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A review of perception sensors, techniques, and hardware architectures for autonomous low-altitude UAVs in non-cooperative local obstacle avoidance

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) can detect and communicate with cooperative obstacles through established protocols. However, non-cooperative obstacles pose a significant threat to UAVs during low-flight operations. These obstacles include static obstacles like buildings, trees, or communication towers and dynamic objects like other UAVs. The application of autonomous UAVs in low-altitude surveillance has motivated research into non-cooperative local obstacle avoidance. This paper provides an overview of such solutions that have been proposed within the last decade. Unlike most literature that limits obstacle avoidance to algorithms, this work provides an in-depth review of obstacle avoidance components, namely the perception sensor, techniques, and hardware architecture of the obstacle avoidance system. This review categorizes the non-cooperative obstacle avoidance techniques into four groups: gap-based methods, geometric methods, repulsive force-based methods, and Artificial Intelligence (AI) based methods. This paper provides a comprehensive resource for researchers working on collision-free surveillance by autonomous UAVs at low altitudes.

1. Introduction

UAVs have the remarkable capacity to access dangerous or difficult-to-reach areas. The development of these UAV platforms has several advantages and is widely used in numerous applications worldwide. As of November 2020, there are 1.7 million registered UAVs in the USA, according to the Federal Aviation Administration (FAA), and in the same year, China had 392,000 registered UAVs with more than 1.25 million flight hours [11]. With a global market share of $127 billion, the global UAV market is predicted to expand with a Compounded Annual Growth Rate (CAGR) of 16.2 % [3,14]. Furthermore, market analysts have given optimistic forecasting regarding the growth of UAV payload markets. Cameras, Inertial Measurement Units (IMUs), radar, LiDAR, communications devices, weapons, and other equipment are examples of UAV payloads. By 2027, the drone payload market is anticipated to increase at a compound yearly growth rate of 12.22 %, around $13.53 billion [17].

UAVs can traverse remote and inaccessible dynamic environments better than Unmanned Vehicles (UVs). This feature increases the likelihood of a collision. Based on statistical data, human error accounts for 80 % of air traffic accidents, with 53 % of these incidents attributed to individual pilot errors [19,20]. Autonomous flight systems can potentially reduce these human errors and improve overall safety. UAVs are a category of aircraft that can fly autonomously. The notion of autonomous UAVs raises the question of how their flight control is achieved. Different methods exist to control the flight of UAVs: remotely piloted, semi-autonomous, and fully autonomous. Remotely piloted UAV is used in [23], where a ground-based pilot uses visual feedback to control the UAV's speed, location, and direction. The UAV must, however, be in the pilot's line of sight for this to work. As an alternative, the UAV can be remotely operated from a command-and-control center, where a telemetry device is used to transmit the flight parameters and position of the UAV as determined by onboard sensors.

With the help of onboard sensors (e.g. GPS module, barometer, magnetic compass, accelerometer, gyroscope), a flight controller controls semi-autonomous UAV speed, heading and altitude [27]. But the waypoints and flying parameters are pre-programmed into the flight controller by the ground control station. In semi-autonomous flights, UAVs can still not make wise decisions like path planning and obstacle avoidance. A completely autonomous UAV conducts flight operations without receiving guidance from a ground control station. It can make intelligent real-time decisions while in flight. This intelligent

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decision-making uses an onboard companion computer (e.g., Raspberry Pi, Jetson Nano, Intel NUC, ODROID XU4) based on the feedback from perception sensors like camera or LiDAR. These intelligent decisions include essential capabilities like navigation, path optimization, localization, and motion planning. Yet, obstacle avoidance is the most critical for low-altitude surveillance applications.

The capacity to navigate to a predetermined destination while avoiding obstacles obstructing the path is an essential element of autonomous flight. As stated in [31], low-flying autonomous UAVs rely on their Obstacle Avoidance System, specifically designed to meet operational needs. As shown in Fig. 1, operating UAVs at lower altitudes causes more obstruction and reduces operational speed compared to those flying at higher altitudes. Most low-altitude UAV applications have a maximum permitted flight level of 122 m [4]. This study focuses on multi-rotor UAV surveillance on low-altitude flights. A robust obstacle avoidance system is necessary for safe operation in all weather conditions. A UAV encounters unanticipated obstacles when flying at low altitudes, so the obstacle avoidance system must be quick and effective. Additionally, the system must recognize and avoid obstacles even when unaware of the local obstacle map.

Obstacle avoidance can be divided into cooperative and non-cooperative categories depending on the extent of cooperation between the flying agents. In cooperative obstacle avoidance, UAVs work together to avoid collisions or share information about their position, altitude, and heading with a third party. According to [11], there are three techniques for cooperative obstacle avoidance: the Traffic Collision Avoidance System (TCAS), the Automatic Dependent Surveillance-Broadcast (ADS-B), and the Flight Alarm (FLARM). These techniques allow the UAVs to convey the warning information and negotiate their trajectories to prevent potential collisions. However, when operating at low altitudes, UAVs may collide with other UAVs and a range of non-cooperative obstacles, including structures, trees, and cables. Thus, cooperative techniques have limitations against non-cooperative obstacles at low altitudes. On the other hand, non-cooperative obstacle avoidance relies on individual UAVs sensing and reacting to their surroundings without coordinating with other flying agents. As a result of these limitations, a lot of research has been pursued in the area of non-cooperative local obstacle avoidance for low-altitude surveillance.

As per findings in [39], non-cooperative obstacle avoidance at low altitudes can be segregated into two categories; global obstacle avoidance and local obstacle avoidance. Global path planning establishes the optimal route between the starting and ending points. Various algorithms have been formulated over the past few years to facilitate global and local UAV path planning. The study mentioned in [25] demonstrates that prior knowledge of the exact map of the environment is critical for global path planning. Many path planning techniques, including heuristic pathfinding [41], Rapidly exploring Random Tree (RRT) [42], breath first search, and the A* algorithm [43], construct the best flight path to avoid obstacles while knowing the map of the environment. These global path planning algorithms seek to identify the most effective route that minimizes flight time and avoids collisions or obstacles. Global obstacle avoidance techniques have several limitations when it comes to low-altitude surveillance. These methods can be prone to errors as they rely on maps, which can be computationally expensive to build and update. Moreover, latency in map updating can increase the likelihood of collisions.

In contrast, localized path planning algorithms require continuous monitoring of the UAV proximity. Without prior knowledge of the area map, the next action vector is decided based on the feedback from the perception sensor to accomplish the goal of real-time obstacle avoidance. Local obstacle avoidance methods incorporate various solutions, such as gap-based, geometric, repulsive-force, and AI-based obstacle avoidance techniques. Gap-based methodologies, such as open-sector collision avoidance [8], the Vector Field Histogram (VFH) [44], and the Nearness Diagram (ND) [3], exploit the presence of localized gaps between obstacles to facilitate the UAV movement through complex environments. With geometric approaches like collision cone [45] and velocity obstacle methods [46], the obstacles' shape, location, and relative velocity are considered to avoid a collision. Repulsive-force techniques, such as the Potential Field (PF) algorithm [25] and Artificial Potential Field (APF) algorithm [47], generate repulsive force fields to avoid obstacles and attractive force functions to move toward the goal. The utilization of AI-based techniques, specifically those based on machine learning, is dependent on the use of training datasets to effectively train Convolutional Neural Networks (CNN) [48] and Deep Neural Networks (DNN) [49] to facilitate obstacle avoidance. Deep Reinforcement Learning (DRL) [50] is another AI-based technique that uses data from perception sensors rather than a dataset to prevent collisions. Nevertheless, the multi-layered obstacle avoidance method in [51] employs both global and local path planners to offer obstacle avoidance trajectories that are both energy-efficient and optimal.

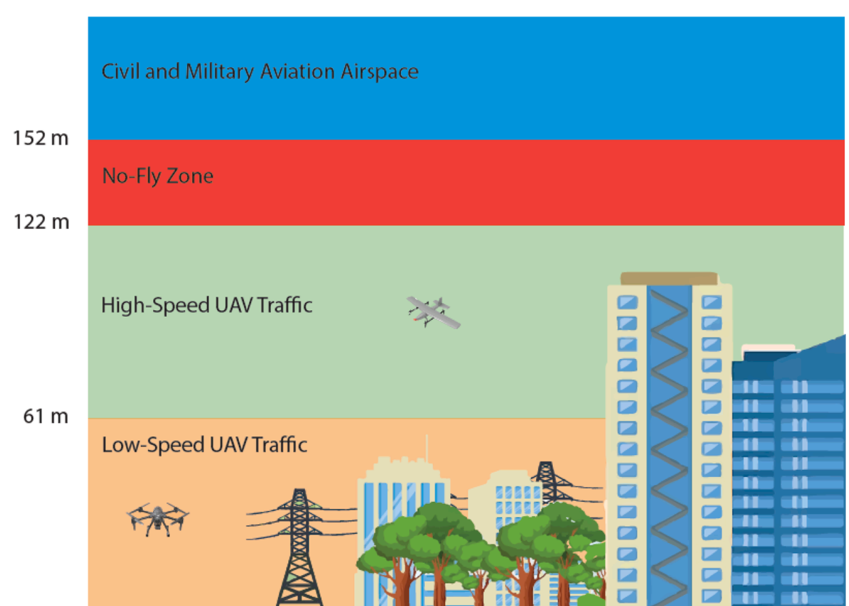

Fig. 1. UAV collision risk at low altitude [4] (see Section 2 for UAV's low-altitude application areas).

This paper reviews non-cooperative and local obstacle avoidance strategies for UAVs and focuses primarily on collision-free navigation systems. In contrast to previous reviews, as shown in Table 1, this work provides an in-depth assessment of the obstacle avoidance components. To our knowledge, the existing literature reviews have a limited scope. They do not compare the different obstacle avoidance strategies and hardware designs used in the reviewed literature. For example, the previous reviews presented in [4,52] focus on future directions for the utilization of UAVs in potential applications, [53] present sensors and classification of obstacle avoidance techniques from a broader perspective and [31] provide a detailed insight into the swarm of multiple UAVs, using computer vision algorithms. The key contributions of this paper are as follows:

- A review of perception sensors for non-cooperative and local obstacle avoidance, including their classification, advantages, and drawbacks.
- A structured review and categorization of the various non-cooperative local obstacle avoidance techniques into four groups.
- Present researchers with an overview of the hardware architectures used in low-altitude local obstacle avoidance techniques.

The rest of the paper is organized as follows. The numerous UAV applications that demand low-altitude operation are described in Section 2 of the paper. Section 3 describes the sensing systems used by UAVs to avoid obstacles. Sensing systems comprise active sensors, passive sensors, and a fusion of both. The obstacle avoidance techniques used to this date in low-altitude surveillance are reviewed in detail in Section 4. Hardware architectures used in the reviewed literature for collision-free navigation solutions are presented in Section 5. The discussion and research directions for the future are presented in Section 6.

Table 1
Summary of previous reviews.

Refs.	Core area	Scope and limitations
[4]	• A survey on UAV civil applications and their future research challenges	• The main topic covered is UAV-based application areas and their research challenges • Perception sensors, hardware architecture and Collison avoidance techniques are not covered
[54]	• Reviews computer vision algorithms and their utilization in intelligent applications	• It only covers vision-based systems • Hardware architecture and non-visual obstacle avoidance systems are not covered. • Low altitude obstacle avoidance systems not discussed
[52]	• UAV classification, application areas, controllers, limitations, and future challenges are discussed	• UAV applications in different sectors are the main topic covered in this review. • Perception sensors, obstacle avoidance, and hardware architecture of obstacle avoidance are not included
[53]	• Reviews the sensors and obstacle avoidance strategies for Unmanned Aerial Vehicles (UAV)	• Discussion on perception sensors and obstacle avoidance techniques from a broader perspective • Hardware architecture for low altitude surveillance applications not covered
[31]	• UAV obstacle avoidance approaches are reviewed, applicable specifically to a team or a swarm of UAVs.	• Path planning and multi-UAVs obstacle avoidance trajectory planning is the main scope of review • Perception sensors and hardware architecture for low altitude surveillance UAVs not covered

2. UAV low-altitude application areas

In the age of Industry 4.0, there is a trend towards intelligent automation, which includes using UAVs in various practical applications alongside other types of robots. UAVs have been extensively employed in low-flight applications, benefiting from their agility, versatility, and ability to operate at lower altitudes. These unmanned aerial systems offer a range of advantages in such scenarios, including enhanced situational awareness, efficient data collection, and reduced risk to human operators. Some of the relevant application areas for UAVs involving low-flight operation include surveillance [6], security [55], search and rescue [32], construction [21] and infrastructure inspection [25], disaster response, precision agriculture [30,39,56,57], delivery of goods [38], traffic monitoring [7] and wireless network coverage [18]. UAVs are presently utilized for a wide range of tasks [52]. It is essential to recognize that their usefulness in novel application areas cannot be dismissed from a future perspective [58]. The diverse sectors that employ UAVs for various uses are listed in Table 2. As suggested in [4], increasing demand for UAVs in the future is expected to create 100,000 new jobs by the end of 2025, leading to an increased number of UAVs worldwide.

