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Aerial Autonomy Under Adversity: Advances in Obstacle and Aircraft Detection Techniques for Unmanned Aerial Vehicles

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Abstract

Unmanned Aerial Vehicles (UAVs) have rapidly grown into different essential applications, including surveillance, disaster response, agriculture, and urban monitoring. However, for UAVS to steer safely and autonomously, the ability to detect obstacles and nearby aircraft remains crucial, especially under hard environmental conditions. This study comprehensively analyzes the recent landscape of obstacle and aircraft detection techniques tailored for UAVs acting in difficult scenarios such as fog, rain, smoke, low light, motion blur, and disorderly environments. It starts with a detailed discussion of key detection challenges and continues with an evaluation of different sensor types, from RGB and infrared cameras to LiDAR, radar, sonar, and event-based vision sensors. Both classical computer vision methods and deep learning-based detection techniques are examined in particular, highlighting their performance strengths and limitations under degraded sensing conditions. The paper additionally offers an overview of suitable UAV-specific datasets and the evaluation metrics generally used to evaluate detection systems. Finally, the paper examines open problems and coming research directions, emphasising the demand for lightweight, adaptive, and weather-resilient detection systems appropriate for real-time onboard processing. This study aims to guide students and engineers towards developing stronger and intelligent detection systems for next-generation UAV operations.

Keywords: UAV detection; obstacle avoidance; aircraft detection; challenging environments; deep learning; real-time processing; vision systems

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1. Introduction

Obstacle and aircraft detection in Unmanned Aerial Vehicles (UAVs) [1,2] directs to the process of sensing, determinating, and finding potential risks in the UAV's aviation route [3]. These risks may have static obstacles such as buildings, trees, electric poles,

and cables, as well as dynamic obstacles like moving vehicles, other UAVs, birds, or manned aircraft. Effective obstacle and aircraft detection is essential to provide the UAV's ability to navigate safely, bypass collisions, and arrange alternative ways when required [4]. It forms a critical component of autonomous UAV operations, allowing drones to operate reliably in difficult, unexpected environments [5]. Precise detection of obstacles and aircraft is required to control mid-air collisions and accidents. Failures in detection can result in UAV collisions, causing damage to property, economic failure, or fatalities in occupied areas. For UAVs working without direct human control, reliable environmental understanding is essential. Separate missions such as container delivery, infrastructure check, supervision, and search-and-rescue tasks rely laboriously on real-time obstacle and aircraft detection to provide safe and effective operation Aviation authorities, including the Federal Aviation Administration (FAA) and the European Union Aviation Safety Agency (EASA), need the integration of crash out capabilities for UAVs, especially in urban environments and communicated airspace [6]. Detection systems are the basic requirement for legal and safe UAV deployment. The ability to detect and respond to obstacles in real time allows UAVs to develop safer and more efficient flight paths. This reduces energy consumption, trims mission duration, and improves the overall success rate of UAV operations [7]. A total of 108 references were included and cited in the preparation of this review, ensuring comprehensive coverage of recent advances and challenges in UAV obstacle and aircraft detection. The significant contributions of this report are as follows: The paper offers an in-depth survey of UAV obstacle and aircraft detection under challenging conditions such as fog, rain, smoke, low light, motion blur, and high dynamic range (HDR) scenes, emphasizing how these aspects impair visibility and evaluating the usefulness of detection methods and sensor robustness in each procedure. It delivers a precise taxonomy of the core challenges in UAV navigation, including detecting thin objects like wires, tracking dynamic obstacles, navigating lush environments, working with quickly motion-blurred images, and working within computational limitations, thus framing the hurdles faced in real-world deployments. The study thoroughly compares key sensor technologies, such as RGB and infrared cameras, LiDAR, radar, sonar, and event-based vision sensors, discussing their capabilities, limitations, and suitability under different environmental conditions to assist in optimal sensor selection for UAV systems. Again, it deviates from classical computer vision techniques (such as optical flow, stereo vision, and SIFT/SURF) with deep learning models (including YOLO, Faster R-CNN, and DETR), tracing their individual powers, limitations, and real-time feasibility on UAV hardware, particularly in degraded environments. The paper also studies significant standard datasets—UAVid, VisDrone, DOTA, and Foggy Cityscapes, concentrating on their environmental diversity, annotation classes, and relevance for training and testing detection algorithms under real-world and synthetic adverse conditions. Standardized performance metrics such as mean average precision (MAP), precision, recall, F1-score, latency, and robustness are summarized as important tools for setting detection methods in safety-critical UAV operations. A complete comparative analysis is delivered as a summary table. It describes detection methods by sensors used, conditions addressed, and their separate strengths and disadvantages, offering a proper decision-making mechanism for researchers and developers. The report also recognizes continuous limitations, including sensor degradation in adverse weather, computational demands of deep learning models, sensor fusion challenges, and poor vision of unknown environments. Finally, it discusses future research directions, highlighting the need for lightweight and power-efficient deep learning models, event-based processing, adaptive multi-sensor systems, and zero-shot detection to enhance robustness and independence in complex real-world UAV scenarios. In addition to conventional camera, LiDAR, and radar-based detection systems, laser-based

visual identification techniques have emerged as effective solutions for multi-UAV detection and coordination, particularly through the use of laser spots or coded beacons as visual markers [8]. The overall structure of the paper is illustrated in Figure 1, which outlines the key sections including introduction, datasets, challenging conditions, detection methods, sensor technologies, and future directions.

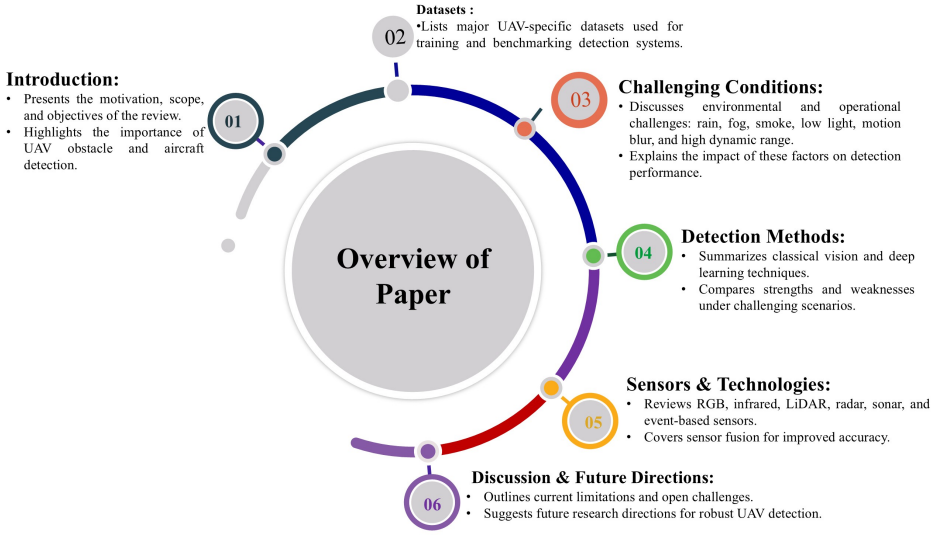


Figure 1. Overview of the paper.

