Received May 8, 2020, accepted June 1, 2020, date of publication June 4, 2020, date of current version June 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3000064

Unmanned Aerial Vehicles (UAVs): Collision Avoidance Systems and Approaches

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This work was supported in part by the Academy of Finland under Project 314048, and in part by the Finnish Cultural Foundation.

ABSTRACT Moving towards autonomy, unmanned vehicles rely heavily on state-of-the-art collision avoidance systems (CAS). A lot of work is being done to make the CAS as safe and reliable as possible, necessitating a comparative study of the recent work in this important area. The paper provides a comprehensive review of collision avoidance strategies used for unmanned vehicles, with the main emphasis on unmanned aerial vehicles (UAV). It is an in-depth survey of different collision avoidance techniques that are categorically explained along with a comparative analysis of the considered approaches w.r.t. different scenarios and technical aspects. This also includes a discussion on the use of different types of sensors for collision avoidance in the context of UAVs.

INDEX TERMS Autonomous aerial vehicles, autonomous vehicles, collision avoidance, active and passive sensors, optimisation-based, force-field based, sense and avoid, geometry based.

I. INTRODUCTION

Development of any unmanned vehicle has several key benefits with the fundamental benefit of being able to operate without a human pilot and to access difficult to reach or hazardous areas without risking human lives [1]. Particularly, fully autonomous Unmanned Aerial Vehicles (UAV), or drones, are of key interest to the research community due to their unique properties and many relevant applications [2]–[4]. There is a lot of work going on in the field of drones and swarm of drones, with recent years witnessing a proliferation in the use of not only unmanned aerial vehicles but also ground and surface vehicles (UGV & USV), mostly for surveillance, mapping, and inspection [5], [6].

The autonomy level of an unmanned vehicle varies according to the tasks at hand or the degree to which the vehicle is able to make decisions without being explicitly controlled by a remote operator [7], [8]. In general, unmanned vehicles have different types of on-board sensors that can be used for situational awareness and autonomous decision making at run-time [9]. Overall, control can be manual, based on e.g. live video received from a camera mounted on a vehicle (remote control); autonomous, based on feedback received from a mounted camera and other types of sensors indicating the approaching obstacles [10]–[12]; or something between these two extremes (hybrid, semi-autonomous). Bearing in mind the considerably low risk to human life, as well as improved durability for longer missions and accessibility in difficult terrains, the demand for such unmanned vehicles is increasing rapidly, and their path planning in dynamic environments remains one of the most challenging issues to solve [13]. Due to their autonomy and ability to travel far from the base stations or their operators (the range naturally depends on the type and size of the vehicle) the need for having an on-board mechanism to avoid collisions with objects and other vehicles is obvious [14], [15].

A collision avoidance system is crucial for both non-autonomous and autonomous vehicles. Collisions can happen due to numerous reasons, let it be due to the operator's/driver's negligence, equipment malfunction, or bad weather conditions. Considering conventional cars, according to the data acquired from World Health Organisation's reports, approximately 20-50 million people are injured in road accidents, and the number of fatal road accidents leading

The associate editor coordinating the review of this manuscript and approving it for publication was Zheng H. Zhu.

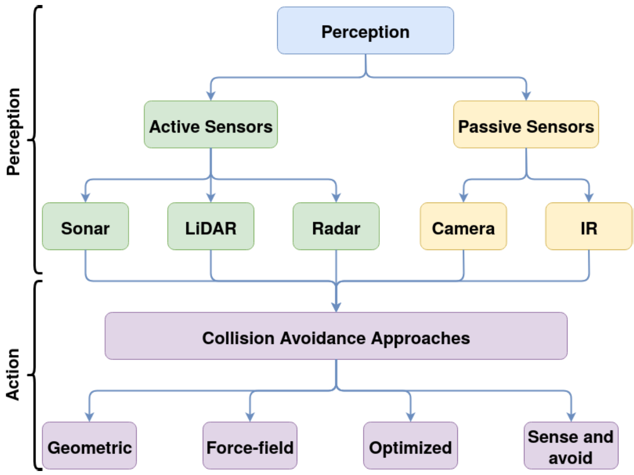

FIGURE 1. **Collision avoidance system generalised modules.**

to deaths is estimated to be approximately 1.25 million annually around the globe [16], [17]. Airplanes are safer; reports from CNN and the Aviation Safety Network show that the amount of annual deaths caused by commercial flight accidents is in the range of a few hundreds [18], [19] in average. However, helicopter and private/military airplane accidents are not included in these statistics. The data for causes of fatal accidents from January 1960 to December 2015 compiled by planecrashinfo.com shows that about 58% of the accidents were due to the human error [20]. This human factor can be minimised by integrating intelligent decision making capabilities such as obstacle detection, collision avoidance, and path planning with the autopilot system to make the system more autonomous. In that way, intelligent autonomous collision avoidance methods can significantly contribute to making airplanes even safer and saving human lives. Moreover, with the increasing usage of unmanned vehicles and especially the exponential increase in the applications of UAVs in public areas and our everyday lives, the need for intelligent and highly reliable collision avoidance systems is obvious and indisputable from the viewpoint of public safety. In contrast with collision avoidance in cars, UAVs have the ability of reaching difficult to reach and dangerous areas while posing no potential danger to humans. Hence, UAVs should be designed to be completely autonomous and able to fly without colliding with other objects, which requires fundamental research [21].

This paper is a general survey to summarise the wide trends and important work on collision avoidance in autonomous systems published till now. In order to sketch different key ideas and approaches, the concept of different collision avoidance methods are encapsulated and summarised into different categories. Figure 1 shows such classification that is based on two main categories, i.e., perception and action. The chronological order in Figure 1 is top to bottom since in collision avoidance first the perception is required and after that the action. Perception, that is mainly obstacle detection, is the first step for any collision avoidance system. In this phase, sensors are utilised, in order to perceive the environment and detect obstacles. There are various different types of sensors available in the market, but they can all be categorised as either active or passive sensors based on the principle of their functionality (see Section 2). Active sensors have their own source which transmits light or emits a wave and read the reflected back-scatter. On the other hand, passive sensors only read the energy discharged by the object, from another source e.g. sunlight, reflected by the object. An action for collision avoidance can be categorised into four major approaches: geometric in which location and velocity information of the node/UAV and obstacles is utilised, usually by simulating the trajectories, to perform the reformation of nodes to avoid the collision, force-field in which attractive/repulsive forces are manipulated for collision avoidance, optimised through which the already known parameters of obstacles are used to optimise the route, and sense and avoid through which run-time decisions for avoidance are made on the basis of obstacle detection.

Collision avoidance systems range from either simply warning the operator of the vehicle [22] to complex process of autonomously controlling the system either completely or partially to avoid the collision. The actuators can be either applying brakes or steering the vehicle away from the detected obstacle. Initially, the research in the field was based on advanced highways (ground vehicles), which provided a good base for advancements also in the areas of intelligent aerial and surface vehicles [23], [24]. The authors in [25] provide an interesting approach in classifying the collision avoidance into global and local path planning problems. Where the global/conventional path planning reacts to the changes in the environment and generates the optimal routes while keeping the whole environment under consideration, whereas in collision avoidance also referred to as local path planning, the changes in the environment are dealt with locally as they are detected and an avoidance maneuver is performed accordingly to avoid the collisions to get back to the originally planned path.