The UAV must eventually descend into a low-altitude flight phase to be used for any of these applications. The collision threats these application areas have that could endanger the UAV or the surveillance site's safety include trees, windmills, wooden electric poles, small houses, communication towers, tall buildings, power lines, bridges, and other UAVs. The types of obstacles encountered during low-altitude flight depend on the application area, as mentioned in Table 2.

3. Perception sensors for non-cooperative obstacle avoidance

Perception sensors used for obstacle avoidance are an essential part of low-altitude navigation. Other sensors include GPS, IMUs, barometers, altimeters, and telemetry sensors. The three categories of perception sensors used for obstacle avoidance are visual, non-visual and sensor fusion. Visual sensing is known for its low cost, less payload and wider field of view [59]. The primary mode of operation for visual sensors is passive sensing. Various sensors can capture visual data, including RGB, stereo, color infrared, multispectral, hyperspectral, and thermal cameras. The second category comprises non-visual sensors that operate on the principle of active sensing. These sensors emit their energy to illuminate the surrounding environment and receive the reflected signal rather than rely on the energy emitted by surrounding structures or obstacles. Active sensors include radar, LiDAR, and ultrasonic sensors. Integrating active and passive sensors, known as sensor fusion, constitutes the third category of perception sensors. This method aims to improve the precision and dependability of obstacle identification and avoidance by combining the strengths of visual and non-visual sensors. Sensor fusion techniques can make a more detailed perception of the environment possible, enabling navigation systems working in low-altitude circumstances to make more reliable decisions.

An extensive categorization of perception sensors is presented in this section, facilitating an in-depth review of their strengths and weaknesses. The reviewed literature on low-altitude obstacle avoidance utilizes a variety of visual and non-visual sensors, as depicted in Fig. 2. Visual sensing uses spectral wavelengths like the visible, near-infrared, and thermal infrared frequency regions. Millimeter-wave, radio-wave, and ultraviolet frequency bands are utilized for non-visual sensing. The selection of an optimal sensor for a given application depends upon multiple considerations, such as weight, cost, detection range, spectral resolution, computational complexity, and the processing capabilities of the onboard companion computer.

A systematic examination of the Web of Science (WoS) database is undertaken to explore the prevailing patterns of publications and countries engaged in the field of "UAV" and "sensors". As shown in Fig. 3, the search queries "UAV" and "sensors" exhibited a notable upsurge in publications since 2014, reaching 1286 by 2022. The results indicated that China, the United States, and Germany are primary contributors to this domain, with the most significant publications. This study considers scholarly literature that satisfies the inclusion criteria for multi-rotor UAVs operating at low altitudes.

3.1. Visual obstacle avoidance

The low cost and lightweight attributes of visual sensors have been employed as perception sensors for UAV applications [60]. In visual sensing, UAV surroundings can be captured in the form of images or a video stream. Utilizing the camera, significant information like obstacle detection, tracking [60], and depth perception [61]. Notably, visual sensors have a wider field of view as compared to other perception sensors. Moreover, they can distinguish and identify obstacles based on their color and texture information. However, employing vision perception sensors in UAVs comes with certain challenges, including variations in lightning conditions, occlusion, and motion blur [54].

This review paper categorizes the vision-based perception sensors into three categories: monocular, stereo vision systems, and RGB-D cameras. Vision-based perception sensors promise to enable advanced capabilities such as autonomous flight and obstacle avoidance for indoor and GPS-denied environments [62]. A detailed overview of vision-based sensors applied in different reviewed articles is compiled in Table 3.

3.1.1. Monocular vision systems

A monocular vision system uses a single camera to capture images of the environment and extract relevant information about objects in the scene. The camera captures light reflected from the objects in its field of view and converts it into a digital image. Monocular cameras lack depth perception. In the cited study [60], the images undergo initial processing to extract salient features like edges, corners and contours. Subsequently, the “Size Explanation Algorithm” is employed, using these extracted features to estimate the obstacle depth. In [62], this obstacle avoidance is achieved using the “Vanishing Point algorithm” by processing the frames of a monocular camera. CNN methodology estimates depth from an RGB monocular camera [61,63]. Another study based on CNN in [48] predicts the collision’s probability and the UAV’s steering angle for obstacle avoidance. A Deep Reinforcement Learning based approach is proposed in [50], learning from a minimal memory of past observations in the form of monocular images. Based on a single-lens camera, monocular vision systems cannot perceive the depth of the obstacle. Multiple frames are utilized for image processing to predict velocity, depth, and future position.

Another technique widely used to estimate depth from a monocular camera is the optical flow technique based on motion parallax. This technique works by analyzing the motion of pixels in successive frames of an image sequence. The displacement of pixels between frames can be used to estimate the direction and magnitude of the motion vector, which can be interpreted as the 2D projection of the 3D motion vector of the corresponding object in the scene. In [59], the optical flow technique achieves local obstacle avoidance, as mentioned earlier. In addition, a global path planner utilizing the RRT algorithm is integrated into the system. The disadvantage of optical flow is that it can be computationally expensive and result in processing delays, mainly when used with multiple high-resolution images or complex scenes with multiple moving objects.

3.1.2. Stereo vision systems

Stereo vision systems provide depth perception and spatial

Table 2
UAV’s low-altitude application areas.

Application (Collision threats)	Description	Purpose	Refs.
Surveillance **(buildings, power lines, trees, and other UAVs)**	• UAV swarm control and routing	• Crowd Surveillance	[6]
	• Dynamic object real-time visual tracking	• Autonomous surveillance	[9]
	• Multi-agent Autonomous UAV control using Deep Learning	• Optimized UAV-based CCTV surveillance in smart cities	[12]
	• Direction of Arrival (DoA) estimation using a microphone array aboard a UAV	• Gunshot Airborne surveillance	[14, 16]
Inspection **(bridges, towers, and under-construction buildings)**	• UAV and Unmanned Ground vehicle (UGV) collaborative inspection system	• Construction site data collection	[21]
	• UAV-assisted image-based three-dimensional (3D) modeling	• Bridge Inspection	[24]
	• Genetic algorithm-based automatic inspection by UAV	• High-rise building surface inspection	[26]
	• Autonomous multi-UAV visual inspection.	• Inspection of intermediate-level nuclear waste	[29]
Search and Rescue **(trees, wooden poles, and other UAVs)**	• UAV and Unmanned Surface Vehicle (USV) based cooperative visual navigation	• Marine search and rescue	[32]
	• Multi-UAV cooperative system	• Wilderness search and rescue	[34]
	• Multi-rotor UAV with an avalanche beacon	• Rescue in Mountain Avalanche	[36]
Delivery **(buildings, power lines and other UAVs)**	• Mathematical modeling for route generating Algorithm for UAV and Ground vehicle	• Delivery of perishable food	[38]
	• Hybrid heuristic algorithm-based path planning	• Energy-optimized UAV delivery system	[40]
Traffic Monitoring **(electric poles, power lines, buildings and other UAVs)**	• Intelligent traffic monitoring using 5 G and onboard speed camera	• Smart traffic monitoring	[7]
	• UAV and wireless sensor network for Traffic monitoring	• Traffic surveillance on highways	[10]
	• Traffic estimation in urban areas	• Emergency vehicle guidance	[13]
	• UAV Network-based, ground vehicle path planning	• Ground vehicle navigation	[15]
Network Coverage **(telecommunication towers, power lines, and other UAVs)**	• Communication coverage in case of Natural disaster	• Damage assessment by providing network coverage to repair crews.	[18]
	• Constrained UAV-assisted networking	• Establishment of emergency communication for post-disaster data dissemination	[22]
Mapping **(trees, tall buildings, and other UAVs)**	• Autonomous UAV with MOX (Metal Oxide) chemical sensor onboard	• Mapping the dispersion of propane in an outdoor setting	[25]
	• Fast and efficient UAV photogrammetry	• Ground displacement mapping	[28]
Agriculture **(trees, windmill, small houses, nylon nets and plant branches)**	• UAV perception systems based on AI	• Precision Agriculture	[30]
	• UAV-based Digital Elevation Modeling	• Evaluation of soil erosion	[33]
	• Wireless Sensor Networks (WSN) and IOT-based precision agriculture UAVs	• Crop monitoring	[35]
	• Infrared Imagery using UAVs	• Mapping agriculture drainage system	[37]

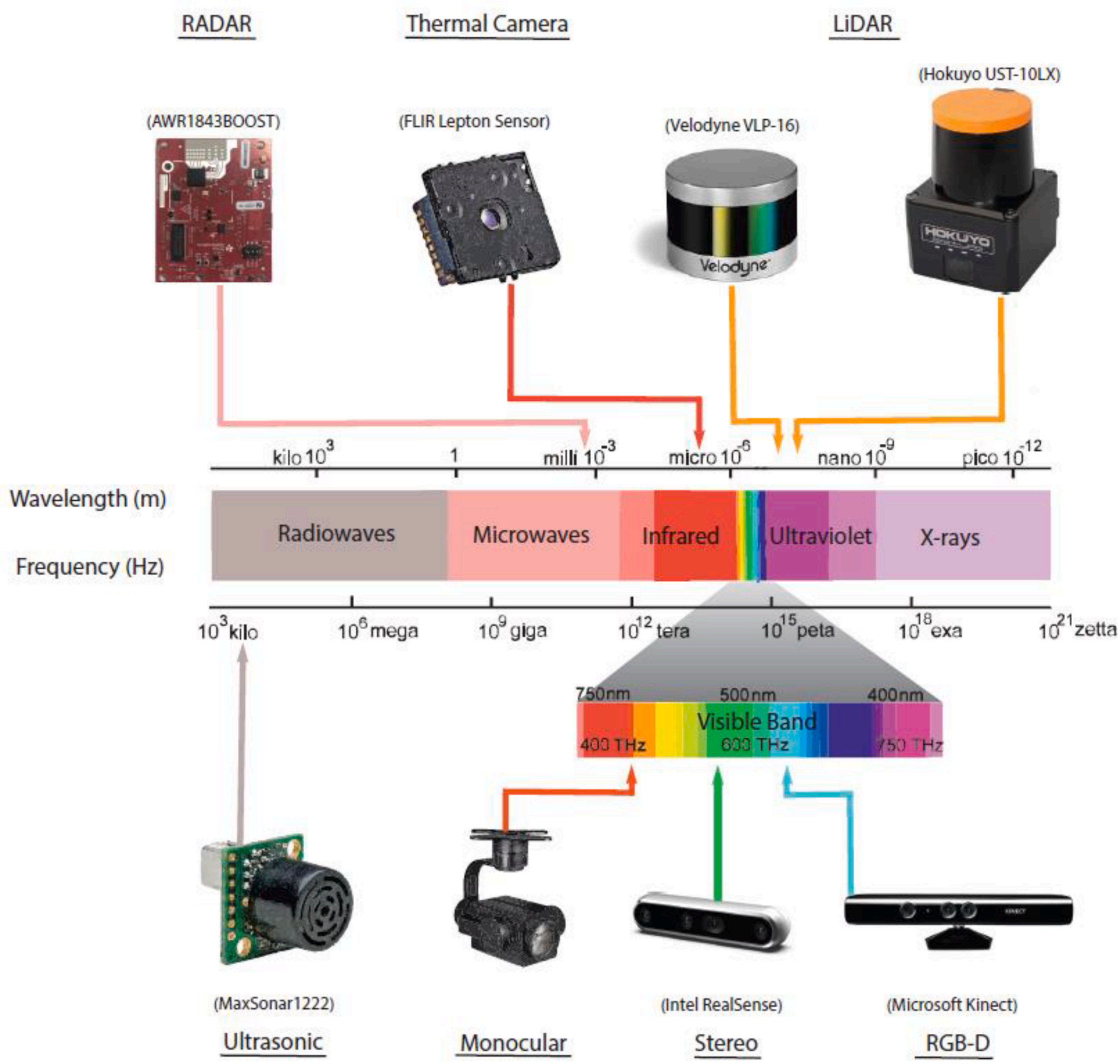

Fig. 2. UAV perception sensors.