2. Environmental Effects on Sensor Reliability

This section strictly focuses on how adverse environmental factors such as fog, rain, smoke, low light, motion blur, and high dynamic range conditions impair sensor input quality for UAV detection systems. The ability of UAVs to notice and avoid obstacles and aircraft in real-time is important for their safe operation, especially in complex conditions like rain, fog, smoke, and low light.Although sensor technology and obstacle recognition algorithms have reached a long way, there is still a need for more robust systems capable to handle dynamic environments with different visibility. Studies still focus on enhancing sensor fusion, developing more powerful algorithms, and employing fog computing to guarantee that even in bad temperature or lighting situations, UAVs may operate independently and securely. The following subsections describe the specific results of each state on UAV detection.

2.1. Impact of Rain on UAV Detection

Rain particularly involves UAV obstacle and aircraft detection, forcing light diffusion, water droplets on camera lenses, and lowered visibility. This challenge causes UAV methods to enhance their robustness by including sensor fusion, such as connecting optical cameras with radar or LiDAR, which are slightly affected by rain [9]. Drizzling conditions even boost the growth of advanced image processing methods like raindrop deduction algorithms and difference enhancement, allowing UAVS to maintain accurate obstacle detection even during serious drizzles. Therefore, rain acts as a useful condition for designing UAVs capable of operating reliably in real-world outdoor environments [10].

2.2. Fog Induced Detection Challenges

Fog makes a thick scattering medium that laboriously attenuates optical movements, creating a classic vision-based detection that is unpredictable. This challenge is driving the advancement of non-visual sensors like millimetre wave radar and the development of deep learning-based fog-robust perception algorithms. Handling fog effectively allows UAVs to detect obstacles and other aircraft even when visibility drops dramatically [11].

The existence of fog enables UAV detection systems to execute early-warning mechanisms and path-planning methods based on degraded sensing, improving overall system security in urban and mountainous areas where fog is common [12].

2.3. Smoke as a Detection Barrier

Smoke is recognized as a major challenge for UAV-based detection techniques as it decreases visibility and alters accurate detection. With varying density and movement patterns, smoke develops dynamic and unexpected visual disturbances. For UAVs, identifying obstacles via smoke issues the reliability of traditional image-processing methods. It motivates studies on multispectral vision and thermal imaging, where smoke penetration is better [13]. Applications like firefighting missions and disaster response depend on the development of systems performing obstacle and aircraft detection in smoky situations, where UAVs must traverse dangerous, smoke-filled locations, preserving precise situational awareness [14].

2.4. Low-Light and Nighttime Detection

Nighttime low-light conditions significantly reduce the use of traditional cameras, which causes poor contrary, noise, and missed detections. This challenge allows UAV systems to incorporate low-light enhancement algorithms, near-infrared sensors, and thermal imaging [15]. Raising the operation window of UAVs by being capable of consistently identifying obstacles and aircraft at night allows them to maintain necessary activities such as delivery, search-and-rescue, as well as nighttime surveillance. Hence, night-time low-light techniques are necessary for making UAV obstacle detection systems truly 24/7 operational [16].

2.5. Motion Blur in High-Speed UAVs

Motion blur in UAV obstacle detection relates to the warping in captured images when the UAV forces quickly or experience sudden directional shifts. During short or high-speed flight, UAVS regularly suffer from motion blur, warping the captured images and hindering obstacle detection precision. This challenge allows the design of fast-shutter imaging, inertial measurement unit (IMU)-based stabilisation, and strong action deblurring algorithms [17]. Overwhelming motion blur is essential for UAVs used in dynamic applications like high-speed inspections, racing, or emergency response, where fast responses are required, and obstacle avoidance must remain accurate despite the UAV's speed [18].

2.6. High Dynamic Range Scenes

Places with both extremely bright and very dark spots develop significant difficulties for obstacle recognition, as ordinary cameras are unable to capture all features at once. This challenge requires adaptable orientation control and High Dynamic Range (HDR) image techniques. By effectively managing such scenarios, UAVs can identify obstacles hidden in shadows or against bright backgrounds like the sun [19]. Resolving the High Dynamic Range (HDR) issue allows UAVs to work consistently in tunnels, at dawn as well as sunset, and close to positively reflective surfaces, thus enhancing their ability to adapt in many settings. These environmental conditions primarily affect sensor input quality and image acquisition [20].

3. Real-Time Perception and Obstacle Detection Challenges

This section focuses on real-time perception challenges during UAV flight, including dynamic object detection, thin obstacle recognition, motion-induced blur, and onboard computational constraints. Unmanned Aerial Vehicles (UAVs) are increasingly employed

in various environments, ranging from urban infrastructure monitoring to disaster response and agricultural surveillance. Yet, sufficient obstacle detection remains a crucial challenge for providing safe and independent navigation. Different environmental and hardware-related elements slow reliable perception, particularly in difficult or dynamic settings. Below are the key challenges that UAVs face in detecting obstacles during flight, which must be managed to improve their operational security and efficiency [21]. These challenges reflect the UAV's need to process visual and spatial information accurately during real-time navigation.UAVs face multiple perception challenges during flight under difficult environmental conditions. These include fog, rain, smoke, and motion blur, which severely affect detection performance. The major challenging conditions for UAV obstacle detection are summarized in Figure 2.

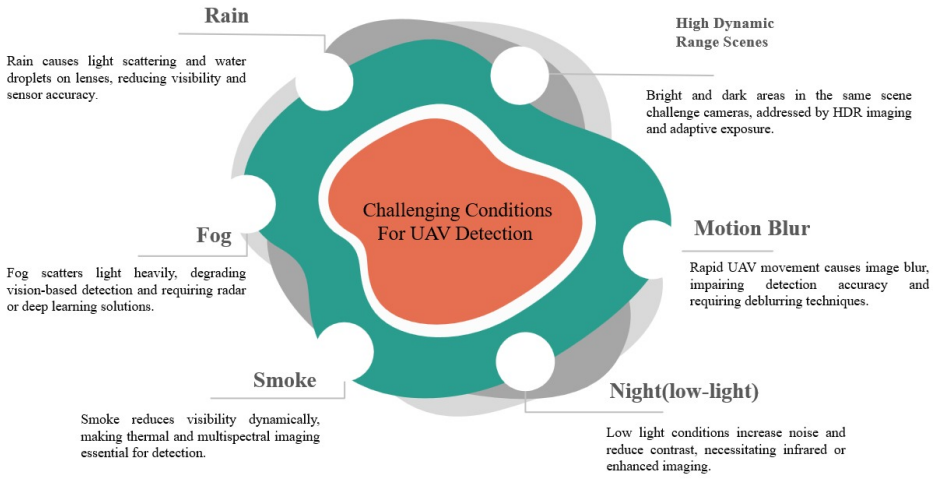


Figure 2. Major Challenging Conditions.