Obstacle detection, collision avoidance, path planning, localisation, and control systems are the key parts required by an unmanned vehicle to be fully autonomous and able to navigate without being explicitly controlled [26]. Due to the ability to work in a collaborative and cooperative manner, swarms of UAVs are gaining even more attention in the research community. The deployment of swarms or multiple UAVs adds significant advantages over single UAVs and has demand in vast and diverse areas, for instance in military or commercial use, search and rescue, monitoring traffic, threat detection especially at borders, and atmospheric research purposes [27]–[29]. In a challenging dynamic environment, tasks may become increasingly difficult for UAVs due to on-board payload limitations (e.g., sensors, batteries), power constraints, reduced visibility due to bad weather (e.g., rain, dust), and complications in remote monitoring. The robotics community is striving hard to address these challenges and to bring the technological level suited for the

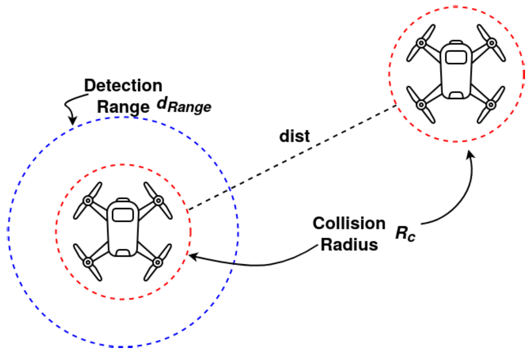

FIGURE 2. Detection range and collision radius.

demanding environments ensuring success and safe navigation of the unmanned vehicles [30]–[32]. Obstacle detection and collision avoidance are one of the most challenging issues for autonomous vehicles and become even more critical in dynamic environments with multiple UAVs and moving obstacles [13], [33], [34].

In an autonomous drone/swarm of drones, a collision is said to have taken place between a drone and any other object, i.e., another drone or an external object or obstacle, when the distance between them is less than the predetermined collision radius R_c [35]. The collision radius and detection range are illustrated in Figure 2. The condition can be mathematically expressed as:

$$||r_u - r_o|| < R_c \tag{1}$$

where r_u and r_o are the position vectors of the drone and the object, respectively.

An object is detected, i.e., obstacle detection takes place, when the distance between the drone and the object is less than the detection range and the object is in the field of view of the on-board sensor system. This can be mathematically expressed as:

$$||r_u - r_o|| < (d_{Range} \;\; \& \;\; FOV) \tag{2}$$

where d_{Range} is the detection range radius and FOV is the field of view of the drone dependent on the equipped sensor system.

A collision avoidance system (CAS) for an unmanned vehicle is responsible for ensuring that no collisions happen with any obstacle whether moving or stationary. A CAS, in order to be able to do that, must address the following questions:

- How to detect an obstacle and determine its attributes e.g., its velocity, size, and position
- How to determine if the object is approaching and there is a risk of collision
- How to perform actual collision avoidance based on the calculations done

There may be different descriptions of CASs stressing over different sides of the system, but basically a CAS is composed of sense, detect, and collision avoidance as shown in Figure 3. The first step is to sense, in which the system observes its surroundings or the environment. As soon as some point of interest i.e., an obstacle comes within the range, the detection phase of the system tries to assess the risk. Based on this, the collision avoidance module does the necessary calculations to compute the amount of deviation needed from the original path in order to avoid the potential collision. As soon as the calculations have been done, the system performs the necessary maneuver to successfully avoid the obstacle.

Different subcategories, the comparison among different categories and the aforementioned subcategories are discussed in more detail in each corresponding section. The rest of the paper is organised as follows. Section 2 briefly overviews and explains obstacle detection, and passive and active sensors are discussed in detail. Section 3 focuses on collision avoidance approaches and the environmental effects in detail. The available methods and solutions are discussed in Section 4 along with conclusion.

II. PERCEPTION: OBSTACLE DETECTION

Perception is the first step in any collision avoidance system. In order to detect obstacles, the drone should be able to perceive its surroundings and environment. For this, it needs to be equipped with one or more sensors working as a perception unit [36]. For remote sensing systems, sensors such as imaging sensors with diverse resolutions are the essential components. The usage of sensors is quite diverse, depending on the needs. Some of the sensors that can be used in observation are LiDAR, visual cameras, thermal or IR cameras, and solid-state or optomechanical devices [32], [37]. The types of sensors are fundamentally divided based on their spectral sensitivity, and the electromagnetic spectrum (see Figure 4) of the bands used by remote sensing systems [38].

In order to detect an obstacle, different types of sensors are used which can be mainly categorised into two sets:

- Passive Sensors
- Active Sensors

A. PASSIVE SENSORS

Passive sensors are the ones that detect the energy discharged by the objects or the scenery under observation. Most of the passive sensors being employed in sensing applications are optical or visual cameras, thermal or infrared (IR) cameras, and spectrometres [39], [40]. There are different types of cameras which work on different wavelengths (see Figure 4), for instance, visible light, infrared (short-wave, near-wave, mid-wave, and long-wave infrared), and ultraviolet band (UV). In [41], the authors present a methodology for tracking and real-time detection of a vehicle using acoustic signals. From noisy data, they extract the robust spatial features and then process them through sequential state estimation to acquire the output. They verify the proposed methodology with practical acoustic data.

Optical or visual sensors are cameras such as monocular or stereo cameras that work in the visible light [42], [43].

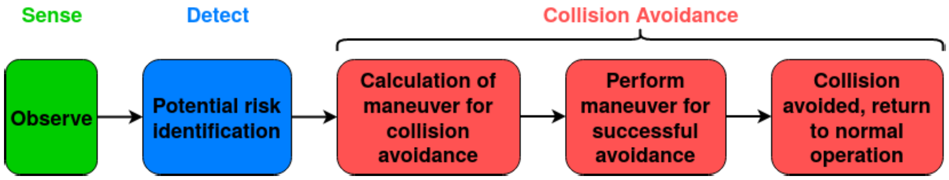

FIGURE 3. General process for collision avoidance.

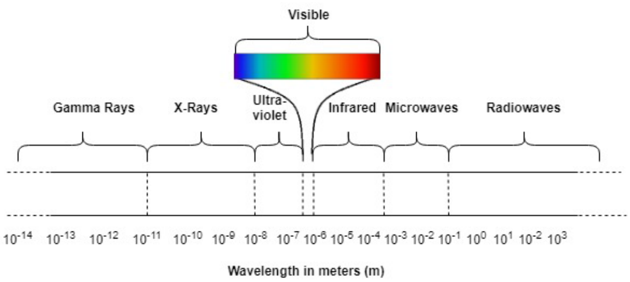

FIGURE 4. Electromagnetic spectrum.

Thermal or infrared cameras, in turn, have a longer wavelength than the visible light range and work in the infrared light, i.e. from 700nm to 14μm. Consequently, the fundamental difference between the two is that visual cameras form an image using the visible light whereas thermal cameras form images based on infrared radiation. While traditional cameras have poor performance in low lighting, IR cameras excel in such conditions [39]. All cameras rely on heavy image-processing in order to extract useful information from the chunks of raw data being provided by the sensor. The extraction of points of interest requires a separate algorithm, besides the additional algorithm needed for the calculation of the range and other parameters of the obstacles, and requires therefore extra processing power [44]. Besides the limitation of field-of-view of the used sensor, visual cameras depend heavily on the weather conditions as well, such as lighting level, fog or rain [45], [46].