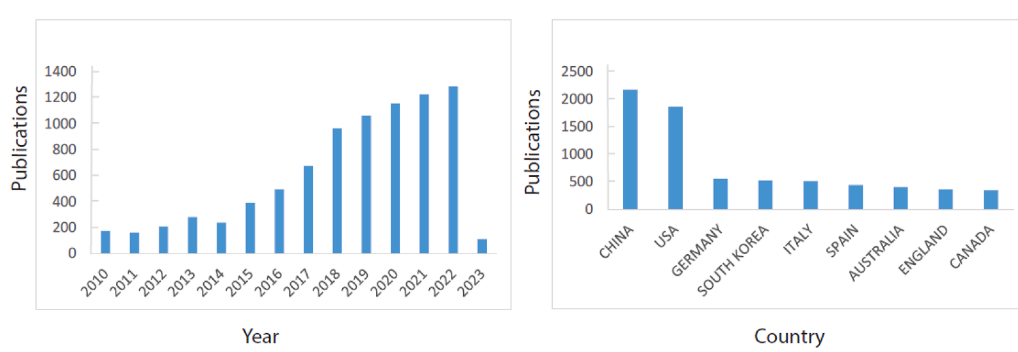

Fig. 3. Results from WoS database as of March 5, 2023, show the publication trend, yearly (left) and country-wise (right), using the keywords "UAV and sensors".

information. Stereo vision systems rely on two cameras placed a fixed distance apart to capture two images of the same scene from slightly different perspectives, enabling them to compute the distance between objects based on their disparity. Using stereo vision systems as sensors, UAVs can accurately detect and avoid obstacles in their path, improving their safety and maneuverability. However, this adds more computational cost and complexity of hardware architecture to the system. A previous study in [64] evaluated the performance of stereo vision showing promising results. However, unlike laser ranging, it exhibited vulnerability to poor calibration under varying lighting conditions. Stereo vision is used in [65] to generate the online 3D occupancy map of the environment. A roadmap study is shown in [66] to use the Infrared (IR) Lepton sensor as a stereo vision system for UAVs to locate hot objects. An object detection algorithm is proposed in [67] based on stereo vision, which can detect targets within a 15 m range. In [68], a laser transmitter-assisted stereo vision approach is presented using a pair of Logitech® HD Webcam C310.

Table 3
Passive or visual sensors for obstacle avoidance by autonomous UAV.

Type	Refs.	Application areas	Consideration
Monocular camera	[50]	• UAV indoor navigation and obstacle avoidance using Deep Reinforcement Learning	• Depth perception is only tested with noisy simulated images
	[59]	• Simultaneous offline path planning and monocular vision-based obstacle avoidance • Optical flow-based depth perception	• It is not tested on moving obstacles. • The success rate decreases significantly in case of multiple obstacles
	[48, 61]	• A CNN-based model for an unstructured environment	• Performance depends on the training data set
	[60]	• Obstacle detection based on size expansion	• The drawback of the system is the monocular camera, as the sensor is sensitive to lighting conditions
Stereo camera	[64]	• Evaluation of stereo vision-based UAV obstacle detection and Navigation • Comparative analysis of a stereo-based system with a 2D laser scanner	• The study is limited to obstacles with significant size • The stereo vision-based system prone to calibration errors
	[68]	• Obstacle avoidance based on stereo triangulation in conjunction with a Laser transmitter	• This approach is suitable for short ranges. Depth estimation performance degrades if distance increases • Tested only in indoor scenarios
	[71]	• Low altitude stereo vision-based obstacle detection and avoidance	• Sensitive to lighting and brightness conditions
RGB-D	[72]	• UAV indoor mapping and collision-free navigation using RGB-D as a perception sensor in GPS denied environment	• For localization, UAV is dependent on a motion capture system
	[69]	• Obstacle avoidance based on RealSense R200 depth camera using depth image segmentation and stratification	• Optimized path planning is not part of the current algorithm but is recommended for future

3.1.3. RGB-D cameras

RGB-D cameras capture both color and depth information simultaneously. They typically use an infrared projector to emit a pattern of light onto the scene and an infrared camera to capture the reflected light. The depth information can be calculated by analyzing the distortion of the light pattern. This information is combined with the RGB color information to create a full 3D model of the scene. Accordingly, based on prior research, UAV obstacle avoidance has been achieved by employing an RGB-D RealSense Camera [69]. The approach involves performing image segmentation based on the depth information gathered from the pixel values. Another study documented in [53] employed the Microsoft Kinect depth-based camera to develop a novel path-planning strategy in an indoor and unstructured environment.

3.2. Non-visual obstacle avoidance

Non-visual sensors working on active sensing offer several advantages over visual sensors for low-altitude obstacle avoidance. One notable characteristic of non -visual sensing, as emphasized in [70], is their ability to operate effectively even in low-light or no-light situations. Furthermore, they exhibit remarkable resilience to interference caused by environmental factors such as fog, rain, and dust. Another noteworthy aspect, as highlighted in [23], is their exceptional ability to detect obstacles irrespective of variation in color and texture accurately. Additionally, non-visual sensors can provide higher resolution and accuracy in obstacle detection and localization than visual sensors [39], which can be particularly beneficial for UAVs operating in complex or cluttered environments. However, non-visual sensors can be more expensive and heavier than visual sensors, limiting their use in small or lightweight UAVs [60]. Overall, using non-visual sensors for UAV obstacle avoidance is a promising area of research, with the potential to significantly enhance the safety and efficiency of UAV operations in a wide range of applications. An overview of reviewed literature on active or non-visual sensing for low-altitude surveillance is presented in Table 4.

3.2.1. LiDAR

LiDAR (Light Detection and Ranging) as a perception sensor in recent years has become an excellent option for its precise and accurate obstacle detection ability [53,58,73]. LiDAR works as a Time of Flight (TOF) sensor, transmitting the light pulses and measuring the time the reflected pulse takes to complete a round trip after reflection from the object's surface. Depending upon the nature of the LiDAR sensor, a 2D [8] or 3D [74] point cloud data representing the is generated. This point cloud data represents the UAV's proximity within the LiDAR's detectable range. The ability of the LiDAR sensor to operate in adverse weather without any degradation in performance parameters makes them practical for outdoor UAV applications. However, using 3D LiDAR sensors in small UAVs is constrained by their higher payload and computational requirements. Consequently, the research is currently underway to use lightweight 2D LiDAR sensors in a computationally efficient way to meet the payload requirement of small UAVs [8,25].

Prior work in [75] demonstrates the use of 2D LiDAR (Hokuyo UST-10LX) for indoor UAV obstacle avoidance, with improved performance using Control Barrier Functions (CBFs) in comparison to APFs. The study in [76] demonstrates a sensor fusion-based approach for fast-moving UAVs in a cluttered environment. In which 2D scanning LiDAR (SLAMTEC RP LiDAR S1) is used as a sensor for depth perception. Light weight LiDAR sensors are used in [77,78] for small UAV indoor navigation applications. In addition to previously discussed research endeavors which mainly focus on autonomous indoor navigation, a recent study in [20] focuses on remotely piloted UAV utilizing a 2D scanning (RP 360° LiDAR) LiDAR in a structured environment to assist a trained pilot in obstacle avoidance. The work in [79] focuses on point cloud correction of 2D LiDAR for obstacle detection.

A computationally efficient way based on finding the open gaps from scanning LiDAR is proposed in [8]; the author achieved obstacle avoidance at a relatively higher velocity with smooth flight. In [80], Simultaneous Localization And Mapping (SLAM) is achieved using LiDAR. Furthermore, it should be noted that the utilization of 3D LiDAR in small UAVs carries the drawback of reducing flight time by increasing the processing demand caused by a substantial volume of data points [78].

3.2.2. Radar

Radar (Radio Detection and Ranging) technology has been widely used in the aviation industry for its effectiveness in obstacle avoidance [70] and terrain mapping [81]. Notably, radar systems have proven advantageous in adverse weather conditions [82], where image-based systems exhibit limitations in performance. Radar uses emitted electromagnetic waves that interact with objects in the surrounding environment, enabling the sensor to detect and capture the resulting echoes. The distance to the obstacle can be determined by measuring the time it takes for the transmitted signal to travel to the object and back to the sensor. It also gives the relative speed between the UAV and the obstacle by detecting the doppler shift introduced in the received signal [82]. Previous studies in [81,82] have shown that radar technology can be computationally more challenging than other sensing systems. Hence it reduces the flight time in small UAVs for low-altitude surveillance.

Table 4
Active or non-visual sensors for obstacle avoidance by autonomous UAV.

Type	Refs.	Application Areas	Consideration
LiDAR	[8]	• Open sector-based UAV navigation system in an outdoor and unstructured environment • Fully autonomous outdoor navigation with UAV flying smoothly around obstacles	• A 2D laser scan is used, and a virtual target is defined for navigation (if the actual target is not in sight) • Unable to reach a goal near and in front of an obstacle, hence using a hybrid approach utilizing PF algorithm
	[25]	• Autonomous chemical sensing aerial robot for outdoor navigation • Used a novel approach, namely Potential Field that Incorporates Past Actions (PF-IPA), for obstacle avoidance	• 2D laser scan is used with a new PF approach to solve the famous local minima problem
	[23]	• Obstacle avoidance system for remotely piloted, semi-autonomous UAV	• 2D spinning LiDAR is used • Collision prediction resulted in reduced speed and increased avoidance distance
	[78]	• 3D LiDAR (Velodyne VLP-16 Puck) is used for obstacle avoidance • Obstacle avoidance system uses angle displacement and edge detection methods	• The system needs to be thoroughly tested with multiple obstacles
	[76]	• UAV uses Sense and Avoid (SAA) method based on Fast Obstacle Avoidance Motion (FOAM) algorithm	• Sensor fusion of 2D spinning LiDAR and the monocular camera is used • Obstacle cluttered scenario has only been tested in a simulated environment
Radar	[42]	• Bi-directional RRT* path planning is used to create a local map based on data from sensors	• Millimeter-wave Radar and monocular camera sensor fusion is performed using Extended Kalman Filter (EKF) • Sensor fusion enables us to get outlines and spatial information on obstacles
	[70]	• MIMO (Multi-Input Multi-Output) millimeter-wave radar is used as both a mapping and obstacle-avoidance sensor	• Obstacle avoidance and 3D mapping were performed in the forward direction • Obstacle avoidance successfully tested with different types of single-target
	[43]	• An improved A* algorithm for path planning is proposed for plant protection UAV	• Data fusion of millimeter-wave radar and the monocular camera has shown improved results • Improvement in results as compared to simple A* algorithm
Ultrasonic	[90]	• Triple Awareness Fusion (TAF) is used for collision avoidance using low-cost sensors	• 12 Ultrasonic (US) and 8 Infrared (IR) sensors array is used for awareness of the surroundings • The scope of the study comprises low-cost sensors for fully autonomous UAV navigation
	[88]	• Ultrasonic and Inertial Measuring Unit-based (IMU) fusion-based UAV localization and obstacle avoidance in an indoor environment	• Localization is based on EKF. Four ultrasonic sensors fused with IMU readings for localization • The computational complexity of the proposed navigation system is low • Not tested indoors with electronic equipment that could interfere with IMU's magnetic compass

Radar sensors are accurate and precise for UAV obstacle avoidance. However, they can produce false readings in cluttered environments due to multiple path reflections. Limited range resolution (in order of meters) of radar sensors [83] can also hinder the detection of small and distant obstacles. Because of radar's increased payload weight and high power requirement, their use is mainly limited to fixed-wing UAVs [84,85] flying at higher altitudes [83]. Recently, the utilization of millimeter-wave radars has gained prominence due to their higher operational frequency, enabling the acquisition of high-resolution radar images of the surroundings [42,43,86]. Most millimeter-wave radars operate in the 24 to 77 GHz frequency range. But at the same time, they are more easily attenuated by atmospheric conditions than the radars operating at lower operating frequencies. The lighter weight and compact size of millimeter-wave radars have made them suitable for small UAVs for obstacle avoidance.

3.2.3. *Ultrasonic*

Ultrasonic sensors are based on the principle of sound waves, which are emitted by a transducer and then reflected when they encounter an obstacle. These reflected waves are then detected by the sensor and used to determine the distance and direction of the obstacle. The frequency range of ultrasonic sensors typically falls between 20 kHz and 200 kHz. Ultrasonic sensors are lighter in weight and cheap [69,84], making them highly suitable for use in UAVs. Ultrasonic sensors are unidirectional and used in multi-sensor configuration [87,88] for complete 360° coverage. A previous study in [88] shows an array of 4 ultrasonic sensors utilized in fusion with an IMU for indoor UAV localization in a GPS-denied environment. Similarly, an array of 12 ultrasonic sensors is fused with IMU in [85] for collision-free UAV autonomous indoor navigation.

Ultrasonic sensors have a limited detection range, typically up to a few meters, making them unsuitable for detecting obstacles from far distances. Additionally, they can be affected by external interferences, including ambient noise and weather conditions, which can impair their performance, as concluded in [89]. Furthermore, their ability to accurately measure the size and shape of obstacles is limited, which may restrict their efficacy in specific scenarios.

To comprehensively understand the various categories of perception sensors, this paper presents a comparative analysis in Table 5. The comparison matrix emphasizes 12 key evaluation metrics that are deemed critical for low-altitude obstacle detection and collision avoidance. This analysis aims to facilitate the reader's comprehension and evaluation of the different sensor categories about their performance capabilities.