3.1. Detecting Wires, Cables, and Thin Branches

UAV navigation encounters problems discovering miniature things like thin branches, cables, and wires. Occasionally, extremely light, difficult to speak from the background, and possibly not efficiently reaped up by classic sensors and such challenges [22]. Overlooking these items could result in substantial damage, especially during low-altitude aviation in towns, forests, or utility inspection operations. Enhancing the capability to find small things provides reliable and safe UAV operations in hard settings [23].

3.2. Real-Time Tracking of Moving Objects

Dynamic obstacles pose more problems because they are always changing positions [24]. Automobiles, people, animals, and other UAVs need a drone to see and anticipate their actions in real time [25]. Secure travelling leans on rapid and accurate identification of dynamic obstacles, mainly in crowded urban areas, disaster zones, or airports [26]. Interacting with cruising objects helps UAVs evade collisions and allows smooth, smart navigation in dark settings [27].

3.3. Handling Dense Stationary Environments

Urban and natural environments are filled with static clutter such as trees, buildings, signposts, and poles [28]. Although these objects are fixed, they can create thick locations, making obstacle detection more challenging. Insufficient handling of static clutter may result in extreme collision risks or conventional flight paths [29]. A healthy detection method must determine significant obstacles from the environment and develop efficient ways, particularly in city missions, mapping, and inspection tasks [30].

3.4. Robust Detection in Harsh Weather Conditions

Weather conditions like fog, rain, smoke, and dust can severely reduce the implementation of UAV sensors [31]. Visibility is decreased, sensor noise grows, and the accuracy of obstacle detection may drop significantly. In observed applications, UAVs must usually work even in less-than-ideal weather [13]. Thus, developing strong detection systems to degrade data is important, assuring that UAVS can continue their missions safely even when environmental conditions are challenging [32].

3.5. Fast Motion Causing Blur and Image Distortion

When drones depart at increased speeds or create quick schemes, the resultant motion blur and image distortions can make it difficult for cameras and detection algorithms to catch evident information [5]. Blurred images reduce the importance of obstacle detection, increasing the risk of accidents. Making systems that can take motion blur allows UAVs to keep correct situational understanding during secured operations, which is essential for urgent deliveries, surveillance, and aerial sports [33].

3.6. Limited Computing Power on UAVs

Due to size, importance, and energy limits, UAVs cannot carry large, robust computers onboard. They must perform obstacle detection quickly using limited hardware. This makes it important to develop lightweight, efficient algorithms that do not overload the system but still provide reliable obstacle and aircraft detection. Real-time processing with minimal resources helps UAVs maintain responsiveness and flight safety while preserving battery life, which is important for completing long missions [34]. Table 1 summarizes how each challenge impacts UAV operations and outlines the corresponding detection requirements.

Table 1. Comparison of Obstacle and Aircraft Detection Methods for UAVs in Challenging Conditions.

Challenge	Description	Impact on UAV Operation	Detection Requirements
Thin Object Detection [35]	Difficulty in identifying small, low-contrast objects like wires, cables, and branches, especially in complex backgrounds.	High risk of collisions during low-altitude or urban flights.	High-resolution sensing, edge-enhancement algorithms, adaptive thresholding.
Real-Time Tracking of Moving Objects [36]	Obstacles like vehicles, humans, animals, and other UAVs constantly change position.	Requires fast decision-making in dynamic environments such as disaster zones or airports.	Temporal tracking, motion prediction, multi-frame data fusion.
Dense Stationary Environments [37]	Urban and forested areas present cluttered scenes with many static obstacles.	Poor detection may lead to inefficient routes or mid-air collisions.	Context-aware detection, semantic segmentation, spatial filtering.
Harsh Weather Conditions [38]	Rain, fog, smoke, and dust reduce visibility and sensor performance.	Degraded perception, increased false detections or failures.	Sensor fusion (e.g., radar + camera), robust feature extraction, weather-resilient models.
Motion Blur at High Speed [39]	Sudden movements or high-speed navigation cause image distortion and blur.	Reduces detection accuracy, especially in fast missions (e.g., surveillance, delivery).	Fast shutter sensors, motion-deblurring algorithms, event-based cameras.
Limited Onboard Computing Power [40]	UAVs have constraints on weight, power, and processing hardware.	Real-time detection becomes difficult without lightweight models.	Efficient algorithms, model pruning, hardware acceleration (e.g., TPU/FPGA).

4. Sensors Used for Detection

To navigate safely and avoid obstacles, UAVs rely on a variety of sensors that capture and interpret information from their surroundings. Each sensor type offers unique advantages and limitations depending on environmental conditions, required range, resolution, and processing capabilities. The following subsections describe the most commonly used sensors in UAV obstacle detection systems, highlighting their working principles and suitability for different applications.

4.1. Visual and Thermal Imaging for Obstacle Detection

Cameras, including RGB, infrared (IR), and event-based types, are generally employed for detecting obstacles in UAVs. RGB cameras capture images employing visible light, showing high-resolution images rich in particular. Infrared cameras, which catch heat signatures, perform competently in low-light circumstances and are particularly helpful in detecting obstacles in full darkness [41]. Event-based cameras vary from traditional cameras by detecting differences in a location rather than capturing full frames. These cameras help track carrying objects at high speeds and in high dynamic range scenarios [42]. Despite their benefits, cameras are defined in bad weather conditions such as rain, fog, and smoke, and may suffer from motion blur in fast-moving scenarios [43].

4.2. High-Resolution 3D Mapping with Laser Pulses

Lidar operates by sending laser pulses and calculating the time it takes for the light to reflect off an object [44]. This method permits the innovation of particular 3D maps of the environment and gives clear depth knowledge about surrounding objects. Lidar serves well in low-light situations and is not dependent on ambient light, unlike cameras [45]. Yet, Lidar can be affected by weather conditions such as heavy rain, fog, and smoke, which spray the laser pulses and decrease accuracy [46]. While Lidar delivers high-precision data, it is more expensive and bulkier than other sensors, making it less suitable for smaller UAVs [47].

4.3. Robust Detection in Adverse Weather Conditions

Radar utilises radio waves to catch objects by radiating waves and calculating the duration taken for the signal to reflect back [48]. Because atmospheric particles scatter radio waves less effectively than light does, it is useful in harsh weather conditions including rain, fog, and smoke [49]. Radar systems are useful for UAVs because they may provide vital information like an object's distance, speed, and direction. They can also function in low-visibility conditions. Radar typically has a lesser resolution than Lidar and cameras, though, and its usefulness can be influenced by clutter and interference, especially in urban settings [50].

