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Recent Developments and Future Prospects in Collision Avoidance Control for Unmanned Aerial Vehicles (UAVS): A Review

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ABSTRACT

The industry has been significantly enhanced by recent developments in UAV collision avoidance systems. They made collision avoidance controllers for self-driving drones both affordable and hazardous. These low-maintenance, portable devices provide continuous monitoring in near-real time. It is inaccurate due to the fact that collision avoidance controllers necessitate trade-offs regarding data reliability. Collision avoidance control research is expanding significantly and is disseminated through publications, initiatives, and grey literature. This paper provides a concise overview of the most recent research on the development of autonomous vehicle collision avoidance systems from 2017 to 2024. In this paper, the state-of-the-art collision avoidance system used in drone systems, the capabilities of the sensors used, and the distinctions between each type of drone are discussed. The pros and cons of current approaches are analyzed using seven metrics: complexity, communication dependency, pre-mission planning, resilience, 3D compatibility, real-time performance, and escape trajectories.

1. Introduction

UAVs and autonomy have grown in popularity since the Industrial Revolution 4.0 (IR 4.0). A UAV, or Unmanned Aerial Vehicle, may fly for long periods without human involvement and be piloted remotely [1], [2]. Due to their wide range, low maintenance costs, easy deployment, mobility, and ability to hover, unmanned aerial vehicles (UAVs) can perform a variety of military and civil/commercial duties [3], [4]. The military uses UAVs for border monitoring, reconnaissance, and target elimination. UAVs are employed in search and rescue, package delivery, precision horticulture, and pharmaceutical distribution. Fig. 1 shows the four main types of drone; Multi-rotor, fixed-wing, single-rotor, and hybrid VTOL drones are included.

Every major drone category has pro and cons. Vertical propulsion systems allow multi-rotor drones and helicopters to hover and fly smoothly. These airborne vehicles require forward force or rotating motion from the drone due to their slow velocity and significant energy consumption [5]. Aerodynamic surfaces and propulsion systems allow fixed-wing and hybrid VTOLs to fly far. Unlike hybrid VTOL drones, fixed-wing drones need a runway to take off and land [5]. Fixed-wing aircraft require much of room for positioning and orientation. Fixed-wing aircraft need aerodynamic lift from air hitting their wings to stay aloft [6].

Fig. 1. Types of drones

This chapter summarizes autonomous system collision avoidance research to date. Simplified and grouped collision avoidance strategies show important principles and approaches. Fig. 2 shows the classification system's two main categories: physical device and action. Collision avoidance system development begins with a hardware device, commonly a UAV for obstacle detection. This stage equips the UAV with sensors to detect impediments and perceive its environment. UAV designs fall into four performance categories: fixed-wing, hybrid VTOL, single-rotor, or multi-rotor drone sensors. Object detection and conflict resolution in sense and avoid, one of seven approaches, provide real-time collision avoidance. The idea is to predict a problem, notify an operator, and maybe fix it. Model predictive control improves constraint-based process control. Optimizing the route utilizing known obstacles and a potential field function to regulate attracted and repulsive forces to avoid collisions. Geometric guidance regulates velocity and location inflections.

Collision avoidance systems range from simple notifications to complex mechanisms that autonomously prevent or lessen crashes [6]. Actuators can brake or steer to avoid obstacles. This research initially focused on advanced road systems for cars on the ground, which provided the framework for intelligent vehicles that function in the air and on the surface [7], [8]. Mujumdar and Padhi classify collision avoidance tasks as global or local path planning [9]. Global or conventional path planning generates ideal paths based on the complete environment and changes. Collision avoidance, also known as local path planning, moves to avoid collisions as the environment changes.

Autonomous vehicles need obstacle detection, collision avoidance, path planning, localization, and control systems to navigate autonomously [10]. The scientific community is becoming interested in UAV swarms due of their cooperative nature. In military and commercial operations, search and rescue missions, traffic surveillance, border protection, and atmospheric research, swarms of unmanned aerial vehicles (UAVs) are sought after for their advantages [11]-[13]. Payload limits (sensors and batteries), power constraints, rain and dust-induced sight loss, and remote monitoring issues might impair UAV missions in dynamic environments. The robotics community is working to overcome these problems and advance technology so unmanned vehicles can operate safely in difficult situations [14], [15]. In dynamic scenarios with many unmanned aerial vehicles (UAVs) and shifting barriers, autonomous vehicles struggle to detect impediments and avoid collisions [6], [16]-[18].