The first metric, robustness, refers to the ability of a sensor to function accurately in diverse and challenging environments (see Table 5 for the comparison matrix). The literature review shows that active sensors such as LiDAR are more robust when compared to monocular and stereo cameras. The second metric deals with the ability to detect multiple obstacles. Detection depends on the sensors' Field of View (FOV). Both cameras and scanning LiDAR have a wider FOV, which enables them to detect and react to multiple obstacles. On the other hand, ultrasonic sensors with a narrower FOV cannot handle multiple obstacles in the environment. The depth perception of the sensor, referred to as the third metric in the comparison matrix, is critical in detecting obstacles in the path of a quadrotor UAV. While all sensors possess depth perception capabilities, monocular cameras cannot perceive obstacle distance. Consequently, CNN-based methods are adopted to predict the obstacle distance. In contrast, a study referenced in [60] avoids estimating obstacle range and instead relies on a size expansion algorithm to avoid obstacles.

In the context of this research, the fourth metric pertains to calibration errors and is identified as a significant concern for visual sensing. Calibration errors are attributed to inaccuracies in the measurement process, which can lead to incorrect depth perception and obstacle detection, ultimately resulting in collisions. As such, it is crucial

Table 5
Performance comparison of perception sensors.
(The black bullet means "Yes", the white bullet means "No", and the dash means not mentioned in the literature).

Type	Refs.	Robustness	Multiple obstacles	Depth perception	Calibration errors	GPS dependency	3D compatibility	Obstacle shape	Outdoor environment	Sensitivity to light	Weather dependency	Computational complexity	Power requirement
Monocular Camera	[50]	○	○	●	●	○	●	●	○	High	High	High	Low
	[59]	●	○	●	●	○	●	●	●	High	Medium	Medium	Low
	[48]	●	●	○	–	○	●	●	●	–	–	Low	Low
	[61]	○	●	●	–	○	●	●	●	High	High	High	Low
	[60]	○	●	○	●	○	○	●	●	High	–	Low	Low
Stereo Camera	[64]	●	○	●	●	●	○	-	●	High	High	Low	Low
	[68]	○	○	●	–	○	●	●	○	High	–	High	–
	[71]	○	-	●	–	○	-	●	-	High	High	High	Low
RGB-D	[72]	●	●	●	●	○	●	●	○	–	–	Low	Low
	[69]	●	○	●	●	○	●	●	○	Medium	Medium	Medium	–
LiDAR	[8]	●	●	●	○	○	○	●	●	Low	Low	Low	Low
	[25]	●	●	●	○	○	●	○	●	Low	Low	Medium	Low
	[23]	○	●	●	○	○	○	●	○	Low	Low	Medium	Low
	[78]	○	●	●	○	○	●	○	●	Low	Low	Low	Low
Radar	[70]	○	●	●	○	○	●	○	●	Low	Low	High	Low
Ultrasonic	[88]	○	○	●	○	○	–	○	○	Low	Medium	Low	Low
Ultrasonic fusion with Infrared	[90]	○	○	●	○	○	○	○	○	Low	Low	Low	Low
Radar fusion with Monocular Camera	[42]	○	●	●	●	●	●	●	●	Low	Low	Medium	–
	[43]	○	●	●	●	○	●	●	●	Low	Low	High	Low
LiDAR fusion with Monocular Camera	[76]	●	●	●	○	○	○	○	●	Low	Low	Low	Low

to address calibration errors to ensure the reliability and effectiveness of visual sensing systems. The fifth metric is the assessment of GPS dependency for achieving a collision-free navigation solution. Although GPS is widely used for navigation purposes, its reliability in indoor and outdoor environments is limited by the potential for real-time data loss. The literature reviewed in Table 5 demonstrates a primary reliance on perception sensors to provide a collision-free solution in GPS-denied situations.

The sixth metric dealing with 3D compatibility in sensor technology evaluates the ability of a sensor to detect and sense the environment in 3D space. With CNN-based prediction methods, sensors such as 3D LiDAR, radar, and cameras can detect and avoid obstacles in 3D space, whereas 2D LiDAR sensors and ultrasonic sensor arrays can only detect and avoid collisions in 2D space. This metric is crucial in evaluating the effectiveness of sensor technology in complex environments where 3D sensing is essential for safe navigation and obstacle avoidance. The seventh metric being analyzed relates to the ability of a sensor to accurately perceive the shape and geometry of obstacles in its surroundings and incorporate this information in obstacle avoidance maneuvers. Visual sensing heavily relies on this metric as it facilitates effective detection and avoidance of obstacles. In contrast, nonvisual sensors, which operate based on detection and ranging, do not consider the obstacle's shape and size when avoiding collisions.

The eighth metric in sensor evaluation refers to obstacle avoidance in outdoor environments that are unknown and unstructured. A comprehensive review of relevant literature revealed that all other sensors, except RGB-D cameras and ultrasonic sensors, are frequently employed in outdoor environments, which is attributed to the relatively good detection range and accuracy. Furthermore, the sensitivity of sensors to light and weather conditions constitutes the following two metrics, which also determine their applicability in outdoor settings. Variations in lighting and weather conditions significantly impact visual sensors, whereas active sensors are the least affected by their change.

The eleventh metric showed that cameras and radars necessitate high computational complexity. Cameras require depth estimation algorithms for obstacle avoidance, considerably increasing their computational demands. On the other hand, radars require onboard signal processing for range and doppler estimation, which significantly contributes to their computational complexity. The final metric in the comparative analysis matrix highlights that all the literature surveyed employed onboard sensors with low power demands, as high-power sensors would inevitably reduce the flight time of the UAV.

3.3. Obstacle avoidance based on sensor fusion

Sensor fusion is frequently employed in UAVs, leveraging multiple sensor types to evade obstacles. This technique facilitates a comprehensive understanding of the UAV's surroundings, enabling informed decision-making and safe navigation in challenging conditions. Active sensors, especially radars, provide accurate readings but have drawbacks like increased processing complexity and payload burden on UAVs, reducing flight time. LiDAR technology enables the accurate measurement of obstacles' distances, but it falls short in providing details on the geometry, texture, and outline of these obstacles [79]. In contrast, passive sensors like cameras have advantages such as low cost and a wide field of view, but they are vulnerable to environmental elements and lighting conditions [53]. The benefits of both sensor types can be exploited in the context of obstacle avoidance through sensor fusion.

The advantages of sensor fusion for UAV obstacle avoidance are numerous. Firstly, the fusion of data from multiple sensors enables a more accurate and reliable representation of the environment in which the UAV operates [42]. Secondly, the redundancy provided by using multiple sensors allows for better fault tolerance, ensuring that the UAV can continue to operate even if one of the sensors fails. Thirdly, sensor fusion can provide better situational awareness, enabling the UAV to make more informed decisions about its actions in real-time.

In [42] monocular camera is fused with millimeter-wave radar with the help of an EKF to estimate the 3D location of the obstacle. This information is based on the Bi-directional RRT* algorithm for path planning. Similarly, [43] also uses a monocular camera and millimeter-wave radar for sensor fusion, achieving improved results in unstructured farmland. The 2D LiDAR is utilized in [76] to generate a Probabilistic Occupancy Map (POM) in the horizontal plane, subsequently integrated with the visual information acquired from camera images. A study by [90] explores the fusion of two low-cost active sensors, an Ultrasonic and Infrared range finder, to design an obstacle avoidance system despite their limited accuracy in providing readings. Another work in [88] utilizes the onboard IMU and ultrasonic sensor array for environment mapping and obstacle avoidance simultaneously.

4. Non-cooperative techniques for obstacle avoidance

Non-cooperative local obstacle avoidance techniques enable UAVs to autonomously detect and avoid obstacles in their immediate vicinity to prevent collisions, particularly when the UAVs lack prior knowledge of the obstacles' flight trajectories and cooperative communication is unavailable [31]. Lack of prior knowledge about the obstacle is particularly relevant in low-flight surveillance scenarios where non-cooperative obstacles are encountered. Using non-cooperative local reactive obstacle avoidance techniques is essential to ensure UAVs' safe and efficient operation in shared airspace. One of the main advantages of non-cooperative techniques is that they allow for obstacle avoidance without prior knowledge of the obstacle map of the environment [8]. Additionally, since the UAVs are equipped with sensors that continuously sense nearby proximity [39,53], the obstacle map is updated in real-time, thus avoiding any latency issues that may result in mishaps.

This section presents a comprehensive review of non-cooperative local obstacle avoidance techniques, crucial for navigating UAVs to their final target by merging the local planner with the global path planner. These techniques are classified into four approaches: gap-based methods, geometric methods, repulsive force-based methods, and AI-based methods. Instead of reacting to obstacles, Gap-based methods utilize the presence of admissible gaps between the obstacles, reducing the probability of collision in densely cluttered environments [8]. Geometric-based methods utilize the obstacle's geometry and velocity information to maneuver the UAV to prevent the potential predicted collision. Repulsive force-based methods respond to the attractive and repulsive forces generated by the target and obstacles [25]. AI-based methods use machine learning models trained on some dataset or a reinforced learning method optimized by a defined policy that maximizes the reward function. AI-based obstacle avoidance systems use real-time situational awareness from perception sensors to make autonomous decisions.

4.1. Gap-based methods

Gap-based methods have been a viable solution for collision-free UAV navigation and pathfinding in recent years. A roadmap of feasible paths is updated based on various algorithms as the UAV traverses through the dynamic environment. Pathfinding is based on the available gaps detected around the UAV's current location. The most suitable gap for the UAV to move through is selected by a pathfinding algorithm under predefined constraints [44]. These methods have shown promising results in densely cluttered environments by avoiding static and dynamic obstacles [3,91]. Moreover, gap-based methods are promising for real-time UAV applications because of low computational requirements with fast reactive decision-making.

4.1.1. Open sector

The underlying notion of Open-Sector (OS) is to divide the UAV's proximity into open and closed sectors as illustrated in Fig. 4 [8]. This algorithm is particularly suitable for real-time applications, as it does not require maps and is computationally efficient. Experimental results show a smooth trajectory at a relatively high speed of 3 m/s demonstrate the algorithm's effectiveness in handling multiple obstacles. The algorithm selects the most appropriate open sector available based on the horizontal 2D laser scan of the environment to determine the action vector θ_V. In the first step, the UAV's circular proximity is categorized into open and closed sectors. In the second step, a virtual target is introduced to enhance the UAV's navigation capability in the presence of path traps. Even when the actual target is not in the line of sight, the UAV can avoid traps by travelling towards the virtual target instead of the actual target. The proposed method incorporates the contribution of past m action vectors into vector A to overcome the local minima problem encountered in the PF algorithm, which is defined in Eq. (1).

$$A = \sum_{i=k-m}^{k} V_i \tag{1}$$

The local minima problem in the PF algorithm is addressed by incorporating the contribution of past actions in the proposed method. Eq. (2) shows the direction of the virtual target is determined by incorporating the contribution of past actions into the actual target direction.

$$\theta_\vartheta = \Psi(\theta_T, \theta_A)u + \theta_T \tag{2}$$

The contribution of past actions is utilized to determine the direction of the virtual target action vector θ_ϑ, with the past actions vector θ_A being assigned a weight $u \in (0,1]$. The proposed method only avoids the obstacles within the maximum look-ahead distance, d_a, and ignores any obstacles that are situated outside of this range. The included angle between the past actions vector θ_A and the target vector θ_T is denoted by $\Psi(\theta_T, \theta_A)$. Once the suitable open sector and virtual target action vector θ_ϑ are determined, the OS algorithm ensures safety by incorporating safety boundaries. If the minimum obstacle detection distance ($r_{m1}$and r_{m2}) is less than the minimum safety distance r_s, the calculation of safety boundaries ($\varnothing_1$and $\varnothing_2$), depending on the shape and distance of the obstacle, is shown in Eq. (3) and Eq. (4).

$$\varnothing_1 = \begin{cases} \dfrac{\pi}{2} - \cos^{-1}\left(\dfrac{r_s}{r_1}\right), & if\ r_{m1} > r_s \\ \dfrac{\pi}{2} - \cos^{-1}\left(\dfrac{r_s}{d_a} - k(r_s - r_{m1})\right), & otherwise \end{cases} \tag{3}$$

and

$$\varnothing_2 = \begin{cases} \dfrac{\pi}{2} - \cos^{-1}\left(\dfrac{r_s}{r_2}\right), & if\ r_{m2} > r_s \\ \dfrac{\pi}{2} - \cos^{-1}\left(\dfrac{r_s}{d_a} - k(r_s - r_{m2})\right), & otherwise \end{cases} \tag{4}$$

The aggressiveness of maneuvers performed by the aerial robot to avoid obstacles is determined by the parameter k in Eq. (3) and Eq. (4). Additionally, the maximum look-ahead distance d_a is influenced by sensor characteristics, environmental factors, and the dynamics of the UAV.