4.4. Ultrasonic Sensing for Short-Range Detection

Sonar works by sending out sound waves and measuring how long it takes to generate sound following an object's strike. While sonar is primarily used underwater, it involves in the air for short-range obstacle detection. It is useful in atmospheres with narrow visual information, such as low-light conditions, and can detect nearby obstacles effectively. Yet, its major limitation is its short-range detection and exposure to environmental noise, making it inappropriate for long-range detection [51]. UAVs rely on multiple sensing modalities to perceive their environment effectively. Different sensors, such as cameras, LiDAR, radar, and sonar, each have unique strengths and limitations under varying conditions. A comparative overview of these sensors and their fusion for robust perception is illustrated in Figure 3. To enhance obstacle and aircraft detection, UAVs utilize different sensor types,

each with unique operational principles and performance trade-offs. A detailed comparison of these commonly used sensors, including their advantages and limitations under adverse conditions, is shown in Table 2.

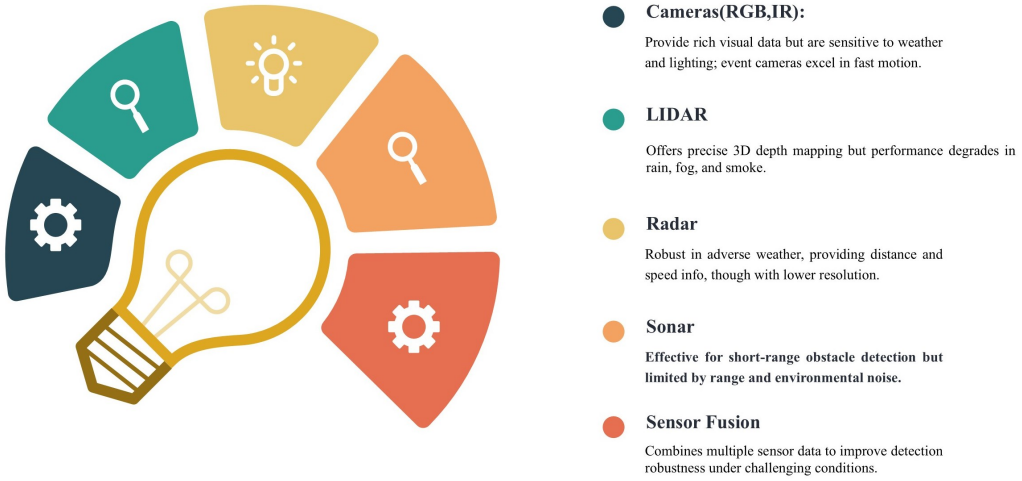


Figure 3. Five key sensor technologies used in UAV systems for detecting obstacles.

Table 2. Comparison of Commonly Used Sensors in UAV Obstacle and Aircraft Detection.

Sensor Type	Working Principle	Advantage in Bad Conditions	Disadvantage in Bad Conditions	Best for Challenging Conditions
RGB Camera [52]	Uses visible light (RGB), infrared (IR) for heat signatures, or detects changes in scenes (event-based).	High-resolution images, cheap, work well in low light, and detect heat.	Efforts in fog, rain, smoke, and low light; poor in weighty rain, fog, and smoke.	Night time detection with IR aid; night-time or thermal detection.
LiDAR [53]	Emits laser pulsations to construct a 3D map of surroundings based on light return time.	Real deep, operates in lower light.	Affected by rain, fog, and smoke.	3D habitat mapping.
Radar [54]	Emits radio waves to detect objects by computing the reflected signals.	Works well in rain, fog, and smoke.	Low resolution, confused in urban areas.	Long-range detection in inadequate visibility.
Sonar [55]	Uses sound waves to detect objects by evaluating sound wave reflections.	Short-range detection, good in low light.	Limited range, impacted by ambient noise.	Close-range obstacle detection.

5. Obstacle and Aircraft Detection Methods

This section presents a comprehensive overview of the key methodologies employed for obstacle and aircraft detection in UAV systems. These methods are broadly categorized into classical computer vision techniques and modern deep learning approaches. Classical techniques—including optical flow, stereo vision, feature tracking, and motion detection—have historically formed the foundation of UAV perception but face challenges under adverse environmental conditions. In contrast, recent advances in deep learning, such as transformer-based models, event-based vision, and sensor fusion networks, have significantly improved detection accuracy and robustness in complex and dynamic scenarios. The subsections below detail these approaches, highlighting their fundamental principles, advantages, and limitations in practical UAV applications.

5.1. Classical Methods

Traditional computer vision techniques laid the groundwork for before UAV obstacle and aircraft detection systems. Optical Flow is one way that calculates objects' movement between two successive image structures based on the obvious movement of brightness patterns [56]. It has been widely utilised for detecting driving obstacles and comprehending depth through image series. However, optical Flow is sensitive to environmental conditions like fog, rain, or motion blur [57]. Rain droplets and fog can yield pixel-level inconsistencies, leading to errors in movement analysis, while fast UAV motion can distort the flow field and result in unpredictable obstacle detection blur [58].

Stereo Vision involves utilising two spatially isolated cameras to simulate human binocular vision and evaluate the deep of objects. It helps specify the distance between the UAV and probable obstacles [59]. While stereo vision serves well in structured environments with good consistency and lighting, it works in low-light or foggy scenes, where fitting corresponding issues between the two images is hard. Moreover, rain and smoke can raise incorrect matches due to the hidden or loud image input [60].

Feature Tracking utilising algorithms like SIFT (Scale-Invariant Feature Transform) and SURF (Speeded-Up Robust Features) notices and checks different components across edges for object localization and search [61]. These methods perform well on textured and static objects but have difficulty when features are washed out due to rain, fog, or fast movement. In high-speed flights, feature blurring and occlusions degrade the matching accuracy, making tracking unstable and error-prone [62,63].

Motion Detection, such as background subtraction, allows for recognizing shifting objects in a video series by approximating the present structures to a reference background model. It is computationally efficient and served for easy surveillance tasks [64]. Yet, background subtraction functions badly under dynamic lighting, fog, or rain. The continuous environmental changes, moving shadows, and sensor noise present relics that compromise the reliability of motion-based detection in real-world UAV applications [43].

5.2. Modern Deep Learning Methods

With the advancement of deep learning, obstacle and aircraft detection in UAVs has witnessed surprising advancements in accuracy and robustness [65]. CNN-based object detectors, such as YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Detector), have become widely utilized due to their capability to know wealthy hierarchical components directly from big annotated datasets [66]. These models detect and classify multiple objects within a single image in real time [67]. While these CNN-based models beat classical methods in accuracy, their implementation in challenging environments, like rain, fog, and night, still relies heavily on the quality and variety of training data [68]. For example, these models may fail to generalise to adverse conditions without exposure to weather-distorted inputs during training [69].

Transformer-based detectors, such as DETR (Detection Transformer) and Deformable DETR, leverage attention mechanisms to more suitable model spatial connections between objects. These models deliver strong performance on disorderly scenes and can catch small or overlapping objects additional reliably than CNNs [70]. Yet, they are computationally fatty, which determines their deployment on resource-constrained UAVs. Their robustness in degraded conditions is good, but still determined by the availability of specialised training datasets [71].