1) CAMERA

Visual sensors or cameras rely on capturing the images of the environment and objects to give useful information to be extracted. Visual cameras are typically monocular, stereo, and event-based cameras [47]–[49]. The benefits of using cameras are their small size, lesser weight, lower power consumption, flexibility, and they can be easily mounted. In contrast, the disadvantages of using such sensors are, e.g., their high dependency on weather conditions, lack of image clarity, as well as sensitivity to lighting conditions and background colour contrast. These factors have a significant impact on the outcome, as the quality of the captured image drops drastically if any of those factors play part in it.

In [50], the authors propose an obstacle detection algorithm based on a monocular camera for ground robots. An improved Inverse Perspective Mapping (IPM) with a vertical plane model is used to perform a coarse obstacle detection in the bottom third of the image, which makes it only appropriate for slow-moving robots (1m/s). Afterwards, the obstacles are segmented using the Markov random field (MRF) framework and the distance between the robot and the nearest obstacle is obtained. On the other hand, the authors in [51] propose an approach based on stereo cameras. Unlike monocular cameras, in stereo cameras the absolute depth is obtained using the intrinsic and extrinsic parameters of the cameras. However, using stereo imagery increases the required computational power. Thus, the authors divide the captured images into nine regions to reduce the computational cost and to cope with highly complex systems with six degrees of freedom (6DoF) such as drones. Moreover, a fuzzy controller is used to smooth the response of the controller. Falanga *et al.* [52] propose an algorithm based on event cameras for obstacle avoidance to cope with high-speed movement of drones. One of the main advantages of using event cameras for obstacle avoidance is that their processing requirement is lighter than that of traditional cameras to detect an obstacle, because of the fact that an event camera only captures the changes in the environment without any redundant data.

2) INFRARED

Infrared (IR) cameras are sensors working in the infrared band and are used in low-light conditions. They can also be used together with visual cameras to overcome their poor performance for instance in night times. However, since the output of a thermal camera is blurry and distorted with lower resolution as compared with RGB cameras, its data can be analysed via extracting artificial control points and analyse them for automatic inclination or the orientation of the image [53]. For instance, the iRobot Roomba vacuum cleaner [54] uses an infrared sensor and bump sensors to detect obstacles. The bump sensor detects obstacles/objects only after bumping into them, which may damage the robot.

B. ACTIVE SENSORS

Active sensors work on the mechanism of emission of radiation and reading the reflected radiation. An active sensor has its own transmitter (source) and receiver/detector. A transmitter emits a signal that can be in the form of e.g. a light wave, an electrical signal, or an acoustic signal; this signal then bounces off an object, and the receiver of the sensor reads the reflected signal [55], [56]. Their ability to penetrate the atmosphere in most conditions is due to the fact that majority of such sensors work in the microwave portion of the spectrum. Examples of ranging sensors are: LiDARs [57], radars [58], sonar or ultrasonic sensors [59], [60], and active infrared sensors [61], [62]. Such sensors have fast response, require less processing power, can scan larger areas quickly, are less affected by the weather and lighting conditions, and can return the parameters of interest of the obstacles, such as distance and angles, accurately. The authors in [63] use millimetre wave (MMW) radar. In their system, by observing the echoes produced by radar signals the distance between the object and the vehicle is calculated for detecting and tracking the objects. The performance is also evaluated in different weather conditions and for different distances. Although the radar based solutions are appealing, they are either too expensive or heavy as a payload for smaller robots such as battery operated UAVs [64], [65].

1) RADAR

A radio detection and ranging (radar) sensor functions by transmitting a radio signal which upon encountering an object bounces off of it back to the radar. Depending on the time it took for the signal to bounce back, the distance between the object and the radar is calculated. Radar systems have been around for decades; they have good resistance to weather conditions and hence are also applied to airborne systems. Although airborne radar systems are quite expensive, they are commonly used to provide data due to their accuracy.

Radars are based on either continuous waves or pulsed waves. A continuous-wave radar, as the name suggests, emits a continuous stream of linearly modulated signals (also known as frequency modulated signals), while a pulsed-wave radar emits powerful and short bursts of signals and hence suffers from a blind spot in contrast to the continuous-wave radars [66]. Radars are also used to detect the motion of the objects such as their speeds. For instance, if an object is moving towards the radar, the frequency of the echo or bounced off signal increases, and the change in the frequency is used to calculate the speed at which the object is moving [67]. Microwave radar sensors are insensitive to weather conditions but have relatively low frequency band and therefore do not provide a sufficient angular resolution. However, the millimeter wave radar sensors have benefits such as a finer angular resolution and small size but are sensitive to weather conditions [68]. The angular resolution is dependent on the aperture size of the antenna but can be enhanced to some extent by increasing the frequency.

Radars are appropriate for outdoor applications due to their immunity against environmental conditions such as the ability to operate irrespective of lighting conditions or overcast weather, and wide range coverage. However, only obstacle detection can be done but exact reconstruction of an object's dimensions is not possible with radars due to their low output resolution [69]. The authors in [67] used small-sized radar for acquiring real-time range under all weather environments. The setup is composed of a small-sized radar sensor and obstacle collision avoidance system (OCAS) processor. The data generated by the radar, such as the velocity of the obstacles, azimuth angles, range of the obstacle, is used by OCAS to calculate the avoidance criteria and send the commands to the flight controller to perform necessary maneuvers to avoid collisions. They evaluated the performance of the system and at the required detection range, the probability of detecting an obstacle is more than 90%. For collision avoidance, four different scenarios were used to analyse its performance. And the results showed that even if there is an error in the radar data, successful collision avoidance probability is more than 85% due to the defined safety margins.

In [70], the authors provide a comprehensive study of the advantages of using radar sensors with UAVs for obstacle detection and the detection and calculation of other attributes of the detected obstacle, such as the velocity of the obstacle and the angular information using multichannel radars. Furthermore, using forward facing radars, radar's simultaneous multitarget range capability, the detection of targets in the wide angular range of $\pm 60^\circ$ in azimuth is shown by experimental results. In [71], in order to implement the proposed autonomous collision avoidance strategy, the authors utilised Ultra-Wideband (UWB) collocated MIMO radar. One of the key benefits of radar cognition is the ability to adapt UWB-MIMO radar transmission waveform for providing improved detection and therefore to guide the UAV it provides approximation of the collision points. In [72], the authors study radar systems for sense and avoid on UAVs as they are one of the most reliable all-weather sensors that precisely provide the ranging and closing speeds. A detailed analysis for three radar bands, i.e., S (3 GHz), Ka (35 GHz), and X (10 GHz) bands is provided and the advantages and disadvantages are discussed for each individual band. After studying the radar bands for sense and avoid technique, the authors concluded with X-band the most favourable solution due to its ease of installation as it can be integrated in the UAV frame without extra volumes, and its cost, and performance such as its ability to provide good angular accuracy. In [73], the authors investigate the performance of radar sensor and proposed the design of a prototype miniature lightweight X-band radar sensor for UAVs, due to the capability of radar sensors to provide comprehensive identification and detection of the targets/obstacles for the UAVs. The Doppler shift caused due to the propulsion of the UAV, is used for the reliable detection of the targets and subsequently utilised to enhance the maneuvers of the UAV for avoiding the collisions. The authors claim that this detection and identification process is scalable and can be used for larger vehicles as well.