The final action vector θ_V is established after verifying that the ideal open sector satisfies the safety boundary condition. However, it should be noted that the algorithm does not account for the aerial robot's dynamics, which may reduce its effectiveness in highly dynamic environments. Moreover, in cases where there are no viable open sectors in a densely cluttered environment, the algorithm switches to the PF-IPA method, which incorporates past actions, as described in [25], to guide the UAV towards the final waypoint.

Another Admissible Gap (AG) method has emerged as a viable approach for reactive obstacle avoidance in autonomous navigation. It offers a safer, more accurate, and easier-to-implement solution than

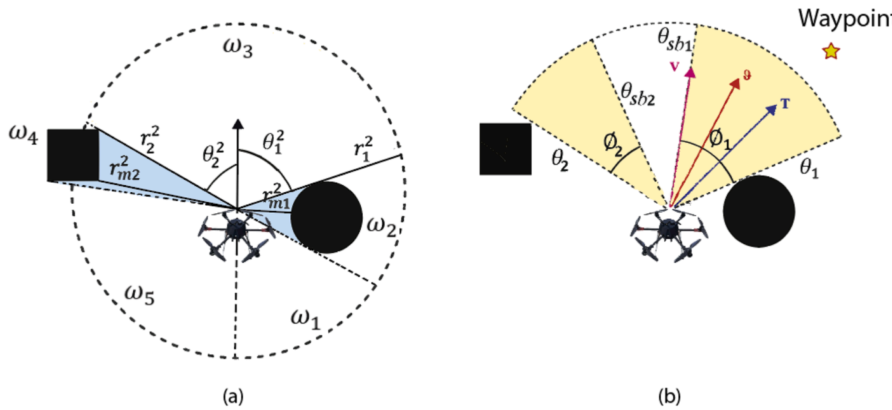

Fig. 4. (a) Segmentation of scan into sectors. Sectors ω_1, ω_3 and ω_5 are identified as open sectors. Sectors ω_2 and ω_4 are identified as open sectors. Each open sector has six parameters like in case of sector ω_3; the start and stop angle θ_1^2, θ_2^2; the range at start and stop angle r_1^2, r_2^2; the minimum ranges in the adjacent closed sectors r_{m1}^2, r_{m2}^2. (b)Illustration of safety boundaries $\varnothing_1$ and $\varnothing_2$; the actual target vector T; the virtual target vector ϑ; the action vector V [8].

other gap-based methods [91]. Although the proposed AG method in [91] employs multiple laser scanners with a wider field of view, it can be applied to sensor types with a limited field of view. This method presents a novel gap detection methodology while considering the aerial robot's geometry and kinematic constraints. However, the AG approach is unsuitable for dynamic obstacles moving abruptly and in a random pattern. The AG method additionally takes the shape and kinematics constraints into account for exploring the admissible gaps, making it computationally expensive method as compared to other gap-based methods.

4.1.2. Nearness diagram

The ND navigation solution, proposed in [3], utilizes a "divide and conquer" strategy to solve the complexity of the navigation problem. This reactive obstacle avoidance outperforms other collision-less navigation methods in densely cluttered and troublesome scenarios. ND method considers the obstacles distribution and final goal location to navigate the obstacle map. Available gaps are identified utilizing the nearness diagram from the robot's center point, as illustrated in Fig. 5. However, the ND method's performance depends on the availability of the clear sensory scan, underlining its limitations in the case of a noisy perception sensor.

Additionally, the ND method solely considers circular-shaped vehicles and overlooks vehicle kinematics and dynamic limitations. In contrast, other approaches, such as the AG method described in [91], consider the robot's shape, kinematics, and dynamics, making them more adaptable to various types of robots. Additionally, as highlighted in [79], the faster a robot moves, the more distortion occurs in the LiDAR point cloud scan, indicating that gap-based methods in [3,91] that rely on clear laser scans may have limitations in applications requiring rapid navigation. Nevertheless, the issue of local traps in highly cluttered environments and U-shaped obstacles has been resolved in [3].

Another gap-based approach for motion planning of robots in constrained workspaces is presented in [92]. The authors propose a two-phase method, where the first phase involves a learning process that constructs a probabilistic roadmap for a given environment. A heuristic evaluator is used to locate difficult areas in the free Configuration Space (C-space) and enhance the roadmap density in those regions. The roadmap is an undirected graph that captures the connectivity of the free C-space. In the second phase, the roadmap is leveraged to process path-planning queries quickly. It should be noted, however, that the method assumes a static workspace and does not account for dynamic obstacles or environmental changes. Additionally, the approach is also

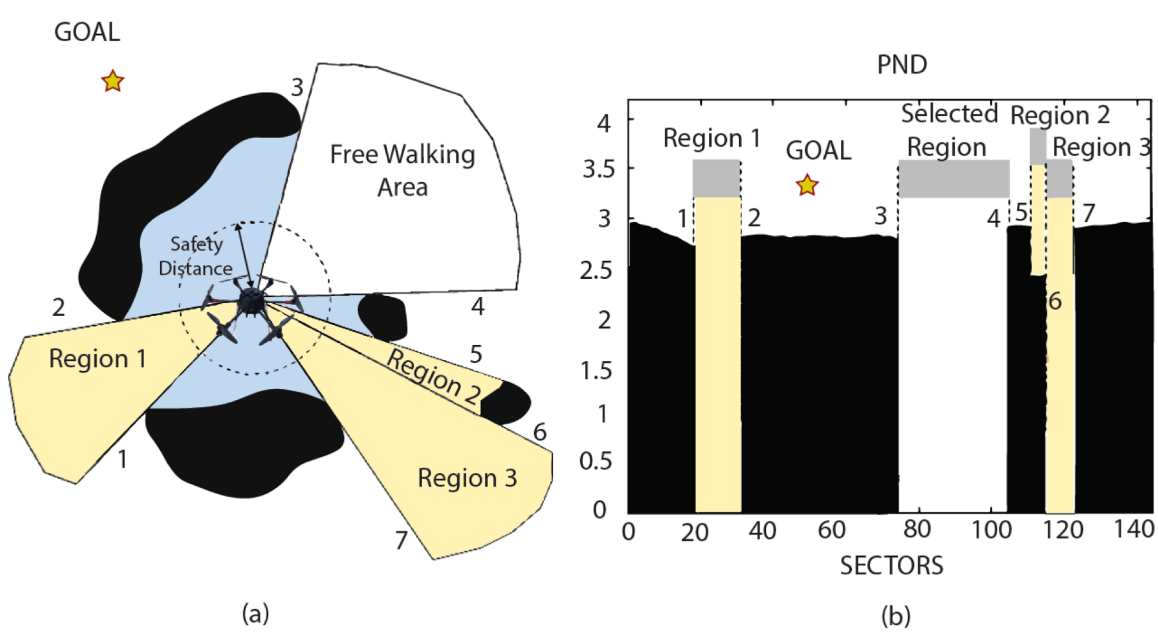

Fig. 5. (a) Obstacles and gaps in the scan (b) ND from center point [3].

inappropriate for real-time applications in dynamic environments, as updating the probabilistic roadmap is computationally time-consuming hence impractical.

4.1.3. Vector field histogram

The Vector Field Histogram (VFH) algorithm is widely recognized as one of the most effective obstacle avoidance methods based on gap analysis. Initially proposed in [2], VFH employs a reactive obstacle avoidance strategy by using a histogram representation of the UAV surrounding environment. The data from the onboard perception sensor discretizes the area around the UAV. This data is subsequently utilized to generate a polar histogram, which depicts the nearby obstacles using polar coordinates. A graphical representation of this approach is shown in Fig. 6.

Upon generating the polar histogram, the VFH algorithm determines a safe trajectory for the UAV to navigate, even in densely cluttered environments, making it suitable for real-time applications [2]. While VFH is an effective local path planning algorithm, it may exhibit cyclic behavior and become trapped in dead-end situations. A global path planner is utilized to aid the UAV in escaping dead ends. In addition to its effective local path planning capabilities, VFH exhibits superior handling of sensor noise and inaccuracies in comparison to alternative gap-based approaches, including the ND [3], OS [8], and AG [91]. VFH's ability to respond to clusters of range readings results in a minor impact of a single inaccurate reading on the UAV path. In a study by [44], the performance of VFH is compared with that of supervisory control logic. The results indicated that VFH exhibited superior trajectory planning and obstacle avoidance capabilities.

A modified real-time obstacle avoidance method VFH+ is proposed in [93]. This method proposes modifications that lead to more reliable and smooth trajectories. The VFH+ mainly incorporates the robot's width and provides a safer solution for collision-less trajectory resulting in enhanced reliability. VFH+ uses the certainty grid and occupancy grid technique to generate the histogram grid representation of the local environment. Vehicle real-time obstacle avoidance capability is further refined with smooth navigation with the help of the proposed improvement in VFH+ methodology.

The Gazebo (Open Robotics) has been used for obstacle avoidance performance evaluation of VFH+ algorithm in a simulated environment [94]. The results indicated that the VFH+ algorithm is proficient in avoiding obstacles, and the LiDAR sensor proved adequate for measuring distances. However, the study did not include a comparative analysis of the VFH+ algorithm with other obstacle avoidance algorithms, which may have provided valuable insights into the relative effectiveness of different algorithms.

Another VFH* [95] method uses the A* search algorithm and cost functions to verify that a given candidate direction guides the robot to avoid an obstacle. The limitation of VFH+ being unable to detect the gaps that may lead to blockages is also shown in [95]. The VFH* algorithm using the A* search algorithm can deal with problematic situations that would require the robot to slow down or even stop substantially.

To summarize, gap-based methods demonstrate notable advantages in managing complex and changing environments, computational efficiency, and ease of implementation, particularly for low altitude and small UAVs. However, the effectiveness of gap-based methods relies on the proper selection of parameters, such as gap size for the open sector and threshold values for the safety distance. Inadequate parameter selection may result in inadequate avoidance paths that increase the risk of collisions.

4.2. Geometric methods

Geometric methods are reactive obstacle avoidance techniques that gather pertinent information about the obstacles' geometric parameters, e.g., position and velocity. This position and velocity information is used to estimate probable collision trajectories [53]. Maneuvering the UAV from the estimated trajectory based on a policy avoids potential collision with the obstacles. Geometric space around the UAV that could lead to collision is recognized based on the obstacles' shape, position, and velocity. Unlike gap-based methods that work on the principle of open spaces within a complex environment, geometric methods are devised to avoid collision based on collision prediction.

4.2.1. Collision cone method

The collision cone is a geometric obstacle avoidance method that identifies a 2D or a 3D conic area in the geometric space around UAV with the maximum collision likelihood. The proposed technique is first presented in [96], visualizing a cone between UAV's and a circular or spherical boundary around the obstacle, as illustrated in Fig. 7. The vertex point of the collision cone is at the UAV's current position. The collision cone represents the range of velocities that potentially causes a collision. The collision cone technique can navigate around moving obstacles with irregular shapes. Moreover, unlike previous obstacle avoidance methods, the collision cone method relaxes the limitations of static obstacles and regular-shaped robots [96]. The detection of potential collisions is based on the velocity vector's presence in the collision cone region. Evasive maneuvers are executed to avoid the collision

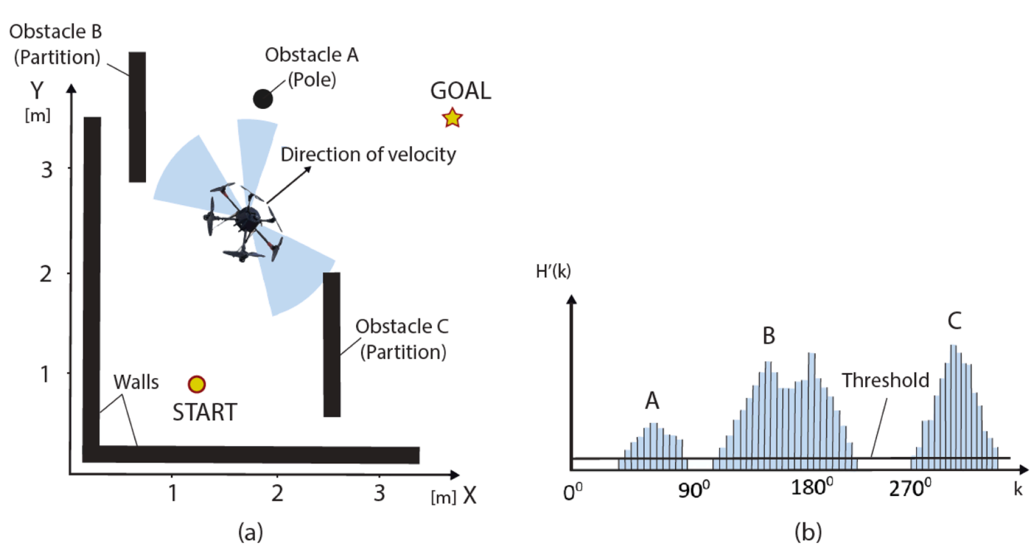

Fig. 6. (a) Obstacles around UAV (b) Linear polar histogram [2].

by directing the UAV's velocity vector outside the collision cone region.