Event-based vision networks are designed to process data from event cameras, which capture changes in the scene at microsecond resolution rather than recording full frames. This technology is positively helpful in high-speed UAV applications, as it takes movement blur effectively. Unlike traditional cameras, event cameras do not suffer from frame-based

disclosure issues and function nicely in low light or fast motion [72]. Yet, the use of event-based networks is still arising and requires additional research and hardware development before it becomes mainstream in UAV systems [73].

Sensor fusion networks aim to overcome individual sensor limitations by integrating data from multiple sources, such as combining RGB cameras with LiDAR. This approach enhances obstacle detection under difficult conditions—cameras provide texture and color information, while LiDAR contributes precise depth data [74]. Deep learning models designed for fusion can handle foggy or rainy conditions better than single-sensor systems, but synchronization issues, calibration complexity, and increased computational demands remain challenges to be addressed [75]. Table 3 provides a detailed comparison of obstacle and aircraft detection methods, outlining their strengths, limitations in degraded conditions, and typical use cases across both classical and deep learning paradigms.

Table 3. Comparison of Obstacle and Aircraft Detection Methods for UAVs in Challenging Conditions.

Method	Type	Strengths	Limitations in Challenging Conditions	Typical Use Cases
Optical Flow [76]	Classical	Estimates motion; useful for dynamic obstacle detection.	Sensitive to rain, fog, motion blur; mistakes in inadequate lighting.	Motion tracking, obstacle avoidance.
Stereo Vision [77]	Classical	Deep analysis; emulates human binocular vision.	Inadequate implementation in fog/smoke; low accuracy in textureless circumstances.	3D mapping, length measurement.
Feature Tracking (SIFT, SURF) [61]	Classical	Dedicated on textured surfaces; rotation/scale invariant.	Fails under blur, low contrast, rain/fog distortion.	Object tracking, navigation.
Background Subtraction [78]	Classical	Easy and quick for detecting rolling objects.	Insufficient under lighting differences, fog, rain; not rich in dynamic scenes.	Surveillance, simple obstacle detection.
YOLO, Faster R-CNN, SSD [79,80]	Deep Learning	Real-time, high accuracy; multiple object detection.	Needs diverse training data; performance drops in unseen bad conditions.	Aircraft and obstacle detection, real-time UAV vision.
DETR, Deformable DETR [81]	Deep Learning	Good for cluttered scenes; models long-range dependencies.	Computationally costly; narrow on UAV hardware.	Tough object detection, multi-target tracking.
Event-based Vision Networks [82]	Deep Learning	Effective in rapid movement and low light; low latency.	Needs event cameras; fixed datasets and hardware help.	High-speed UAV navigation, blur-resistant detection.
Sensor Fusion (Camera + LiDAR) [83]	Deep Learning	Combines depth and texture; improves detection in fog/rain.	Complex calibration; high computational load.	Robust UAV detection in bad weather.

5.3. Obstacle Detection Methods

Obstacle detection refers to the identification of static or semi-static physical objects in the UAV's flight environment, such as buildings, poles, trees, terrain features, and power lines [84]. These obstacles pose a threat to UAV navigation and require reliable, often short-to-mid-range sensing solutions. Generally used sensors for obstacle detection include RGB cameras, stereo vision, LiDAR, ultrasonic sensors, and event-based cameras. Conventional techniques depend on optical flow, edge detection, or SLAM-based algorithms. In recent years, deep learning techniques such as YOLO, Faster R-CNN, and semantic segmentation have seriously enhanced the robustness and rate of obstacle detection [79].

Sensor fusion methods, incorporating data from numerous sources (e.g., RGB + LiDAR), have demonstrated effectiveness in harsh conditions like fog or low light. For close-range

hazard release, monocular depth estimation and structure-from-motion methods are also used [80].

5.4. Aircraft Detection Methods

Aircraft detection concentrates on identifying and following other airborne objects that may intersect the UAV's flight path [85]. This contains human-crewed aircraft, different drones, and even flocks of birds [86]. Unlike static obstacle detection, aircraft detection needs high-speed, long-range sensing and prediction mechanisms. Techniques usually affect radar, infrared imaging, thermal sensors, ADS-B transponders, and long-range visual tracking operating object detection models [87].

Detection of non-cooperative aerial targets that do not publish title calls depends laboriously on computer vision and machine learning methods. Deep learning models introduced on aerial imagery (e.g., DOTA, VEDAI) are utilized for detection and trajectory estimation [88]. Temporal standards like Kalman filters or LSTMs are also used for the prediction of moving targets [89]. Table 4 highlights the key differences between obstacle and aircraft detection, focusing on detection range, response time, motion patterns, and sensing technologies involved.

Table 4. Comparison of Obstacle and Aircraft Detection Methods for UAVs in Challenging Conditions.

Detection Type	Sensors Used	Algorithms/Models	Limitations in Challenging Conditions	Typical Use Cases
Obstacle Detection	LiDAR, RGB/stereo cameras, ultrasonic, event cameras	SLAM, YOLO, optical flow, semantic segmentation [76,77,79]	Sensitive to fog, rain, thin objects, motion blur; short-range limitations	Urban navigation, low-altitude flight, indoor mapping, precision landing
Aircraft Detection	Radar, infrared, thermal, long-range vision, ADS-B	Kalman filter, tracking networks, CNN/DETR models [90]	Issues with long-range accuracy, small object visibility, dynamic flight paths	Airspace monitoring, collision avoidance, multi-UAV coordination

5.5. Laser-Based Visual Identification Techniques for Multi-UAV Detection

Laser-based identification techniques offer precise and scalable solutions for detecting and localizing multiple UAVs in real time, especially under GPS-denied or visually degraded conditions [91]. These systems typically integrate a laser range finder (LRF) with a camera-telescope setup, co-aligned using a dichroic mirror. A fast steering mirror (FSM) dynamically adjusts the alignment based on the angular position of UAVs within the field of view, enabling accurate distance estimation at up to 14 Hz per target. To improve autonomous landing precision, a hybrid approach combining LiDAR and visual cameras has been proposed [92]. This method relates the color of landing markers to laser point cloud intensity, enabling UAVs to locate landing zones even in low light or adverse weather. At closer distances, visual corner detection is used to refine position estimates and guide precise landings [93]. Another solution focuses on emergency landing in unstructured environments using LiDAR point clouds and Principal Component Analysis (PCA) to identify flat regions based on slope, roughness, and obstacle proximity. The system continuously evaluates potential landing sites and selects the safest option in real time [94].

6. Standard Benchmark Datasets

High-quality datasets are essential for making and setting obstacle and aircraft detection techniques for UAVs under challenging conditions. These datasets must describe different real-world strategies, including overcrowded environments, changing weather

conditions, low-light scenes, and motion-induced blur. A well-curated dataset allows researchers to prepare rich detection models and benchmark their performance under real conditions. Below are some of the numerous widely employed and appropriate datasets in this domain.