2) LiDAR

A light detection and ranging (LiDAR) sensor works very similar way to radars. LiDAR sensors operate in two parts: one part emits laser pulses onto the surface(s) and the other reads their reflection to measure the time it took for each pulse to bounce back in order to calculate the distance. Data collection using LiDAR is fast and also extremely accurate. LiDAR systems have become more affordable during the past

TABLE 1. Sensor attribute comparison for Obstacle Detection: short (0-100 m), medium (100 - 1000 m), long (> 1000 m).

Sensor	Mode	Accuracy	Weather Condition	Light Sensitivity	Range	Sensor Size	Processing Requirement	Power Required
LiDAR	Active	High	Low Dependency	No	Medium	Small	Low	Medium
Radar μ-wave	Active	High	Not dependant	No	Long	Large	Low	High
MMW	Active	High	Dependant	No	Long	Small	Low	Medium
Ultrasonic	Active	Medium	Partial Dependency	No	Short	Small	Low	Medium
Thermal or IR	Passive	Medium	High Dependency	No	Medium	Small	High	Low
Camera	Passive	Medium	High dependency	Yes	Short	Small	High	Low

two decades. Furthermore, over the years LiDAR sensors have become much smaller and compact in size and lighter in weight as compared with the earlier versions and are now feasible for mounting on small and micro UAVs as well [69], [74]. The systems based on LiDAR, especially 1D and 2D LiDAR sensors, are more economical than the radars. The authors in [57] tested their developed system under various conditions with good accuracy, with different types of laser scanner mounted on a vehicle. 3D LiDARs, also known as 2-axis LiDARs, are conventional sensors for 3D mapping or 3D obstacle detection [75]. Due to the continuous movement and ranging of LiDAR, motion warping present in the acquired data makes the usage of these LiDARs strenuous. The authors in [76] suggest that a way to overcome this is by incorporating other sensors along with LiDAR. Exact pose estimation of objects can be made with 3D LiDARs only. The authors in [77] present a solution for distortion, caused by the motion, by extracting intensity images from the 3D LiDAR scans and matching the visual features.

Since LiDAR uses a short wavelength, it has the ability to detect small objects and can reconstruct a monochrome coloured 3D image of the environment. LiDAR's major weakness is that it cannot detect transparent objects such as clear glass. Therefore, LiDAR needs to be accompanied by another sensor, such as an ultrasonic sensor, that can overcome this issue.

3) SONAR

Ultrasonic sensors work on the principle of emitting sound waves and listening to its reflection back from an object to calculate the distance between the object and the sensor [78], [79]. The sound waves are generated at a frequency too high, i.e., 25-50 KHz, for the human hearing frequency band [80]. The basic principle used to calculate the distance is similar to the one used by radars or LiDARs, i.e., emit a wave, wait until the bounced off wave from an object arrives, and calculate the distance based on how long it took for the wave to reflect back by using this simple formula:

$$d = \frac{(v * t)}{2} \tag{3}$$

where d is the distance, v is the speed of the wave, and t is the time of flight.

Ultrasonic sensors are readily available and are much cheaper than most of the other ranging sensors available in the market. Unlike LiDARs, ultrasonic sensors are unaffected by the transparency of the object; for instance, LiDARs have difficulty in detecting clear glass while ultrasonic sensors are not affected by the colour of the objects. However, if the object reflects the sound wave in a different direction than the receiver or if its material has the characteristics of absorbing sound, the sonic sensor's readings will be unreliable.

Table 1 shows that all the sensors have some limitations and strengths over the others, making it evident that not one specific sensor can be used to cover the collision avoidance problem comprehensively. More than one sensor can be used to cover larger area and make up for blind spots, or multiple sensor types can be fused together, where the weakness of one sensor can be counterbalanced by the other(s).

According to Table 1, it can be understood that mainly active sensors have better accuracy in contrast with inactive or passive sensors. However, active sensors have higher power consumption as compared with passive sensors, as active sensors first transmit the signal and after that capture the data for computation, while passive sensors rely on some external power source for transmission, such as sun light or object's own source, and only reads the signal for computational purposes. Another important comparison is the processing requirement. The data captured via active sensors is *directed* data, i.e., the data is specified for the detection, it does not contain unnecessary data, like what exists in e.g., cameras. This makes the processing of active sensor data easier as compared with passive sensor's data. Another issue as the consequence of this phenomenon is the computation power of processing the data that for active sensors is lower than for passive sensors. For instance, in the case of camera(s), due to heavy computations for image processing and filtering the unnecessary information from the image, the processing power is higher as compared with a LiDAR sensor whose data is directed.

The other interesting analysis based on Table 1 is the effect of noise, e.g., weather condition or light sensitivity, on the data. Active sensors, because of directing the captured data and having their own source for transmitting waves, are less prone to noise than passive sensors. For instance, LiDAR or ultrasonic sensors work in most environmental conditions

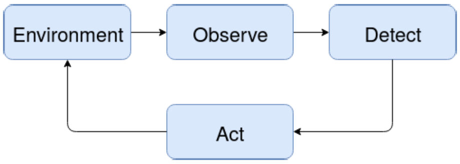

FIGURE 5. **Reactive collision avoidance.**

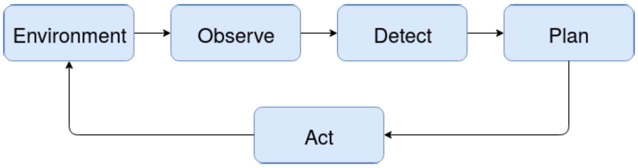

FIGURE 6. **Deliberative collision avoidance.**

with or without daylight; cameras, on the other hand, need optimal lighting to be able to create an image of the environment.

Furthermore, using a passive sensor for detection of obstacles is highly questionable as the algorithm designed may not be able to distinguish between one or more objects in scenery and can thereby cause collisions. One major example of such an issue is that of a fatal accident involving a Tesla car, whose collision avoidance system failed to distinguish between a brightly-lit sky and a tractor trailer [81].

III. COLLISION AVOIDANCE

In general, collision avoidance approaches work on either of the two principles: reactive or deliberative planning. Figure 5 shows that in reactive control the agent/robot gathers the information about its surroundings using local on-board sensors and react based on that information. It allows for rapid response to sudden changes in the environment. However, reactive control can lead to a local minimum, may get stuck in it, and may require another navigational technique to overcome this problem.

In deliberative planning, shown in Figure 6, the agent senses and updates the environmental map. Once the map has been updated, an optimal path with collision free route is calculated keeping the initial goal as a reference, and that optimal route plan is then executed. For this, an accurate map of the environment is needed to be able to work perfectly, which requires more computational power to do all the required computations. This approach, as such, is not suitable for dynamic environments in which variables change over time. Hence, a hybrid approach, that can switch between the reactive and deliberative modes depending on the environmental needs, is more appropriate.

