its tentacles are being redesigned to fit several unmanned aerial vehicles (UAVs). When time is limited, the study prefers iterative route optimization over iterative tentacle optimization. The method is indeed viable and successful in simulation. Multiple UAVs can overcome the threats provided by other UAVs while present, as well as other UAVs in formation and unknown objects.

Perez-Carabaza suggested a Minimum Time Search (MTS) planner, which combines communication and collision avoidance requirements, based on ant colony optimization[36]. Search missions employing MTS algorithms enable to provide search trajectories that reduce the time required to find the objective. A primary goal is to have a multi-hop connection to the GCS while avoiding collisions amongst UAVs. CEO and GA outcomes are superior to those of the other MTS techniques, as shown by the suggested algorithm. It might be anywhere from 2.16 to 49.10 % for CEO, and 4.00 to 47.05 % for GA.

Hu *et al.*[37] proposed a distributed velocity-aware algorithm and collision avoidance approach for numerous UAVs. Because UAVs are aware of their surroundings, they have a good grasp of the network, making it difficult to obtain information about other UAVs. UAVs can malfunction at any time, so they prepare for the worst. The paper presented the velocity-aware A* algorithm, the collision prediction strategy, and the collision avoidance algorithm. In this situation, despite the higher practical path length and time cost, the provided approach has a high success rate. This depends on the situation, in particular the actual location of departure and arrival. More UAVs and a larger map increase path complexity and construction time. Due to these processes, the average UAV velocity is around 0.65, with variability due to accelerations and decelerations.

Discussion and Conclusion

We provided a more in-depth analysis of collision avoidance systems and tactics utilized for autonomous vehicles in the previous sections. To understand how collision avoidance systems are built, the different types that are relevant to unmanned autonomous vehicles (UAV) were categorized based on AGV, UAV, AUV and USV. Following a careful assessment, the research team separated collision avoidance systems into seven key categories: sense and avoid, conflict resolution, model predictive control, artificial neural network, potential field function, geometric guiding, and optimization based methods. Class approaches have some advantages and trade-offs, as illustrated in Table 1.

Computed approaches to avoiding collisions can be assessed using multiple frameworks and metrics. Typically, the assessment measures are dependent on the algorithm's use case and the platform's capabilities. When looking at collision avoidance algorithms, it is important to consider which metrics are used to evaluate the various algorithms, as each has its own pros and downsides. When a full evaluation of the benefits and drawbacks of the most prevalent approaches in the present state of the art is provided, this is demonstrated in Table 1 to exemplify a comparative examination of several algorithms, we created a table with ten metrics and described each as follows.

The first metric is complexity: The complexity meter for the various approaches is derived from the design of algorithms. The geometric, model predictive control, conflict resolution, and force-field approaches have the highest algorithm design complexity (computational cost). As far as complexity is concerned, artificial neural networks and optimization-based approaches are similar, while sense and avoid approaches are quite simple.

The second metric is communication dependence: In contrast to cooperative methods that share information, sense and avoid methods do not require on any communication to function since they deal with everything locally and take decisions on their own without talking with other UAVs or systems. In the few studies that used force-field methods, most research did not, indicating that force-field approaches rely less on communication reliance. Some additional systems, however, are based on UAVs contacting other nodes or other UAVs. The third metric is pre-mission planning: Pre-mission path planning is not required for the development of either Sense & Avoid, conflict resolution, or artificial neural network. The collision zone and the velocity obstacle serve as points of reference in geometric path planning. Pre-mission path planning is required in order to utilize optimization and force-field approaches.

The fourth metric is robustness: All mentioned approaches are capable of being robust depending on the way they are implemented.

The fifth metric is 3D compatibility: Sense and avoid, geometric, artificial neural network, and optimization algorithms all have a significant amount of work to do when dealing with three-dimensional surroundings. However, a significant number of scholars are examining the viability of utilizing force-field methods, model predictive control, and conflict resolution in three-dimensional dynamic systems.