6.1. High-Resolution Urban UAV Video Dataset

UAVid is a videotape dataset captured by UAVs in metropolitan environments. It concentrates on thick, real-world locations with driving vehicles, buildings, trees, and pedestrians. The videos contain high-resolution frames with pixel-level semantic annotations, making this dataset suitable for estimating UAV-based background understanding and object detection models. UAVid represents real-world conditions but is limited in terms of adverse weather variations [95,96].

The UAVid dataset provides high-resolution UAV images of complex urban scenes, making it ideal for evaluating obstacle and object detection methods in realistic environments. Figure 4 shows a sample image from this dataset, illustrating the challenges of urban UAV perception.



Figure 4. Sample Images from the UAVid dataset [97] (UAVID Dataset, https://www.kaggle.com/datasets/giavuongnguyen/modified-uavid-dataset, (accessed on 28 June 2025)).

6.2. Diverse Urban Object Detection Dataset

VisDrone is another popular UAV dataset collected from various cities in China. It includes thousands of images and videos captured in crowded urban areas, containing a wide range of object classes such as pedestrians, cars, buses, and bicycles. It features different times of the day, weather conditions, and scene complexities. The dataset provides bounding box annotations, making it ideal for training object detection and tracking algorithms. VisDrone is based on real-world data and is highly valued for its diversity and scale [98].

The VisDrone dataset provides diverse aerial images captured by drones in urban environments Figure 5, featuring detailed annotations for vehicles, pedestrians, and other objects. It is widely used to train and evaluate object detection and tracking algorithms for UAV-based surveillance and traffic monitoring [99].

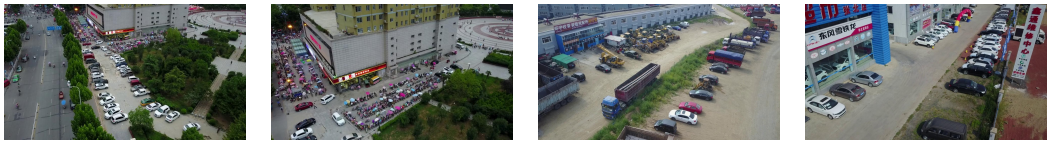


Figure 5. Sample Images from the VisDrone [98] (VISDRONE Dataset, https://www.kaggle.com/datasets/abhimanyubhowmik1/visdrone(acccessed on 28 June 2025)).

6.3. Large-Scale Aerial Object Detection Dataset

DOTA (Dataset for Object Detection in Aerial Images) is a large-scale dataset specifically designed for detecting objects in aerial views [88]. Unlike traditional datasets, DOTA includes objects at multiple orientations and scales, such as airplanes, ships, tanks, and vehicles [100]. It is particularly valuable for evaluating detection systems that must operate in aerial surveillance and UAV-based monitoring tasks. The dataset consists of

high-resolution satellite and aerial images, and it is based on real-world scenes [101]. The Figure 6 shows multiple orientations and scales of different Objects in different conditions.

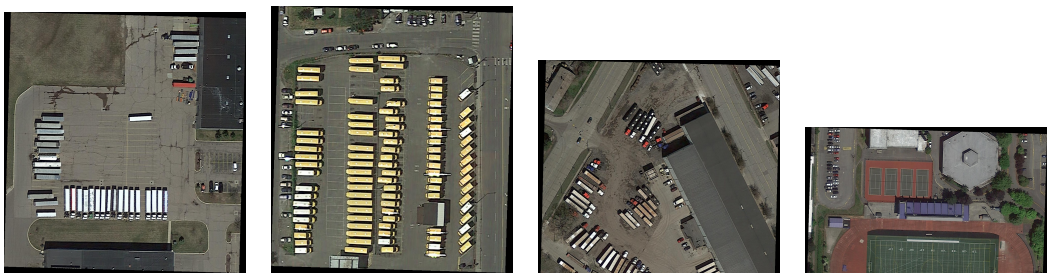


Figure 6. Sample Images from the DOTA dataset [88] (DOTA Dataset,https://www.kaggle.com/datasets/chandlertimm/dota-data(acccessed on 28 June 2025)).

6.4. Synthetic Fog for Adverse Weather Evaluation

Foggy Cityscapes is an extension of the Cityscapes dataset with synthetic fog added to simulate real-world foggy weather [102]. While not captured from UAVs, it is used to train models that need to operate in low-visibility environments [103]. The dataset provides pixel-wise semantic segmentation labels, helping researchers assess how detection algorithms perform under degraded visibility [104]. Although synthetic, it allows controlled experimentation for adverse weather training [105].Figure7 shows a variety of cityscapes shown in different conditions.



Figure 7. Sample Images from the Foggy Cityscapes dataset [106] (FOGGY CITYSCAPES Dataset (https://www.kaggle.com/datasets/yessicatuteja/foggy-cityscapes-image-dataset (accessed on 28 06 2025))).

A summary of widely used benchmark datasets for UAV and aerial image-based detection tasks, highlighting their characteristics and application scenarios, is presented in Figure 8.

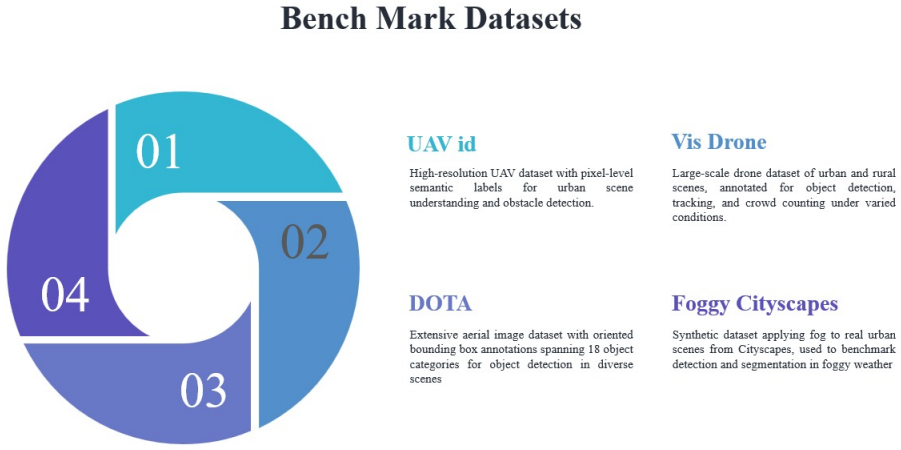


Figure 8. Overview of standard benchmark UAV Detection Datasets.

A detailed comparison of commonly used UAV detection datasets, including their environments, conditions, annotation types, and key applications, is presented in Table 5.

Table 5. Summary of Common UAV Detection Datasets.