Collision avoidance algorithms can be categorised into the following major methods: 1) *geometric* methods that work by computing the distance between the agent/UAV and the obstacle utilising the information such as velocities of both UAV and obstacle and location of obstacle [82]–[85]; 2) *force-field* methods, in which main idea is inspired by attractive or repulsive electric forces that exist among charged objects. In a swarm of drones, each UAV node is considered a charged particle, and attractive or repulsive forces between them and the obstacles are used to generate the path or the route to be taken [4], [86]; 3) *optimisation-based* methods that aim at finding the optimal or near-optimal solutions for path planning and motion characteristics of each drone w.r.t. the other drones and obstacles. These techniques rely on static objects, with known locations and sizes, for calculating the efficient route within a finite time period [87], [88]; and 4) *sense-and-avoid* methods that mainly focus on reducing the computational cost, with short response time, by simplifying the process of collision avoidance to an individual detection and avoidance of obstacles for each drone and deviating the drone from its original path when needed, independently of the other drones' plans [35], [89], [90]. Each method is explained in more detail in the following sections.

A. GEOMETRIC METHODS

Geometric approaches rely on the analysis of geometric attributes to make sure that the defined minimum distances between agents, e.g. UAVs, is not breached. This is accomplished by computing the time to collision by utilising the distances between the UAVs and their velocities. If Automatic Dependent Surveillance Broadcast (ADS-B) sensing is used to obtain the mentioned attributes, the usage of the method is restricted due to the sensitivity of ADS-B towards noise. It is also classified as cooperative sensing as ADS-B needs cooperation between UAVs. However, if a UAV is equipped with a vision-based sensor that can detect an obstacle's location, size and velocity using a passive device, a non-cooperative sensing methodology is obtained, drastically increasing the amount of on-board processing required [85], [91]–[93].

To optimally solve the problem of collision between two aircrafts, the authors in [94] present an analytical approach for a planar case to resolve that conflict. Utilising the geometric characteristics of the trajectories, closed-form analytical solutions are acquired for optimal combinations of commands for resolving the conflict. Minimum deviation from the normal flight plan is achieved by minimising the velocity vector changes. In [95], using a mixed geometric and collision cone approach along with the information such as the coordinates and the velocities of the aircrafts, conflict avoidance in a 3D environment is achieved. However, for the most general cases, the authors rely on numerical optimisation methods and acquire analytical results for special cases only.

In [96], the authors study geometry based collision avoidance strategies for a swarm of UAVs. The proposed approach uses line-of-sight vectors in combination with relative velocity vectors while considering the dynamic constraints of a formation. By calculating a collision envelope, each UAV can determine the available direction for avoiding a collision and decide whether the formation can be kept while avoiding collisions. For cooperative UAVs in a 3D environment, [97] proposes a method for providing a selected UAV with an optimal flight path. Considering changes only in vertical directions, the authors use an integration equation of distance, track adjustment costs and time, under certain restrictions such as performance and distance constraints, to generate an optimal flight path to be navigated upon. An approach in which tracking control is integrated with a geometric collision avoidance method is proposed in [98]. Upon detection of obstacles, the obstacles with the highest risk are first selected. Then, a boundary sphere is generated for each obstacle to define the safe and risk areas, and tangent lines from the UAV to the sphere, together with information on the direction of the UAV's movement, are used to calculate a collision detection angle to determine the best direction of deviation to avoid the possible collision.

In [99], the authors presented a new methodology of Fast Geometric Avoidance Algorithm (FGA) based on kinematics, the probability of collisions, and navigational limitations by combining the geometric avoidance and the selection of start time from critical avoidance. In multiple obstacles scenario, instead of avoiding the obstacles simultaneously, FGA can assign different threat levels to obstacles based on the critical time for avoidance and avoid them sequentially and hence increasing the avoidance success rate. Simulation results, in same environment, showed a comprehensive reduction in the computational time for FGA as compared to other similar way-point generation method.

In [98], the authors proposed a methodology of guiding the UAVs from mission start to destination whilst avoiding colliding with any obstacles in their path and keeping a track of the pre-defined trajectory. In order to achieve this optimally, the authors propose combining the collision avoidance control with the trajectory control of the system while solving these tasks independently and later combining them by a designed movement strategy. Making the computations simplified and faster as collision avoidance control is provoked only in the presence of obstacles. A tracking control law is designed by computing the tracking errors, from the geometrical relation between the UAV and pre-defined trajectory, to make sure that the UAV stays as close to the reference as possible. Similarly, upon detection of a possible collision, collision avoidance control calculates the risk zones and angles to calculate the best avoidance maneuver. However, the effectiveness of the proposed approach was tested under static conditions and more work is required to verify and validate the usability in dynamic environments.

B. FORCE-FIELD METHODS

Force-field methods, also known as potential field methods, use the concept of a repulsive or attractive force field either to repel an agent/robot from an obstacle or to attract it towards a target [92], [100]–[102]. The position where the obstacles lie in the environment and their shape must be known, as this approach relies on the motion and geometry of the robot and the obstacles. In dynamic environments, these attributes of the obstacles are not known in advance. In [103], the authors present an idea of placing a potential field around a robot rather than obstacles. In [104], the authors propose an artificial potential field for finding the shortest path between starting and destination points. A robot is repelled from and attracted towards obstacle and target points, respectively, due to the repulsive and attractive forces generated by those respective points. Based on these two types of forces, the robot calculates the aggregate force which then determines the characteristics of the robot's motion. A major drawback of this method is that, for symmetric environments, it is very sensitive to local minima and therefore does not necessarily lead to a globally optimised solution.

In [101], the authors proposed a novel artificial potential field approach called "enhanced curl-free vector field" for optimal collision free routes generation under dynamic conditions with multiple obstacles, where other UAVs are also considered as moving obstacles as well. Instead of utilising the conventional potential field, in this approach, enhanced curl-free vector field, i.e., conservative field, is used by generating the field around the obstacle and determining the field vectors, i.e., direction of the curl-free vector, based on the velocity vector of dynamic obstacles and the corresponding position vector's angle from UAV to the obstacle and the path angle of the UAV. The usability of this approach was tested with simulations, however, this approach still needs to be validated in 3D environments with static and dynamic variables.

In [105], the authors present an optimised artificial potential field algorithm to provide smooth and safe trajectories for UAVs in a 3D space. The proposed optimised artificial potential field (APF) algorithm provides an improvement over the traditional APF algorithms by considering other UAVs and their interactions as part of the method. The algorithm sees other UAVs as dynamic obstacles while planning navigation towards the target. The authors simulated various scenarios to test their algorithm for unreachable target problem that exists in the classical APF algorithm. Furthermore, the optimised navigation was also tested through simulations where the algorithm allows the UAV to plan at every instant while taking into account the obstacles, other UAVs, and the destination.

In [106], a vehicular collision avoidance algorithm based on artificial potential fields is presented. By relying on the dimensions and also on the shape of the potential fields of the obstacles/vehicles, the algorithm can appropriately guide a vehicle either to slow down or accelerate to pass another vehicle, depending on the vehicles' velocities and the surrounding traffic. However, this method has its limitations. For instance, complex maneuvers can take place around other vehicles due to local minima. Moreover, the step size used for the time function has to be precisely adjusted, because a too large time step can cause collisions or unstable behaviour.