The collision cone approach is not limited to single UAVs in the literature. Researchers have extended the collision-cone concept to the formation of UAVs [97]. They propose a simple algorithm with low computational requirements and define the collision avoidance envelope while considering dynamic constraints and obstacle detection range limits. The guidance law for collision avoidance is analyzed for stability using the Lyapunov theory. Moreover, the pioneers of the collision cone method address the problem of a team of n UAVs pursuing a swarm of intruder UAVs on a 2D plane [98]. The guidance laws are developed for situations where the intruder swarm is confined to a bounding circle, which may vary in size with time. The collision cone method serves as the foundation for these pursuit guidance laws. Simulation results indicate that the target UAV swarm is successfully surrounded by the chasing UAV. However, the proposed strategies in [97,98] do not consider communication delays between UAVs, sensor noise in range detection and other factors such as wind, turbulence, or other environmental factors affecting the system's performance in real-world scenarios.

In [45], researchers propose a reactive obstacle avoidance strategy for a multirotor UAV to avoid potential collisions in 3D space. This strategy utilizes a LiDAR sensor to detect a single moving obstacle, and a Kalman filter is incorporated into the collision cone technique to estimate the obstacle's position, velocity, and acceleration. However, the accuracy of the LiDAR sensor and the Kalman filter is crucial to the algorithm's performance, and any errors in these components may affect its effectiveness. In contrast, the algorithm proposed in [99] can avoid multiple obstacles simultaneously and is superior to other 3D navigation algorithms, such as the one presented in [45], which can only avoid obstacles one at a time. The study in [99] proposes a modified 3D vision cone-based reactive navigation algorithm that enables small quadcopter UAVs to avoid collisions while navigating around crowd-spaced 3D obstacles.

Previous collision avoidance techniques discussed in this section did not consider time a constraint. The method proposed in [100] uses the time-efficient collision cone approach to predict collisions. The comparative analysis considers heading change, speed change, and the fusion of both approaches. The study demonstrates that in terms of UAV's flight time the heading-based obstacle avoidance strategy is the most efficient of the three. A DJI Matrice 600 Pro hexacopter has been used as a platform for experimental testing. The outcome shows effective obstacle avoidance while minimizing the UAV flight time.

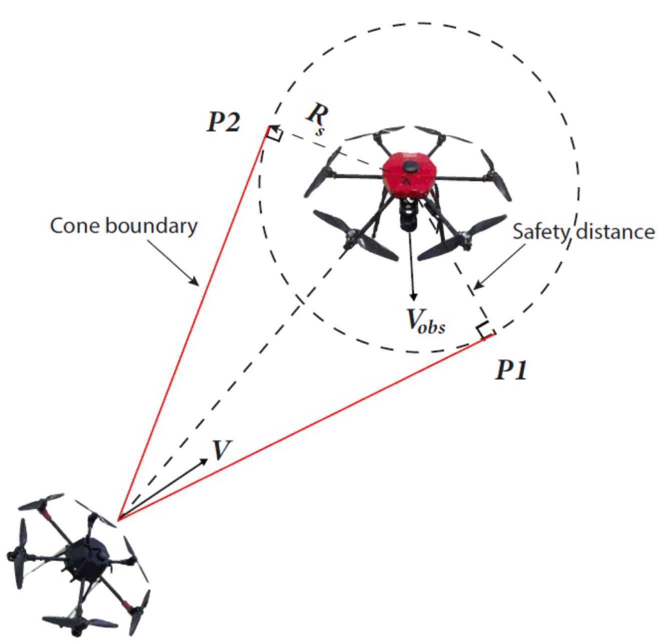

Fig. 7. Collision cone region.

4.2.2. Velocity obstacle method

Velocity Obstacle (VO) is a geometric method that works by estimating the collision region based on the velocity vector v_B of the obstacle. UAV defines its velocity obstacle space by considering the velocities of the obstacles in its vicinity. Two primary components of VO method are determining the velocity barriers for each obstacle and choosing the UAV's velocity outside the velocity obstacle region. The velocity obstacle region of an obstacle is the set of all velocities that would result in a collision if the UAV continued along its current trajectory. The avoidance maneuvers are generated by selecting the UAV's velocities outside the velocity obstacles. To select the velocity obstacle region, we move the collision cone by obstacle velocity v_B, as first shown in [101].

There are many improved variants of the VO method in the literature. Many multi-agent navigation algorithms, such as the original VO face common oscillation problems. As a solution to the oscillatory behavior, a new method called the Reciprocal Velocity Obstacle (RVO) is proposed [102]. The method guarantees safe and oscillation-free motions for each agent. It is applied to agents' navigation in densely populated environments containing static and moving obstacles. In RVO contribution of the velocity vector of the UAV, i.e., v_A is introduced by changing the position of the velocity obstacle by $\frac{1}{2}(v_A + v_B)$ as shown in the Fig. 8.

The Hybrid Reciprocal Velocity Obstacle (HRVO) in [5] considers obstacles in the environment, uncertainty in radius, position, and velocity, as well as the dynamics and kinematics of the robots. In this method, both VO and RVO are calculated and based on the velocity of the UAV, i.e., v_A. If the velocity of the UAV v_A is on the right side of the center line of RVO, then the region of RVO is extended up to the VO region on the left side, as shown in Fig. 8. Otherwise, in the second case of v_A the region of RVO is extended up to the VO region on the right side. A hybrid reciprocal velocity obstacle is reported in [5] to provide better results in collision-free and oscillation-free navigation of multiple agents compared to simple VO and RVO.

All the VO variants, including RVO and HRVO, utilize the information on the agent's shape, position, and velocity information. These methods ensure collision-free and oscillation-free navigation, but no one ensures the time to avoid the collision. In [1], the author presents an Optimal Reciprocal Collision Avoidance (ORCA) method, which introduces a safety time τ to avoid the collision earlier than the actual collision time. As shown in the Fig. 9 the obstacle appears to be near the UAV because of the scaling factor τ introduced.

4.3. Repulsive force-based methods

Repulsive force-based methods offer a promising low-altitude navigation solution to encounter non-cooperative obstacles. Repulsive force-based methods model the space around the obstacle and target as repulsive and attractive potential force fields. The cumulative sum of these force fields determines the direction of UAV, whenever it comes under the influence of these force fields [103]. Despite being useful, repulsive force-based algorithms inherently have certain limitations. Repulsive-force methods while navigating are prone to get stuck in local minima [25,104] and Goals Not Reachable with Obstacles Nearby (GNRON) [105]. These are the limitations that UAV faces when navigating through obstacles in a densely cluttered environment. Much research has been conducted to address these limitations, including local minima and GNRON problems.

4.3.1. Potential field algorithm

The Potential Field (PF) algorithm is a simple but effective repulsive force-based obstacle avoidance method. PF navigation performance

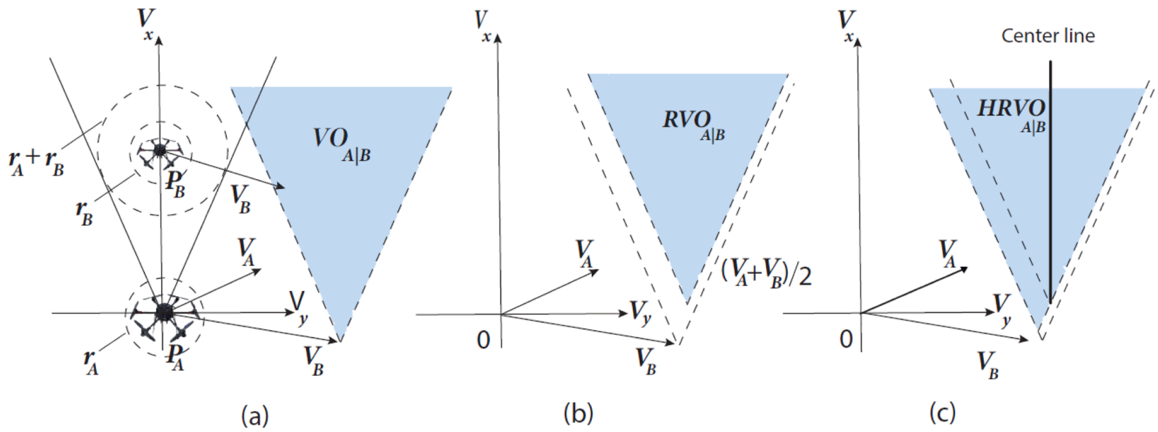

Fig. 8. (a) Velocity Obstacle $VO_{A|B}$ of UAV A induced by obstacle B (b) Reciprocal velocity obstacle $RVO_{A|B}$ of UAV A induced by obstacle B (c) Hybrid reciprocal velocity obstacle $HRVO_{A|B}$ of UAV A induced by obstacle B [5].

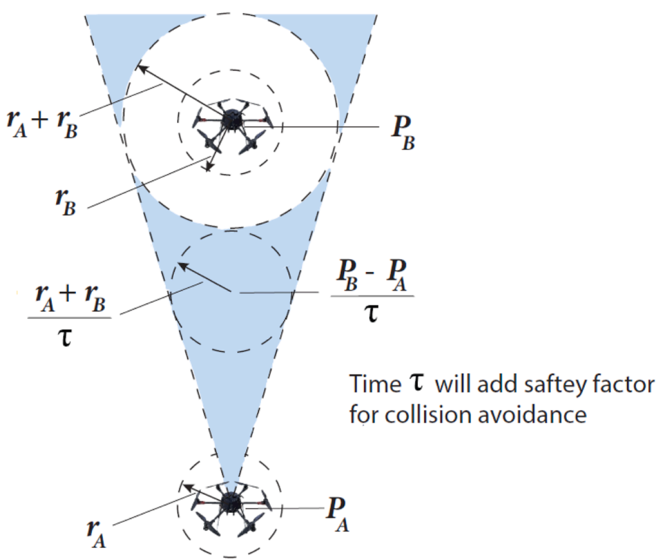

Fig. 9. Optimal reciprocal collision avoidance [1].

depends on initial conditions and is limited by local minima problems. The study in [103] uses a PF controller to track the dynamic targets while avoiding static obstacles in the environment. Simple PF navigation gets stuck into the narrow passages where the cumulative sum of attractive and repulsive forces cancels each other, referring to the situation as local minima [25]. Many modified PF algorithms have been proposed to solve local minima problem.

The APF method relies on two interacting forces to guide the movement of a robot in an environment. Specifically, a robot is attracted towards a desired destination through an attractive force while being repelled from obstacles by a repulsive force. By combining these forces, a path can be generated from the starting point to the target location along the direction of the net force. The APF can be expressed through the following equations [106].

$$U_{att} = \frac{1}{2}k_\alpha\left(p - p_g\right) \tag{5}$$

$$U_{rep} = \begin{cases} \frac{1}{2}k_\beta\left(\frac{1}{\|\vec{d}_o\|} - \frac{1}{r_{safe}}\right), & \|\vec{d}_o\| \le r_{safe} \\ 0, & \|\vec{d}_o\| > r_{safe} \end{cases} \tag{6}$$

$$F_{att} = k_\alpha\left(p_g - p\right) \tag{7}$$

$$F_{rep} = \begin{cases} k_\beta\left(\frac{1}{r_{safe}} - \frac{1}{\|\vec{d}_o\|}\right)\frac{\vec{d}_o}{\|\vec{d}_o\|}, & \|\vec{d}_o\| \le r_{safe} \\ 0, & \|\vec{d}_o\| > r_{safe} \end{cases} \tag{8}$$

$$F_{total} = F_{att} + \sum_i F^i_{rep} \tag{9}$$

where U_{att} in Eq. (5) and U_{rep} in Eq. (6) are attractive and repulsive potential field functions; F_{att} in Eq. (7) and F_{rep} in Eq. (8) are the force field functions of their respective potential fields; k_α and k_β are attractive and repulsive force constants; $\vec{d}_o$ is the distance of the obstacle from the UAV and r_{safe} is the threshold safety distance from the obstacle; p_g is the position of the goal, and p is the position of the UAV.

In [107], a 2D Gaussian Mixture Model (GMM) of the obstacles provides the potentials at different coordinates of a two-dimensional environment. Potential vectors are defined by using the derivative of the defined potential functions. The GMM-based approach is adopted to handle complex-shaped objects, which is one of the limitations of the simple PF algorithm. The inability of the PF algorithm to pass through the narrow passage has been addressed in [25]. A PF-IPA has been proposed. The strategy to navigate the obstacle accommodates the repulsive forces from the obstacles, the direction of the next waypoint, and the contribution of the past action vectors. The magnitude of the contribution is determined experimentally.