Dataset	Environment	Weather/Lighting	Type	Annotations	Key Applications
UAVid [97]	Urban (real-world)	Mostly clear, daylight	Real-world	Semantic segmentation	Urban scene understanding, object detection
VisDrone [98]	Urban, crowded scenes	Varies (clear, overcast, etc.)	Real-world	Bounding boxes, object class, tracking	Object detection, tracking, crowd analysis
DOTA [88]	Aerial/satellite images	Clear (daylight scenes)	Real-world	Oriented bounding boxes	Aircraft/vehicle detection from aerial views
Foggy Cityscapes [106]	Urban (synthetic fog)	Foggy conditions (simulated)	Synthetic	Pixel-level segmentation	Adverse weather evaluation, semantic segmentation

7. Performance Evalution Metrices

- Mean Average Precision (MAP): Mean Average Precision is one of the numerous widely employed metrics in object detection. It estimates how well a detection model recognizes objects with both high precision and recall. For each class, Average Precision is calculated based on the area under the precision-recall curve, and MAP is the mean of all MAPS across all classes [107]. In UAV applications, MAP delivers a complete view of the model's ability to correctly see obstacles like wires, vehicles, or aircraft under different conditions, such as rain or fog. A high MAP indicates constant and accurate detection across multiple object types and scenarios [108].

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{1}$$

where N is the number of classes or recall levels, and AP_i is the Average Precision for class i.

- Precision and Recall: Precision calculates how many detected objects are appropriate, while Recall estimates how many suitable objects are detected. In UAV obstacle detection, high precision means more occasional wrong warnings (e.g., detecting a shadow as an obstacle), and high Recall points more occasional missed detections (e.g., not detecting a thin wire) [109]. These metrics are especially critical in safety-critical applications like midair collision avoidance, where missing an obstacle (low Recall) or detecting a non-existent one (low precision) could lead to serious consequences [110].

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

where TP is the number of true positives and FP is the number of false positives.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

where FN is the number of false negatives.

- F1 Score: The F1 Score is the harmonic mean of precision and recall. It delivers a single metric that negates both values, making it particularly useful when there's an unstable trade-off between precision and recall [111]. In UAV detection schemes, the F1 Score is a helpful indicator of how well the technique performs overall, specifically

in disorderly environments or low-visibility conditions where false positives and false negatives are likely [112].

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

This balances both precision and recall.

- Latency: Latency refers to the time taken from the point an image is charged to the point an obstacle is detected and the reaction is triggered. In UAVs, lower latency is essential because decisions must be made in real-time to avoid collisions [113,114].
- Robustness under Degraded Conditions: Many models that perform well in ideal scenarios often degrade significantly in real-world environments. Robustness is evaluated by testing the model on datasets specifically designed to simulate or contain real-world degradation. It is a key requirement for UAVs operating in unpredictable outdoor conditions [115]. To evaluate the effectiveness of object detection systems in UAV applications, several key performance metrics are employed. These include precision, recall, F1 score, latency, and robustness, which collectively help assess detection accuracy and real-time responsiveness. An overview of these performance metrics is shown in Figure 9.

A wide range of detection methods has been developed for UAV obstacle and aircraft detection, each with different sensor requirements, environmental handling capabilities, strengths, and limitations. A comparative analysis of these methods is presented in Table 6.

Table 6. Comparative Analysis of Detection Methods.

Method	Sensors Used	Conditions Handled	Strengths	Weaknesses
Optical Flow [76]	RGB Camera	Limited fog, moderate motion blur	Simple, lightweight	Fails in poor lighting, sensitive to noise
Stereo Vision [77]	Dual RGB Cameras	Good in daylight, not in fog/rain/night	Depth estimation	High computation, unreliable in bad weather
Feature Tracking (SIFT, SURF) [61]	RGB Camera	Clear, moderately cluttered scenes	Robust to scale/rotation	Fails in low-texture, fog, smoke
Motion Detection [116]	RGB Camera	Static backgrounds, low clutter	Fast, low resource	Not effective in UAV motion/dynamic scenes
YOLO/Faster R-CNN/SSD [79,80]	RGB/IR Camera	Some fog, night with IR	High accuracy, fast inference	Needs large dataset, struggles in dense fog/rain
Deformable DETR [81]	RGB Camera	Clutter, blur, partial occlusion	Captures global context	Heavy model, higher latency
Event-based Neural Networks [82]	Event Camera	Fast motion, low light, blur	Excellent for motion blur, low latency	Expensive hardware, limited datasets
Sensor Fusion (Camera+LiDAR) [83]	RGB/IR Camera + LiDAR	Fog, clutter, occlusion	Combines depth/image, robust	Complex calibration, degraded in heavy rain
Radar-based Detection [117]	Radar (Camera)	Rain, fog, smoke	Works in harsh weather, long range	Low spatial resolution
Sonar-based Detection [55]	Sonar	Short-range, indoor/low-speed	Lightweight, noise resistant	Limited range/accuracy



Figure 9. Key performance metrics used to assess object detection systems.

8. Limitations of Current Detection Approaches

This section highlights the limitations of current detection systems, including deep learning generalization issues, sensor fusion complexity, dataset gaps, and reduced performance under adverse conditions. Despite notable improvements in obstacle and aircraft detection systems for UAVs, several key hurdles remain. One of the numerous ongoing issues is achieving high detection accuracy in unfavourable weather conditions such as rain, fog, smoke, and snow [5]. These environments decrease visibility, warp sensor data, and introduce noise, resulting in improved false positives and missed detections. Cameras struggle due to reduced contrast and lens obstructions; LiDAR sensors are scattered by rain droplets; and radar, while more robust, lacks the resolution for small or thin obstacles. Current detection methods, especially deep learning-based models, still fail in real-world dynamic scenarios, particularly when exposed to motion blur from high-speed flights, changing lighting, and small or fast-moving objects. This problem is further exacerbated by the strong dependence of CNN-based models on the specific characteristics of the training datasets. As shown in [118], convolutional architectures often struggle to generalize across datasets with differing levels of class imbalance, manipulation complexity, or annotation granularity, issues which in similar way may affect aerial perception tasks in adverse environments. These models often require large, annotated datasets for training, and when such conditions are not well-represented in the dataset, performance drops sharply. Moreover, they demand high computational resources, which are often not feasible for lightweight, power-limited UAV platforms. Comparable concerns regarding model complexity and inference speed have been addressed in other domains, such as medical imaging, where lightweight CNN architectures have demonstrated exceptional accuracy while ensuring real-time performance on embedded systems [119]. Sensor fusion the combination of multiple sensors (e.g., RGB camera + LiDAR or radar) is a promising direction to mitigate individual sensor limitations. While it enhances reliability and environmental adaptability, it presents challenges in calibration, synchronization, and real-time data fusion, mainly under hardware constraints [31]. Each sensor also gets its own loss points, and inadequate performance in one can impact the mixed output. Event-based cameras, which catch differences in brightness asynchronously, offer incredible stuff for motion blur and low-light techniques. Yet, their high cost, little commercial availability, and the complexity of data processing and algorithm techniques pose useful challenges. Their result varies fundamentally from conventional image frames, demanding novel methods for detection tasks.