The authors in [107] propose a 1D virtual force field methodology for detection of moving obstacles. They claim that the problem of efficiency loss in a traditional obstacle force field (OFF) method is due to the lack of taking the obstacles' motion into account. This can be resolved by the proposed prediction based obstacle force field method. Focusing on unmanned ground vehicles (UGV), the approach equips a UGV with a frequency modulated continuous wave radar to determine the predicted obstacle force field (POFF) to accommodate the problem of moving obstacles, addressing thereby the major weakness of conventional 1D virtual force field algorithms. Using the obstacle's velocity, the time-to-collision is calculated, based on which the approach predicts the estimated point of impact and generates the POFF.

In [108], the authors consider a robot a particle in a force field. Upon insertion of the robot in the potential field, the repulsive forces generated by the obstacles will repel the robot away from them, and the attractive forces generated by the target will attract the robot towards it. Experimental results through simulations showed that the response of this approach can be fast and reactive for static environments, requiring further work in analysing the response of this approach in dynamic environments. Furthermore, the proposed algorithm does not tackle the problem of local minima where the sum of attractive and repulsive forces is zero.

C. OPTIMISATION BASED METHODS

Optimisation based methods rely on calculation of the avoidance trajectory based on geographical information. Probabilistic search algorithms aim to provide the best search areas based on the available uncertain information. To address the high computational complexity of these algorithms, several optimisation methods have been developed, such as ant-inspired algorithms, genetic algorithms, Bayesian optimisation, gradient descent based methods, particle swarm optimisation, greedy methods, and local approximations. In [109], for instance, the authors use a minimum time search algorithm with ant colony optimisation to ensure successful calculation of optimised collision-free search paths for UAVs under communication-related constraints.

Focusing on unmanned surface vehicles (USV), the authors in [110] discuss collision detection and path planning methods by considering global and local path planners, analysing the most common techniques from the classical graph search theory as well as intelligent methods like artificial neural networks and evolutionary algorithms. The authors highlight the inadequacy of existing methods by concluding that almost none of the existing approaches appropriately address sea or weather conditions and/or involve the dynamics of the vessel when the path is generated. Hence, further studies are needed in this area.

In [111], the authors present an algorithm that predicts the next coordinates of a UAV based on the set of possible commands it is going to execute in a short period of time. The algorithm formulates a cost function for the optimal trajectory by considering the target coordinates and the current position of the UAV. Based on this cost function, the best set of future commands is selected. Then, a collision detection method is applied, and if a potential collision is found, the next best set of commands is chosen and evaluated similarly. The process can involve several recalculations of the cost function to eventually find the optimal collision-free solution.

In [112], the authors propose a new methodology, based on particle swarm optimisation, for path planning of autonomous vehicles in unknown environments. In this approach, the data on the environment gathered by the sensors is utilised by assigning different weights to different types of territories, and based on those weights the algorithm classifies different possibilities of navigating through the terrain. The algorithm then selects the optimal path based on this classification.

D. SENSE & AVOID METHODS

Sense-and-avoid methods mainly focus on reducing the computational power needed, with short response times, by simplifying the process of collision avoidance to individual detection and avoidance of obstacles, to control the path of each drone in a swarm without knowledge on the plans of other drones. In a formation, the location of each drone w.r.t. the other drones is defined, and the collision avoidance process deals with individual path planning for drones in order to avoid possible crashes both between drones within the swarm and between drones and external obstacles in the environment. Sense and avoid based collision avoidance is known for its ability to react quickly and it is therefore an appropriate method for dynamic environments. In this approach, an agent/robot is equipped with different types of sensors such as LiDAR, sonar, and radar. For instance, radar reacts quickly to any object that comes within the detection range of the sensor, even though it cannot see the details of the object [35], [113], [114].

A 2D LiDAR based approach, proposed in [115], presents a methodology where the objects are classified into two categories, static or dynamic. The algorithm is also capable of approximating the velocities of the dynamic obstacles. The proposed algorithm is demonstrated to be efficient as compared with similar existing methodologies in terms of required computational power and memory.

The authors in [116] use a computer vision technique for detecting animals and avoiding collisions with them. They have used more than 2200 images to train their system and performed tests based on video clips of animals on highways. The algorithm provides satisfactory results with 82.5% accuracy and successfully detects animals in order to avoid collisions. However, the proposed solution is highly speed dependent and will not help in preventing collisions at speeds exceeding 35km/h. In fact, at higher speeds, it may not be able to detect objects at all. Furthermore, the provided solution can have a very poor performance especially in bad weather conditions, in low or too bright lighting, in foggy conditions, as well as in shiny (highly reflective) surroundings.

In [117], the authors use five ultrasonic (US) sensors along with a predefined neural network module in MATLAB to triangulate and detect the precise position and shape of objects. They consider three different shaped objects for their testing. Furthermore, the five US sensors used in their solution are more than required for locating a detected object, as the precise 2D location can be found using only two US sensors, and the third dimension (depth) can be found by adding the third US sensor. Moreover, their results are satisfactory only when the objects are regular shaped; they report that their neural network is not able to correctly identify objects with irregular shapes.

In [3], the authors use low-cost sensors (US sensors and IR scanners) to develop a simple solution for obstacle detection and collision avoidance. They employ inertial and optical flow sensors as a distance derivative for reference to get better data fusion. The resulting solution has a low computational cost, saving memory and computing time, and it enables a UAV to efficiently avoid collisions without any need for simultaneous localisation and mapping.

In [118], the authors fuse an US sensor with a binocular stereo vision camera to implement object detection and avoidance. A new path is calculated by an algorithm based on the Rapidly exploring Random Tree (RRT) scheme, using stereo vision as the main approach to detect obstacles around a UAV. The US sensor is utilised especially in situations where the camera fails to detect the obstacles [118].

In [119], a real-time 3D vehicle detection method (RT3D) is proposed, using a pure LiDAR point cloud to predict the location, orientation and size of vehicles. The authors use a pre-RoI pooling (region of interest pooling) convolution technique to pre-process most of the data in order to maximise efficiency. Furthermore, to increase the detection accuracy of location, orientation and size of vehicles, they also propose a pose-sensitive feature map design activated by relative poses of vehicles. Using the KITTI benchmarks data-set [120], [121], they demonstrate that the designed RT3D system delivers a competitive accuracy compared with the existing state-of-the-art methods, reportedly being also the first approach that completes detection within 0.09s, i.e. in a time shorter than the scan period of mainstream LiDAR sensors.

The author in [122] proposes a 3D reactive obstacle avoidance technique. The algorithm detects an obstacle in a UAV's path, makes the craft hover on its position, calculates the best escape route, and then instructs the UAV accordingly. This proposed method was efficient enough in detection of various obstacles such as trees, communication towers, with the mean collision time being 0.08ms and the mean escape point search time being 0.49ms. The method is demonstrated using stereo vision and laser-based sensing schemes. The limitation of such methodology is the on-board memory for 3D maps as the escape point search can only be done within the bounds of the saved map, so increasing the size of map will increase the efficiency of escape point search.