Another solution to the local minima problem by introducing the virtual target is introduced in [104], an improved algorithm that generates a virtual target within the neighborhood of the local minimum point to avoid falling into a local minimum point in a complex environment with many obstacles. APF algorithm has also been used for multi-UAV formation control and obstacle avoidance systems [108, 109]. In [108], along with the APF algorithm, a sliding mode control is established to ensure the UAVs follow the desired trajectory and maintain the desired formation. The saturation function is used to avoid chattering. This study introduced a robust formation control and target tracking algorithm for multiple UAVs, which can effectively achieve formation flight and target tracking while improving the system's robustness. Similarly, in [109], a comprehensive optimal obstacle avoidance mechanism of UAV path planning using an APF algorithm for multi-UAV systems in a complex environment. This method saves UAV's energy and solves UAV local minimization problems.

Another method proposed in [106] generates a real-time reactive collision-free path for UAVs flying in dynamic airspace. The method is based on the Dynamic Artificial Potential Field (DAPF) algorithm and aims to guarantee flight safety while minimizing the effect of surrounding obstacles. According to [106], the safety distance between the UAV and obstacles is referred as a variable threshold that scales adaptively based on the relative motion states of obstacles and the performance parameters of the UAV. This adaptive safety distance helps to resolve conflicts between the UAV and obstacles and improves operation efficiency and safety. Secondly, the potential field functions are modified to adjust automatically based on the threat levels of the surrounding obstacles. The relative position, speed, and flight behavior between the UAV and the obstacle define the obstacle's threat level. In the DAPF algorithm, the repulsive force of the classic APF algorithm is retained, and a steering force is added to shift the flight direction of the UAV to accelerate obstacle avoidance.

4.3.2. Improved potential field algorithm

Extensive research has been undertaken to address limitations in repulsive force-based methods for obstacle avoidance. For instance, significant attention has been dedicated to solving jitter problems in the APF algorithm. Furthermore, efforts have focused on enhancing obstacle avoidance with the constraint of finding the shortest possible path between the start and endpoints. In [105], the proposed method improves upon the APF method by adding a distance correction factor to the repulsive potential field function to solve the inherited GNRON problem in APF and using a standard hexagon-guided method to improve the local minima problem. Additionally, the proposed method uses the relative velocity method for moving object detection and avoidance in dynamic environments. The repulsive force function is divided into two parts, as shown in Eq. (10), to address the issue of GNRON with the APF algorithm [105]. Doing this allows the repulsive force to gradually lessen as the objective point is approached with nearby obstacles.

$$F_{rep} = \begin{cases} F_{rep1} + F_{rep2}, \ \| \vec{d}_o \| \leq r_{safe} \\ 0, \ \| \vec{d}_o \| > r_{safe} \end{cases} \tag{10}$$

where F_{rep1} and F_{rep2} are defined in Eq. (11) and Eq. (12) as

$$F_{rep1} = k_\beta \left(\frac{1}{\| \vec{d}_o \|} - \frac{1}{r_{safe}} \right) \frac{\vec{d}_g^{\,n}}{\vec{d}_o^{\,2}} \tag{11}$$

$$F_{rep2} = \frac{n}{2} k_\beta \left(\frac{1}{\| \vec{d}_o \|} - \frac{1}{r_{safe}} \right)^2 \vec{d}_g^{\,n-1} \tag{12}$$

where $\vec{d}_g$ and $\vec{d}_o$ are the distance of the goal and obstacle from the UAV, respectively. As UAV approaches to goal with obstacles in the nearby vicinity, the $\vec{d}_g^{\,n}$ and $\vec{d}_g^{\,n-1}$ approaches zero, and UAV moves towards the goal under the influence of only attractive force F_{att}, solving the GNRON problem.

Another obstacle avoidance method for a swarm of UAVs in [110] uses a combination of the second-order consensus algorithm and an improved potential field (IPF) algorithm. A "leader-follower" strategy is used by the swarm of UAV, where the leader UAV flies autonomously in accordance with the mission requirements, while the follower UAVs follow the leader using a second-order consensus algorithm. The method combines the target's attractive force and the obstacle's repulsive force to control the UAV's subsequent movement. The technique significantly eliminates the inherited jitter problem in the classical APF method.

A Bi-directional APF-RRT* algorithm with a goal-biased strategy is proposed in [47]. The path finding is carried out by the proposed algorithm using two alternating random search trees to speed up convergence. The APF method is incorporated into the Bi-directional search tree to reduce the number of iterations significantly. Moreover, the proposed algorithm uses cubic spline interpolation as the fitness function to optimize the trajectory and evaluate the shortest collision-free path length from the starting point to the endpoint.

In [111], an improved version of the APF method for UAV navigation in a 3D space is proposed. The proposed algorithm modifies the repulsive function according to the influence range of obstacles on UAV and divides the repulsive forces exerted by obstacles at different distances.

4.4. AI-based methods

Numerous studies have been conducted on applying AI to UAV obstacle avoidance. These approaches are categorized based on learning techniques, with supervised and unsupervised learning algorithms being the most common. AI approaches, particularly supervised learning, are primarily used in path planning on obstacle maps to process data and extract useful information. AI algorithms have become a crucial resource for processing and analyzing the enormous amounts of data that UAV sensing systems produce. The advancements in cloud computing, graphics processing units (GPUs), and parallel computing have made it computationally possible for these AI algorithms to process an unprecedented volume of data in real-time. Machine learning and deep reinforcement learning are the two most often applied AI-based techniques for avoiding obstacles.

4.4.1. Deep reinforcement learning

Deep Reinforcement Learning (DRL) is an AI technique that combines reinforced learning with deep neural networks. It learns to take actions based on feedback in the form of a reward or a penalty signal. This feedback about reward and penalty defines the policy that maximizes the reward function. This policy is represented as the neural network whose input is the current state and output is the probability distribution of possible actions. Inherently reinforced learning is well suited for the application without having a training data set. In deep reinforcement learning, the decision is made based on feedback from the environment.

A DRL method using a monocular camera for UAV obstacle avoidance utilizes information about the ambient environment for decision-making is proposed in [50]. It uses recurrent neural networks (RNNs) with temporal attention to retain relevant information about the environment structure to make better future navigation decisions. The proposed method can be integrated with a high-level planner, which inputs an overall path objective with a start and a goal position. The experimental results show that the proposed method outperforms the Deep Q-Network (DQN) and Double Deep Q-Network (D3QN) algorithms regarding distance covered by UAVs without collisions. The paper concludes that the proposed method can be used for practical obstacle avoidance of UAVs in cluttered and unseen environments.

In [112], Probability Distribution-Based Collision Avoidance (PICA) and Reinforced Learning-Based Collision Avoidance (RELIANCE) algorithms are proposed for avoiding collisions while saving energy consumption in UAVs. The RELIANCE method has demonstrated superior performance to PICA in dynamic environments with multiple UAVs. Test results highlight its effectiveness in terms of obstacle avoidance and policy convergence. The study, however, did not consider the impact of communication delays between the UAV and Multiaccess-Edge Computing (MEC) on the performance of the proposed algorithms.

A deep reinforcement learning system with a map-based architecture is given for environments devoid of communication [113]. This map-based approach uses the Distributed Proximal Policy Optimization (DPPO) algorithm to train neural networks. In the case of noisy data from the perception sensors, it has been claimed that this map-based multi-robot obstacle avoidance solution outperforms conventional reinforced learning methods. The present study adds substantially to our understanding that DRL is particularly well suited to applications involving high-dimensional input data, such as images or other sensor data.

4.4.2. Machine learning

Machine learning algorithms are trained on images and sensor datasets to identify potential environmental obstacles and hazards. The quality and size of the dataset have a significant impact on the performance of machine learning algorithms. Large-scale datasets are used for training to improve system performance on untrained datasets. The DRL-based scheme proposed in [50] increases decision accuracy by utilizing collected data over time. However, its limited applicability arises from the requirement of the UAV to repeatedly operate in the same workspace, posing a challenge in utilizing the system in safety-critical environment.

A two-stage CNN-based learning scheme for a quadrotor UAV to avoid obstacles automatically in unknown and unstructured environments is proposed in [48]. It uses a forward-facing monocular camera as a perception sensor. The first stage uses a CNN-based model as the prediction mechanism, simultaneously predicting the steering angle and the collision probability. The second stage involves mapping the steering angle to an instruction that changes the yaw angle of the UAV, and the collision probability is mapped as a forward speed to maintain the flight or stop going forward. Similarly, in [61], CNN is used to estimate the depth of the RGB image, further using this depth prediction as input to the obstacle avoidance mechanism. But the platforms used for experiments in [48,61] rely on wireless LAN, which imposes restrictions on communication distance between UAV and ground control station.

Researchers have recently investigated machine-learning techniques to optimize obstacle avoidance performance on resource-constrained hardware with minimal processing requirements. The proposed scheme in [49] uses a machine learning-based approach to reduce the memory footprint of the cost tables used by Airborne Collisions Avoidance Systems (ACAS-Xu) for collision avoidance in UAVs. Instead of a classical cost table, using trained DNN to predict cost vectors considerably reduces the memory size required by a factor of 500. Moreover, the performance of ACAS-Xu is not degraded using DNN to approximate the classical cost table. A framework of energy-efficient UAV surveillance network is proposed in [114]. In this study, CNN is utilized to extract features of the moving objects from UAVs. But the proposed framework in [114] is tested in a simulated environment, and the real-world implementation may have different challenges and limitations. A categorized summary of the existing obstacle avoidance techniques is shown in Table 6.

While comparing, each non-cooperative local obstacle avoidance method has its advantages and disadvantages. In summary, compared to repulsive force-based methods, gap-based methods exhibit smooth navigation and are computationally efficient [8]. However, the noise in the sensory scan affects their performance and lowers their navigation speed [3]. In contrast to gap-based methods, repulsive force-based methods are more likely to become trapped in local minima and GNRON [105]. The challenge of navigating a swarm of UAVs is an issue that geometric methods can handle in addition to a single UAV [97]. Furthermore, in contrast to previous approaches, geometric methods make use of the obstacle's shape, position, and velocity information to guarantee collision-free navigation. Lastly, AI-based obstacle avoidance methods are appropriate for applications involving enormous amounts of data from perception sensors. Machine learning algorithms are computationally expensive as their performance depends on the size and quality of the dataset. AI-based methods using DRL have limited applicability because UAVs need to be repeatedly operated at the site to collect data over time [50].

5. Hardware architecture for non-cooperative obstacle avoidance

The hardware architecture of a UAV plays a vital role in its obstacle avoidance performance and capabilities. This section introduces the classification of hardware topologies used in UAV obstacle avoidance. The hardware architecture of a UAV consists of many essential components like types of airframes, propellers, motors, GPS modules, magnetometer, gyrocompass, accelerometer, gyroscopes, and onboard sensors. Regarding obstacle avoidance in UAVs, three hardware topologies can be segregated into three categories in terms of flight controllers and flight computers.

The first category directly incorporates obstacle avoidance capabilities into the flight controller. This hardware topology integrates multiple sensors such as LiDAR, camera, and ultrasonic sensors and employs the flight controller's onboard processing power to make real-time decisions. A laser sensor TFmini integrated into Pixhwak hardware is utilized in [116] for range and direction estimation of obstacles near a quadrotor UAV. Moreover, the study employs the Dijkstra method locally to search for possible paths, and an improved particle swarm optimization algorithm is utilized to obtain the globally optimized path.

The second hardware topology utilizes a companion computer alongside a primary flight controller to handle intelligent tasks such as autonomous obstacle avoidance. In this hardware configuration companion computer is an additional computing unit responsible for processing sensor data, executing complex algorithms and sending navigation commands to the flight controller for executing avoidance maneuvers. This configuration allows for more computational power and flexibility in implanting advanced obstacle avoidance strategies. Table 7 summarizes combinations of flight controllers and companion computers for UAV obstacle avoidance. Arduino nano is used as a flight controller in [117,118]; other flight controllers utilized in hybrid architecture include Pixhawk [23,76–78,116,119–123], Mateksys H743-WING [124], DJI A3 [8] and Pixracer R15 [75]. Most UAV obstacle avoidance applications utilizing visual perception sensors employ Jetson Nano as companion computer [76,117,118,123,124]. Other companion computers using single or multiple perception sensors include different models of Raspberry Pi [77,120–122], ODROID [8,23] and Intel NUC [75,78,119].

The third scheme uses additional hardware components specifically dedicated to obstacle avoidance. That additional hardware often includes a dedicated obstacle avoidance system such as ADS-B receivers that can detect other aircraft. An obstacle avoidance system combining a Thermal-Infrared (TIR) camera with an ADS-B receiver is proposed in [125]. The proposed obstacle avoidance scheme estimates the detected aircraft range by matching the TIR images with the corresponding ADS-B message. Another study in [126] used a sampling-based approach on ADS-B data for obstacle avoidance path planning. It has been validated in Software-In-the-Loop Simulation (SITL) using ADS-B data from commercial aircraft flying over the Phoenix Sky Harbor airport.