Despite the rapid advancements in detection systems for UAVs, some tough challenges still linger. Most methods struggle when the environment becomes complicated, such as in fog, heavy rain, or low-light conditions, which can all affect accuracy. Even though combining sensors like LiDAR and cameras can improve results, it's not a perfect solution.

These methods usually become bulky, costly, and more difficult to process in real-time. Event-based cameras, while promising in motion-heavy scenes, are somewhat unique and arrive with their own technical and economic hurdles. The big takeaway here is that existing explanations are good but not yet completely dedicated across all methods. There's still space for advancement in creating UAV detection systems that are smarter, faster, and more flexible, particularly in the dirty conditions that exist beyond regulated environments. This section discusses the systemic limitations of existing technical solutions. Real-time multi-sensor systems often involve trade-offs between latency, detection accuracy, and robustness. Studies such as [120] have evaluated fusion frameworks integrating LiDAR and vision, demonstrating detection latency under 50 ms and F1-scores above 0.85 in controlled environments [121]. These improvements, however, come with increased computational demands, often requiring specialized edge hardware like NVIDIA Jetson Xavier or Intel Movidius to meet real-time constraints in UAV applications.A detailed overview of the key limitations affecting UAV obstacle and aircraft detection systems, including their causes and operational constraints, is illustrated in Figure 10.

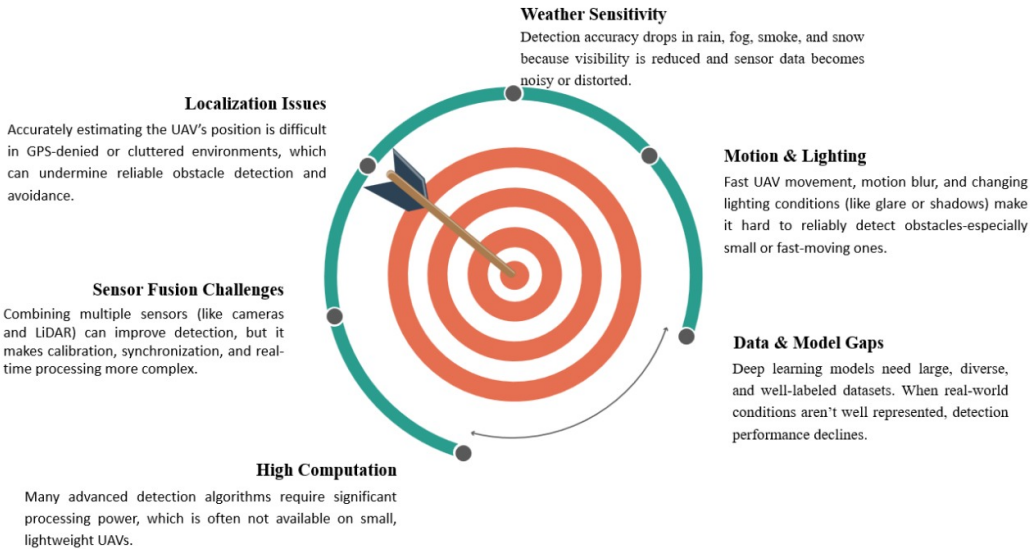


Figure 10. Key limitations of UAV obstacle and aircraft detection systems.

9. Future Directions

As UAV technology continues to develop, several open challenges remain in performing rich, autonomous aerial navigation under unfavorable conditions. Future work could focus on deploying ultra-lightweight deep learning models such as YOLOv8n, Mobile-DETR, or EfficientDet-D0, which offer fast inference with fewer parameters, suitable for real-time UAV tasks. These models offer reduced parameters (<5M) and fast inference times on edge devices, though often at the cost of slightly reduced accuracy under complex backgrounds. The following future research directions are recognized as particularly crucial:

1. Real-time Processing under Low Visibility: Adverse weather, such as fog, smoke, and heavy rain, particularly debases sensor inputs. Coming systems must improve computational efficiency to allow quick and dependable detection under such visibility conditions.
2. Lightweight Deep Learning Models: Deep neural networks deliver high accuracy, but are usually computationally rich. There is a requirement for optimized, resource-efficient measures that maintain high detection accuracy while working within the limited memory and power capabilities of UAV platforms.

3. Event-based Vision Processing: Event cameras show important benefits in high-speed or low-light techniques by capturing only differences in a scene. However, existing algorithms for processing such data are immature. Further work is required to design robust algorithms and incorporate them effectively with UAV techniques for dynamic obstacle and aircraft detection.
4. Adaptive Multi-Sensor Fusion: Combining inputs from RGB, LiDAR, radar, and event cameras can enhance detection robustness. Future strategies should dynamically adjust sensor weighting based on the environment (e.g., increasing radar weight in fog)—however, challenges in sensor calibration and data synchronization remain.
5. Zero-Shot Detection: This method enables UAVs to detect unrecognized objects during deployment without prior training. It carries enormous promise for unpredictable scenarios, such as natural disasters or emerging threats. Future work must concentrate on improving generalization capabilities and semantic knowledge.
6. Human-Machine Interfaces for UAV Control: Reflexive control systems, such as gesture-based interaction (e.g., wearable gloves), can improve responsiveness in real-time, particularly in domain operations. Such systems lower cognitive load and permit seamless human-drone collaboration.

These directions collectively aim to make UAV detection systems more intelligent, flexible, and resilient, ensuring reliable operations regardless of environmental or hardware limitations.

10. Conclusions

Obstacle and aircraft detection play a critical role in the safe and autonomous navigation of UAVs, especially as they become more prominent in areas like delivery, surveillance, and disaster response. Ensuring that UAVs can reliably detect and avoid both static and dynamic obstacles is vital to prevent collisions and enable dependable performance in real-world environments. Throughout this study, we studied a broad range of detection techniques, beginning with classic methods such as optical flow, stereo vision, and feature tracking. These classical techniques are applied as the basis for current systems, but they struggle with insufficient visibility or high-speed techniques. In contrast, deep learning models especially those based on CNNs and Transformers—have got important advancements in detection accuracy, particularly when supported by sensor fusion systems incorporating multiple modalities like LiDAR, radar, and cameras. Despite these improvements, significant challenges remain. Most existing systems struggle under degraded conditions such as fog, rain, and low light. Many are also computationally heavy and difficult to deploy on lightweight UAV platforms with limited onboard resources. Additionally, few models generalize well to unseen obstacles or rapidly changing environments. As a result, the field now requires a shift towards more robust, weather-resilient, and real-time solutions. This encloses the action of lightweight models, sufficiently event-based processing, adaptive multi-sensor frameworks, and methods capable of taking unknown problems via zero-shot learning. A persistent study in these areas will be required to make the next era of UAV systems that can pass safely and autonomously, no matter the conditions.

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