In [123], the authors propose a solution in which the possible paths are represented by lines with different colours. A robot having the ability to distinguish between various colours can then select the desired line autonomously to reach the target. This system is not viable in dynamic environments nor in bad lighting conditions. Furthermore, the robot is totally dependent on the visibility of the lines and does not take into account the presence of an obstacle on a line itself, lacking dynamic capabilities completely in such situations.

In [124], the author proposes to equip vehicles with adaptive cruise control along with a collision avoidance system in such a way that collisions with other vehicles are autonomously avoided by braking at slower speeds and by steering at higher speeds. In [125], forward-looking cameras are used for real-time obstacle detection and avoidance. The presented fuzzy control based method is in principle applicable to different types of unmanned vehicles; in the paper, it is experimented on a small quadrotor UAV. The authors use a camera that is mounted in front of UAV to avoid collisions via visual servoing through image processing. In this approach, the collected data is wirelessly sent to a laptop for further processing, where obstacles are marked with specific colours, and this information is then employed to guide the UAV around the obstacles. The algorithm avoids the obstacles by pushing them to either the left or right side of the image. A potential problem in this setup is that communication delays between the drone and the controlling computer can lead to an accident in situations where an obstacle is very close or moves rapidly towards the UAV.

In [126], the authors propose a methodology which uses two cameras for detecting the obstacles in the range of 30 to 100 meters and up to the speed of about 22km/h. In order to differentiate between the sea and sky, this approach relies on the sea-sky line and assumes that the obstacles are moving in a regular manner. Different filters are applied to detect the obstacles. A limitation of the scheme is that it does not take into account rough sea waves, haphazardly moving obstacles and overcast situations.

In [127], a simulated UAV equipped with a LiDAR sensor is inspected using a feed-forward based algorithm. The UAV is mainly controlled by the operator, and the algorithm estimates the path of the UAV by using the current inputs from the operator and the future for a predefined period of time. The algorithm checks for any possible collisions with objects and diverts the UAV from the original path when needed by keeping it as close to the operator's input as possible.

E. ENVIRONMENTAL EFFECTS

Environmental disturbances exist in all industrial systems and have a huge impact over especially UAVs and therefore are one of the key factors in the design of stability controllers of such systems. This environmental disturbance, such as safe and controlled landing of the UAVs under dynamic conditions such as oscillatory or moving platforms [128] or maintaining the geometric configuration of multiple or swarm of UAVs [129] or wind effect [130], is estimated by the designed controller and then a feedback control action is taken based on that. Different methodologies or algorithms designed to deal with such uncertainties have the common goal of estimation of uncertainties or disturbances to design a compensation controller that minimises their effect on the system. Such methods are also referred to as disturbance/uncertainty estimation and attenuation (DUEA) [131]–[133].

In [133], in order to optimise the coverage in urban areas, presence of obstacles, the authors proposed a method of triangular mesh generation which also considers the wind field and perform online adjustments accordingly to minimise the energy loss due to the identified wind field. For wind field identification, the proposed methodology analyses the behaviour of the wind vector statistically and for sequencing/re-sequencing of way-points and optimisation of trajectories it is then added to the next generation autonomous UAS flight management systems. 11% improvement of energy consumption is reported in the presence of wind, while in the presence of gusts of wind an energy efficiency of upto 9% is reported in the results.

In [134], the authors proposed an ce rejection control (ADRC) guidance law for collision avoidance of UAVs to tackle with the instability caused by disturbances such as wind, sensor noise, and unknown obstacle acceleration. The designed ADRC controller was overlapped with the collision avoidance as a stabilising feedback control system. The stability of the nonlinear ADRC is proved using simulations and the results show that the designed technique can deal with multiple disturbances.

In [135], the authors developed a two mode controller to tackle with extreme winds that may take the UAV out of its stability bounds. The designed controller functions in normal mode if the thrust and sensor limitations are not exceeded by the environmental conditions or in case they are, then the controller switches to the drift mode, in which a drift frame is generated, based on the UAV's thrust, drag and wind estimation, and the stabilising trajectories are generated. The stabilised trajectory is generated by the UAV by intertial frame trajectory tracking requirement in the drift frame. Authors validated the performance of the designed controller through simulations by comparing the performance of controller equipped UAV with the UAV which does not utilise the drift mode.

IV. DISCUSSION AND CONCLUSION

In the previous sections, we presented a comprehensive literature review on collision avoidance systems and strategies used for unmanned vehicles. As any collision avoidance system needs a means to be able to sense or perceive its surroundings, we also analysed the different types of sensors relevant to unmanned vehicles, classifying them into active and passive devices in a traditional manner. The considered collision avoidance approaches were divided into four main categories: geometric methods, force-field methods, optimisation based methods, and sense and avoid methods. These different classes of approaches have some benefits and trade-offs that are assessed and summarised in this section.

An active sensor has its own transmitter, a source of energy, for emitting a wave, with a given range of wavelengths, and a receiver for reading incoming waves reflected back from objects in the environment. A passive sensor, in contrast, only detects the light or energy discharged or reflected by objects, relying on an external source of energy to be present. For instance, a camera, a passive sensor, relies on an external light source to illuminate the scenery for it to work properly, whereas LiDAR, an active sensor, emits its own laser pulses onto the scene under observation and reads the back-scatter for further processing. Therefore, accuracy of data provided by a camera depends on the quality and intensity of an external light source, while LiDAR does not have such a limitation.

As active sensors contain both transmitter and receiver, they consume in general more power than passive sensors that just read data. On the other hand, active sensors capture directed data, i.e., reflected versions of the signals emitted by the sensors themselves, which simplifies the data processing phase significantly. In the case of passive sensors such as visual cameras, the computational requirements are very high, because the raw image data needs to be thoroughly filtered and processed to find the relevant points of interest. Consequently, a camera based collision avoidance approach has a high computational cost, making it challenging especially for scenarios where very fast object detection and decision making is needed. On the other hand, in appropriate lighting conditions, it can provide more detailed information on the environment than an approach based on an active sensor such as LiDAR, sonar or radar. Having said that, lower processing needs (i.e. faster response times) and better tolerance against difficult lighting and weather conditions make ranging systems more suitable for efficient collision avoidance compared with camera based methods.

Discussed collision avoidance approaches can be compared from different perspectives and by defining different evaluation metrics. The evaluation metrics generally are determined based on the expected goals of the algorithm in its use case and limitations of the platform. Each collision avoidance algorithm has its own pros and cons w.r.t. the different evaluation metrics that make the algorithm suitable for a specific use case. An overview of the advantages and disadvantages of the most common methods in the-state-of-the-art is shown in Table 2. To illustrate a general comparison among different aspects of the algorithms, we have categorised the algorithms independently based on ten evaluation metrics that are depicted in the table and explained as follows:

The first metric is real-time performance: The RTP of sense and avoid and geometric is better than compared to the force-field and optimisation methods, as sense and avoid does not required too much processing to avoid any changes in the environment i.e., obstacles approaching. Also geometric methods are fast and computationally light. However, disadvantage of geometric methods as compared to sense&avoid is that in geometric the time of computation and algorithm complexity is highly dependant on the algorithm implementation.

The second metric is velocity constraint (VC), i.e., the velocity of the obstacles is taken into consideration: According to the literature reviewed, taking VC into consideration, it is to handle VC using sense&avoid and geometric approaches, however force-field and optimisation methods are more suitable for pre-defined planning and does not take into account the UAV dynamic at each interval.