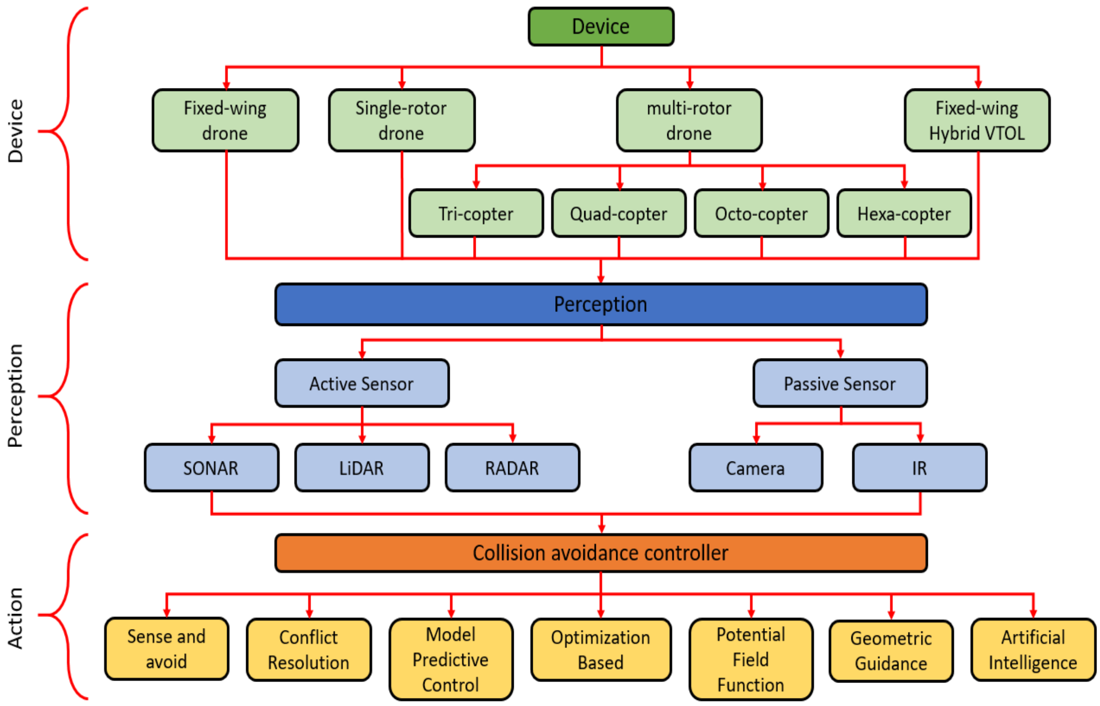

Fig. 2. Collision avoidance controller modules

2. Device: UAV Design and Development for Collision Avoidance System

A fundamental requirement for any collision avoidance system is the integration of appropriate hardware. Drones, in particular, need to perceive their surroundings to identify obstructions, which necessitates the use of obstacle-detecting sensors [19]. Remote sensing systems leverage imaging sensors of varying resolutions based on the application requirements. For observation, technologies such as LiDAR, visual, thermal, infrared, and solid-state or optomechanical sensors are employed [15], [20]. Sensors are characterized by their ability to detect distinct wavelengths of light and the electromagnetic radiation used by remote sensing systems [21]. UAV can be categorized into four primary types: fixed wing, hybrid VTOL, single rotor, and multi-rotor. Each type is specialized to optimize specific parameters such as velocity, maneuverability, stability, payload, capacity, security, size, or battery life.

The following sections analyze and compare subcategories in further detail. The paper's succeeding sections follows this format. Section 2 provides a brief introduction and explanation of fixed-wing, fixed-wing hybrid VTOL, single-rotor, and multi-rotor drones. Section 3 offers an in-depth analysis of collision avoidance controllers. Section 4 discusses various methods and solutions before concluding the paper.

2.1. Fixed-Wing Drone

Design and construction of fixed-wing and multi-rotor drones differ greatly. Like airplanes, they have a 'wing.' Since they cannot hover, fixed-wing drones do not need continual energy input to fly. They continue their pre-set trajectory or follow directions from a guide control (which may be a human-controlled remote unit) until their energy runs out. Fixed-wing aircraft's primary advantage is their ability to fly long distances on a single battery. Due to their superior engine efficiency, most commercial models can fly for an hour or more and covering an area of approximately 400 hectares. This makes them ideal for surveying oil pipelines [22], electricity towers [23], surveillance systems [24], monitoring systems [25] and agriculture applications [26].

Zhao et al. presented a curved route for fixed-wing UAV guidance [27]. To safely transport UAVs without collisions, a hybrid path following and collision avoidance system is presented. This project uses virtual structures and kinematic models to construct a cooperative curved route following system. Multiple UAVs flying close together or changing formations enhance collision risk. However, fixed-wing aircraft must maintain a minimum airspeed and cannot stop. The vehicle's minimum speed and turning capabilities must be known to avoid accidents. Using a modified vector field histogram (VFH), evasive maneuvers only work close enough to prevent collisions.

Lin et al. proposed a very efficient three-dimensional collision avoidance technique for fixed-wing unmanned aerial systems (UAS) [28]. The method aids airplane operators in efficiently avoiding collisions with diverse impediments, so enabling them to achieve mission objectives. Fast Geometric Avoidance (FGA) utilizes kinematics, collision probabilities, and navigation requirements to calculate the optimal moment to initiate geometric obstacle avoidance. FGA significantly decreased calculation time by 90% in comparison to a previous method of generating waypoints, all while successfully navigating around obstacles. This technology enables the Unmanned Aerial System (UAS) to evade collisions and revert to its original trajectory. Various mission simulations demonstrate that this method is significantly more efficient in evading multiple obstacles. The efficacy of the algorithm is verified by Monte Carlo simulations and aircraft simulator flight missions.