The sixth metric is real-time performance. The real-time performance of sense and avoid, geometric, artificial neural network, and model predictive control methods is superior to that of force-field, conflict

Table 1 — Performance comparison between state-of-the-art collision avoidance approaches

CA approach	Complexity	Communication dependence	Pre-mission planning	Robustness	3D compatibility	Real-time performance	Escape trajectories
Sense & Avoid	Low	χ	χ	√	3D	√	Local/Run-time
Conflict Resolution	High	√	χ	√	2D	√	Negotiation protocol
Model Predictive Control	High	√	√	√	2D	√	Hybrid system
Artificial Neural Network	Medium	√	χ	√	3D	√	Optimized
Potential Field Function	High	χ	√	√	2D	√	Force-field based
Geometric Guidance	High	√	√	√	3D	√	Protocol based
Optimization Based	Medium	√	√	√	3D	√	Pre-defined

resolution, and optimization methods, as sense and avoid do not require excessive processing to avoid changes in the environment, such as approaching obstacles. Additionally, geometric approaches are quick and computationally efficient. However, the disadvantage of geometric approaches over sense and avoid is that the time required to compute and the complexity of the algorithm are greatly reliant on the algorithm implementation.

The seventh metric is escape trajectories: The escape trajectories offered by various approaches can be summarized as follows: sense and avoidance offer escape trajectories at run-time and locally, conflict resolution offer escape trajectories based on the negotiation protocol, model predictive control using hybrid systems for escape trajectories, artificial neural network offers optimized escape trajectories, escape trajectories for optimization.

A clear trade-off exists between computing time, complexity, optimal solutions, pre-mission path planning, and the ability to respond to static/dynamic situations. The appropriate algorithm must be chosen based on operational requirements, or alternatively, various collision avoidance strategies (or two-layered collision avoidance method) may be combined to meet needs[51]. Additionally, to ensure the safety of UAVs, the deployment of sense and avoid methods is a safe choice in all sorts of situations. These approaches are the simplest and most robust, with the least data overhead and reaction times. But it needs a better path planning algorithm to avoid local minima and reach the destination without colliding. The sense and avoid strategy can also be utilized as a failsafe/standalone approach to assure the UAVs' safety, particularly in highly dynamic environments where situations might change rapidly and a great degree of adaptivitiy is necessary.

Unpublished research on optimizing UAV system parameters utilizing LIDAR data for identifying and avoiding collisions while in flight mode appears to be rare. Yiao *et al.*[52] builds an obstacle identification and intrusion detection algorithm (ALORID) using LiDAR scanning data. In another example, Ponte *et al.*[53] employs input parameters from a LiDAR sensor combined with Kalman Filter estimation to maneuver the drone in hazardous conditions, identify obstructions or intruders, and perform precise hovering and landing procedures. However, the LiDAR sensor data has not been optimized to fully autonomous obstacle detection and avoidance based on LiDAR distance measurements. As a result, their method may perform poorly, causing ambiguity about the UAV's position and path. As a result, our research will focus on optimizing and adapting sense and avoid collision avoidance controllers for real-time applications. Using a LiDAR-based UAV collision avoidance controller could dramatically improve autonomous flight and collision avoidance. A higher level of collision avoidance may be achieved by combining detect and avoid systems with sensor fusion optimization.

For future development, further research and development can be directed on the extension and validation of the developed algorithms in 3-dimensional environments with dynamic constraints bringing the simulations closer to real world environments and moving towards the real-time testing. For instance, the hybrid system using sense & avoid method combine with optimization based on the real-time data from various sensor equipped by the UAV. Therefore, it is required to propose hybrid system to realize collision avoidance under different scenarios with high real-time performance, scale scalability and overall safety and efficiency.

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Conflict of Interest

The authors certify that they have NO affiliation with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Author Contributions

MBB gathered, analyzed and evaluated all the relevant articles. MHH conceived the report, and SSA & MSMA oversaw the overall direction and planning of the research.

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