The third metric is static and dynamic environment: For handling the dynamic environments, sense&avoid approach is the easiest and lightest since it offers local computations to react to any changes observed by the on-board sensor system

TABLE 2. Performance comparison between state-of-the-art collision avoidance approaches: real-time performance (RTP), velocity constraint (VC), static and dynamic environment (SDE), deadlock (DL), swarm compatibility (SC), robustness (R), 3D compatibility (D), communication dependence (CD), escape trajectories (ET), pre-mission path planning (PPP).

CA Approach	References	RTP	VC	SDE	DL	SC	R	D	CD	ET	PPP
Geometric	[96] [99] [136] [137]	✓	✓	✓	✗	✓	✓	3D	✗	✓	✗
	[138]	✓	✓	✗	✗	✓	✗	3D	✓	✓	✓
	[139]	✓	✗	✗	✗	✓	✓	3D	✓	✓	✓
	[98] [140] [141]	✓	✓	✓	✗	✓	✓	3D	✓	✓	✓
Force-Field	[101] [105]	✓	✓	✓	✗	✓	✓	3D	✓	✓	✓
	[107]	✓	✓	✓	✗	✓	✓	1D	✗	✓	✓
	[104] [108]	✓	✗	✗	✓	✗	✗	2D	✗	✓	✓
	[142]	✓	✗	✓	✗	✓	✓	2D	✗	✓	✓
Optimisation	[110] [111] [143]	✗	✗	✗	✗	✗	✗	2D	✓	✓	✓
	[112]	✓	✗	✓	✗	✓	✓	2D	✓	✓	✓
	[144]	✓	✓	✓	✗	✓	✓	3D	✓	✓	✓
Sense & Avoid	[115] [3]	✓	✓	✓	✓	✓	✓	3D	✗	✓	✗
	[117] [126]	✓	✗	✗	✓	✗	✗	3D	✗	✗	✗
	[119]	✓	✓	✓	✗	✗	✓	3D	✗	✗	✓
	[122]	✓	✗	✓	✗	✓	✓	3D	✗	✓	✗

and can work both indoors and outdoors in static or dynamic environments. Force-field does not have good performance in narrower passages and in dynamic environments it has a common issue of leading to a local minima. Optimisation on the other hand is best suitable for static environments, as it requires pre-planning and has to optimise the whole routine for any changes detected. It would also require more memory to store the large areas of map for better optimisation.

The fourth metric is deadlock: Optimisation and geometric methods does not have the deadlock/local minima issue. Force-field methods can lead to a local minima, however, sense&avoid methods do not handle this issue locally and require another methodology to tackle this issue.

The fifth metric is swarm compatibility: All the mentioned approaches can be utilised for large teams of UAVs. However, sense&avoid method requires the assistance of an additional algorithm for communication handling between the UAVs.

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

The seventh metric is dimensions: Sense&avoid, geometric, and optimisation methods have a lot of work handling 3D environments. However, a lot researchers are focusing on testing feasibility of utilising force-field methods for 3D dynamic environments.

The eighth metric is communication dependence: Sense&avoid methods do not have communication dependence as they work locally and take decisions locally without communicating with other UAVs or systems. Some discussed literature based on force-field methods rely on communication with other UAVs, while most other work does not, showing that force-field methods do not rely that much on CD and it depends on the model and implementation. Other approaches, however do rely on communication with other nodes/UAVs.

The ninth metric is escape trajectories: The escape trajectories offered by different approaches can be summarised as: sense&avoid offer escape trajectories at run-time and locally, the escape trajectories for optimisation methods are pre-defined based on the optimised path chosen, force-field methods offer escape trajectories based on the E-field that offers attraction/repulsion, and geometric methods have protocol based escape trajectories.

The tenth metric is pre-mission path planning: Sense&avoid and geometric methods do not require pre-mission path planning.In geometric methods path planning is done based on the collision cone and the velocity obstacle. Optimisation and force-field methods require pre-mission path planning to perform optimally.

Based on the discussion and our understanding, we provide a summarised attributes table as in shown in Table 3. Among the approaches, the geometric and force-field methods have the highest complexity level in terms of algorithm design (computational cost). The optimisation based methods are of medium complexity, while the sense and avoid approaches rank lowest for complexity in this comparison.

The geometric and force-field approaches are communication dependent. i.e., they rely on close interaction between the individual agents/robots constituting a swarm. The optimisation based methods are quite static and have therefore no concept of communication. The sense and avoid approaches are not communication dependent either as they are based on local sensing of the environment and local processing of the information in each individual agent/robot separately.

According to Table 3, it is quite evident that among the approaches the optimisation based collision avoidance methods are suitable only for static environments, since the whole

TABLE 3. CAA comparison w.r.t. summarised attributes: indoors (In), outdoors (Out).

CA Approach	Complexity	Communication Dependence	Escape Trajectories	Pre-mission Path planning	Static		Dynamic	
					In	**Out**	**In**	**Out**
Geometric	High	✓	Protocol based	✗	✗	✓	✗	✓
Force-Field	High	✗	E-field based	✓	✓	✗	✓	✗
Optimisation	Medium	✓	Pre-defined	✓	✓	✓	✗	✗
Sense&Avoid	Low	✗	Locally/Run-time	✗	✓	✓	✓	✓

environment needs to be known in detail, and the optimal solutions are discovered based on high-definition maps and pre-defined coordinates. Hence, they require pre-mission path planning unlike the other considered approaches.

The sense and avoid methods run locally and do not require any pre-planning, are the most robust among the considered approaches, and are suitable not only for static indoor and outdoor environments, but also for dynamic indoor and outdoor environments. In contrast, the force-field methods are only suitable for static indoor or outdoor environment, as they require more processing time and do not provide appropriate results for dynamic environments on their own, without help of other approaches.

Based on the literature studied, there is a clear trade-off between computational time requirements, complexity, optimal solution requirements, pre-mission path planning, and the ability to adapt to static/dynamic environments. Depending on the demands of operational requirements, in which the algorithm is to be deployed, the appropriate algorithm needs to be selected or one can also look into combining more than one collision avoidance techniques (or two layered collision avoidance strategy [145]) to meet their needs. Moreover, to ensure the safety of the UAVs, the deployment of sense and avoid methods, which are the simplest among the considered approaches and robust with low data overheads and low response times, would be a safe choice in all kinds of environments for avoiding the static/dynamic obstacles locally. However, a more efficient path planning algorithm needs to be integrated along with it to make sure it does not get stuck in a local minima and manages to reach the destination after avoiding the collisions. Furthermore, since sense and avoid approach is not dependant on any external communications and reacts immediately to any chances in the environment, has quick response times, and low data overheads, so it can be used as a failsafe/standalone approach to ensure the safety of the UAVs especially for highly dynamic environments, where situations can change rapidly and a high degree of adaptivity and flexibility is of utmost importance.

Furthermore, 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 3-D collision avoidance algorithm designed in [93], collision avoidance and navigation using translational coordinates in [113], formation control and collision avoidance in [35], efficiency of the designed controller for countering the environmental disturbances in [130], can be further extended and tested under various realistic scenarios.

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