In conclusion, the first hardware topology that exclusively incorporates a flight controller is unable to navigate precisely to achieve the optimal trajectory [116]. In principle, the flight controllers, namely Pixhawk, Arduino Nano, and DJI A3, serve as the autopilots, responsible for real-time flight stabilization, control, and localization sensor data processing. These flight controllers can integrate various types of sensors, such as a GPS module, gyroscope, and accelerometer, to sustain stable flight and execute autonomous flight as planned by the remote pilot. However, this hardware architecture has limitations in the form of processing power, computational capabilities, and hardware interfaces with higher data rates.

In contrast, the subsequent hardware architecture, as shown in Table 7, employs a hybrid configuration with companion computers (Jetson, Raspberry Pi, ODRIOD, and Intel NUC) in conjunction with a flight controller that serves as an autopilot. Each of these companion computers comes with a variety of interfaces, including USB and Ethernet, capable of facilitating networking and extracting data from perception sensors at higher data rates. With its dedicated GPU (Graphics Processing Unit) with CUDA cores, Jetson outperforms the Raspberry Pi, rendering it a more viable option for implementing AI-based obstacle avoidance methods that involve the execution of deep learning and machine learning algorithms.

Table 6
A summary of Non-cooperative obstacle avoidance techniques.

Type	Ref	Methodology	Sensors	Performance
Gap-based	[8]	• Reactive obstacle avoidance algorithm that uses 2D scan to detect obstacles and determine open sectors for collision-free navigation	Laser rangefinder: Hokuyo UST-10LX	• Computationally efficient and does not require maps • Smooth trajectory at a relatively high speed of 3 m/s in unstructured urban/suburban environment
	[91]	• AG method for reactive obstacle avoidance in robotics • Exact robot shape and kinematic constraints are considered, which improves the safety and efficiency of robot navigation	Laser rangefinder1: Hokuyo UTM-30LX Laser rangefinder2: Hokuyo URG-04LX	• The AG approach outperforms the other methods in terms of success rate and path length • Outstanding navigation performance is achieved in unknown dense environments • AG approach performance has not been compared in terms of computational efficiency
	[3]	• The ND navigation method uses a "divide and conquer" strategy to simplify the difficulty of navigation in very dense, cluttered, and complex scenarios	The paper mentions robots equipped with • 3D laser • Ultrasound sensors • 2D laser (Exact names are not mentioned)	• It navigates robots in troublesome scenarios where other methods present a high degree of difficulty in navigating • It does not consider the robot's shape, kinematics, and dynamics, which makes them more suitable for different types of robots
	[94]	• Designing an obstacle avoidance system for Hexacopter using the Vector Field Histogram-Plus (VFH+) algorithm	Laser rangefinder: 2D LiDAR resolution of 1^0 (Exact sensor model is not mentioned)	• The obstacle avoidance system is tested in the Gazebo environment running on Robot Operation System (ROS) • This work needs to be tested in a real environment for accuracy and reliability analysis
Geometric	[100]	• Proposing a heading change algorithm for time-efficient obstacle avoidance for aerial drones using collision cone-based approaches	-	• UAVs can avoid collisions with dynamic obstacles by changing their speed, heading, or both. The paper proposes a purely heading-based method to be the most efficient • The proposed algorithm does not consider the limitations of the UAV's sensors, such as their range and accuracy
	[115]	• The paper proposes a 3D velocity obstacle method to avoid collisions with multiple dynamic and static obstacles for UAVs	Laser sensor	• Introducing improvements to the existing velocity obstacle cone and presenting a tall cylinder shape protected zone to approximate all kinds of static obstacles • Presented the velocity obstacle pyramid to handle 3D obstacles
Repulsive force-based	[25]	• Use of a potential-field algorithm for collision-free monitoring in areas with obstacles • UAV uses a modified PF algorithm that avoids the local minima problem in a simple PF algorithm	Laser rangefinder: Hokuyo UST-10LX	• The paper presents a novel and advanced system for autonomous chemical sensing and monitoring in complex environments • The system is tested in outdoor environments with obstacles such as buildings and trees; but requires further evaluation in complex and dynamic environments
	[111]	• An improved algorithm based on the traditional APF method for quadrotor UAV in a three-dimensional space	-	• The proposed algorithm is only tested in a simulation environment, not a real-world scenario. Therefore, the algorithm's effectiveness in a real-world environment must be further investigated
AI-based	[48]	• A two-stage obstacle avoidance architecture utilizing camera as perception sensor • A CNN-based model predicts the steering angle initially • The control system changes the UAV's yaw angle in the second stage	Front-facing monocular camera	• The system uses a low-cost sensor, lightweight network topology, strong learning capability, and environmental adaptability • Wi-Fi is utilized as a protocol for communication with the ground control station, which limits the operational range of the UAV
	[50]	• A Deep reinforcement learning-based method is proposed for UAV obstacle avoidance in unstructured and unknown indoor environments.	Monocular RGB Camera: Image size $84 \times 84 \times 3$ pixels	• The problem of partial observability is addressed in obstacle avoidance using a recurrent neural network with temporal attention. • Outperforming prior works in terms of distance covered without collisions • The method requires a lot of training data to learn effective obstacle avoidance behavior, which may be difficult to obtain in certain situations • The method assumes static environment and does not account for moving obstacles or outdoor scenario

6. Discussion and future directions

This paper accounts for non-cooperative obstacle avoidance solutions for low-altitude surveillance UAVs. The following are the key findings derived from the comprehensive analysis of the reviewed literature.

- In aerial surveillance applications, diverse types of UAV platforms have been employed. The airspace above an altitude of 122 m is categorized as a "High-speed UAV traffic" area, and the risk of collision is considered relatively lower in this zone. However, conducting aerial surveillance at low altitudes poses a significant risk of collision, necessitating the selection of appropriate UAV platforms. In this regard, rotary-wing multi-copters offer several advantages, such as their hovering capability and lower speed of operation, making them a more suitable option for low-altitude aerial surveillance. It is anticipated that the utility of rotary-wing UAVs integrated with cutting-edge sensing technologies will increase in the future. Hence, there is a need for a regulatory framework to ensure the safe use of multi-rotor UAVs in various industries.
- In the context of low-altitude UAV surveillance, two sensing technologies, namely visual and non-visual sensing, were thoroughly examined and compared. Non-visual sensing employing active sensors is less affected by lighting conditions, calibration errors, and weather and offers more resilience and accuracy. Visual sensing, relying on favorable conditions in contrast, offers insight into obstacle shape and texture information. However, obstacle avoidance based on visual sensing in low-light and adverse weather is still a challenge and is expected to draw attention from researchers in years to come.

Table 7
A summary of onboard hardware architecture for obstacle avoidance.

Companion Computer	Refs.	Flight controller	Sensors	Application
Jetson Xavier NX	[124]	Mateksys H743-WING	• Intel RealSense L515 LiDAR • Intel RealSense T265 tracking camera	• Autonomous navigation by multirotor UAV in an unfamiliar GPS-denied environment utilizing visual navigation, black lane segmentation and neural network models
Jetson Nano	[123]	Pixhawk	• Intel RealSense D435i camera	• A simple and robust approach for reactive obstacle avoidance using spirals for escape in unknown scenarios
	[76]	Pixhawk 4	• Slamtec RP LiDAR S1 • Logitech C930e web camera	• Fast Obstacle Avoidance Motion (FOAM) algorithm for sense-and-avoid operations in a cluttered environment using multi-sensor fusion
	[117]	Arduino Nano	• 2D LiDAR sensor	• Implementation of SLAM and the development of an autonomous robot using a 2D LiDAR sensor
NVIDIA Jetson TX2	[118]	Arduino Nano	• Velodyne VLP-16 LiDAR	• A path-following and obstacle avoidance system for autonomous surface vehicles
Raspberry Pi Zero	[122]	Pixhawk 2	• LiDAR-Lite v3 sensors	• A computationally inexpensive obstacle avoidance control of a drone for infrastructure inspection
Raspberry Pi 3 Model B	[77]	Pixhawk 2.0 Cube	• Scanse Sweep Laser Scanner • PX4Flow Flow camera	• Guidance Navigation and Control (GNC) system architecture for lightweight UAV autonomous indoor flight using ROS
	[120]	Pixhawk 2.4.8	• RPLiDAR A1	• A low-cost Obstacle Detection and Collision Avoidance System for multi-rotor drones based on Coulomb's inverse-square law
Raspberry Pi 4 Model B	[121]	3DR Pixhawk Mini	• Ouster OS1–16 LiDAR	• UAV indoor mapping to support disaster management in GPS-denied environment.
ODROID XU4	[23]	Pixhawk	• RPLiDAR 360°.	• A model-based automatic obstacle avoidance algorithm for remotely piloted UAVs
ODROID-C2	[8]	DJI A3	• Hokuyo UST-10LX LiDAR.	• A reactive-based obstacle avoidance method that does not require maps and is computationally efficient
Intel NUC	[75]	Pixracer R15	• Hokuyo UST-10LX LiDAR • T265 RealSense camera	• Comparison of APFs and CBFs for obstacle avoidance in mobile robots
	[119]	Pixhawk 2.1	• Ouster OS1–16 LiDAR • Intel T265 camera. • Pozyx ultra-wideband (UWB) positioning system	• An indoor navigation solution for UAV in areas where GPS and magnetometer sensor measurements are unavailable
	[78]	Pixhawk 2	• Velodyne VLP-16 LiDAR	• An obstacle detection and avoidance system for a multicopter UAV using LiDAR data
Others	[127]	–	–	• An air pollution source tracking algorithm based on APF and particle swarm optimization
	[116]	Pixhawk	• TFmini Laser Sensor	• A new obstacle avoidance strategy for UAVs using Dijkstra method and an improved particle swarm optimization

- LiDAR-based active sensing, which has been utilized in a few works, is one of the most promising non-visual sensing technologies. It provides accurate and high spatial resolution without additional computational requirements, as compared to other non-visual sensors, e.g., Radar. Its extended detection range makes LiDAR suitable for applications like aerial surveying and surveillance. Notably, LiDAR facilitates real-time data acquisition without adding computational overhead, making it a suitable option for integration with other sensors in a sensor fusion framework.
- Sensor fusion, which integrates multiple perception sensors, including both visual and non-visual sensing, enhances redundancy, reliability, and decision-making in the UAV's obstacle detection and avoidance systems. The field of sensor fusion remains nascent in non-cooperative and local obstacle avoidance and is anticipated to be a key area of exploration in the forthcoming years. Moreover, in the future, there is a need to focus on optimizing energy consumption in the sensor fusion framework, prioritizing smart utilization of sensors based on operational needs.
- In this paper, four distinctive methods for non-cooperative and local obstacle avoidance, i.e., gap-based, geometric, repulsive force-based, and AI-based methods, have been systematically classified. Due to their fast and efficient computation, gap-based methods are effective for low-altitude obstacle avoidance. Nevertheless, the efficacy of gap-based methods degrades when confronted with noisy sensor data from the environment scan in complex and cluttered environments. Moreover, several studies have been conducted to address oscillations in the UAV flight trajectory, and local minima are problems encountered in geometric and repulsive force-based methods. These challenges constitute an active area for prospective research in the field of non-cooperative obstacle avoidance.
- AI-based methods have shown great potential in enhancing the adaptability and flexibility of obstacle avoidance systems by learning through training datasets or by reinforced learning through information gathered from perception sensors. AI-based methods can make accurate and timely decisions by analyzing vast amounts of data and adapting to changing environments and unexpected situations. Furthermore, given that AI-based obstacle avoidance techniques are still in their infancy, future research will be directed towards exploring energy-efficient AI models and exploring low-power hardware solutions to meet the constraint of extended operational endurance of small UAVs.
- This paper provides an account of different hardware topologies for UAV obstacle avoidance. The investigated topologies include flight controller-based configuration, hybrid architecture, and dedicated obstacle avoidance architecture. While flight controller-based architecture exhibits simplicity, its limited computational resources result in less accurate performance in obstacle avoidance. On the contrary, hybrid architecture is more complex but affords more computational capabilities, improved navigation accuracy, and the ability to handle complex decision-making processes. The dedicated obstacle avoidance architecture incorporates a dedicated subsystem for obstacle avoidance, yet only the hybrid topology provides a platform for future upgrades by assimilating new sensors as technology evolves, thereby enhancing companion computers' capabilities.

CRediT authorship contribution statement

Muhammad Zohaib Butt: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. **Nazri Nasir:** Funding acquisition, Project administration, Supervision, Validation, Visualization, Writing – review & editing. **Rozeha Bt A . Rashid:** Supervision, Validation.

Declaration of competing interest

The authors declare that none of the work reported in this publication could have been influenced by any known competing interests.

Data availability

No data was used for the research described in the article.

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