2.2. Fixed-Wing Hybrid VTOL Drone

These hybrids combine fixed-wing (longer flying duration) and rotor-based (hovering) features. This idea was tested unsuccessfully in the 1960s. Advanced sensors like gyros and accelerometers have revived and redirected this paradigm. Automatic and manual gliding are used in hybrid VTOL aircraft. Vertical lift lifts the drone to the sky. Gyros and accelerometers stabilize the drone (autopilot). The drone can be controlled via remote or pre-programmed instructions.

Vertical take-off and landing (VTOL) fixed-wing UAVs have various benefits over multi-rotor and fixed-wing UAVs. Superior aerodynamic efficiency, high cruising speed, and lengthy flight duration are advantages. Additionally, VTOL fixed-wing UAVs have reduced flatness and area landing site requirements. Thus, VTOL fixed-wing UAVs are widely used in remote sensing [29], power line inspection [30], geological mapping [31], and urban comprehensive patrol [32]. In addition to aerodynamic interference from the tilting propeller, VTOL fixed-wing UAVs must meet strict design strength requirements and fit their power systems to diverse flight situations. These factors prevent full and reliable safety assessments, slowing VTOL fixed-wing UAV development.

2.3. Single-Rotor Drone

Single-rotor drones resemble helicopters in design and structure. Unlike multi-rotor drones, single-rotor drones have one large rotor and a tail-mounted smaller rotor that controls direction. Unirotor drones are more efficient than multirotor ones. These aircraft can fly for long periods and use gasoline engines. An item's rotational speed is inversely related to its rotor count in aerodynamics. Quadcopters are more stable than octocopters because of this. This is where single-rotor drones excel. Single-rotor helicopter blades are long, resembling revolving wings rather than propellers. The helicopter's efficiency is enhanced by this design.

The author recommended monitoring systems using mono-copter or single-rotor UAVs in [33], [34]. These UAVs have a long flight time, can fly at different heights, and hover well. However, they are harder to fly. Agriculture uses single-rotor drones widely. The authors in [35] suggested CFD modeling of the single-rotor UAH N-3 downwash distribution. They did this by improving the software model and validating the measurement experiment with a new device. With a boundary velocity of 0.5 m/s, the downwash efficiently covers a 3.0 m circular region, double the rotor's radius. This velocity is used to calculate aerial spraying width. Simulations and experiments show that downwash velocity rises with radial distance. High-velocity downwash covers 25%–75% of the rotor radius. Additionally, downwash velocity has a local minimum and maximum range as longitudinal height increases.

The author suggested employing a gas-powered autonomous robotic helicopter with a rotor diameter of 1.78 meters, together with flight control and software [33]. This aircraft would be utilized for planning flights over tests ranging from 0.5 to 3 hectares in size. The helicopter would utilize three camera images to extract, align, and evaluate several experimental field plots. Within a span of 40 hours, the system successfully executed more than 150 flights, each carrying a maximum weight of 1.5 kg for a duration of 30 minutes or 1.1 kg for a duration of 60 minutes. Examples include of sorghum ground cover during the early season, sugarcane canopy temperature during the middle season, and wheat three-dimensional crop lodging factors during the late season. The combination of this hardware platform and enhanced software for automated orthomosaics, digital elevation models, and plot data extraction will enhance the efficiency of field-based phenotyping systems.

2.4. Quad-Rotor Drone

Quad-copters have four rotor blades. These devices usually use brushless DC motors. Two motors rotate clockwise, two counterclockwise. It helps locate quad-copter landings. Previously, lithium polymer batteries powered these devices. Four propellers distinguish quad-copters from helicopters. Additionally, helicopters have tail rotors for pitch control. It maintains flying stability. Quad-copters lack pitch control since their four rotors stabilize flight.

Quad-copters are small flying devices with cameras to record flight. The quad-copter has two clockwise and two counterclockwise propellers. Thus, the quad-copter can fly and hover. Four rotors give the quad-copter more lifting power than a helicopter of equivalent size. Synchronized rotors lift the quad-copter's mass into the atmosphere. Additionally, it can carry more cargo than a comparable helicopter. Military and commercial drones benefit from this technology. The craft's four rotors can carry heavy loads without engineering changes. Thus, the vessel improves functionality while remaining economically viable. Quad-copters are agile. They smoothly hover and move in any direction. Quad-copters are used in surveillance systems [36], [37], monitoring systems [38], health diagnosis systems [39], agriculture applications [40], searching operations [41] and solar farm inspections [42].

The author proposed a quad-copter drone obstacle avoidance system with six ultrasonic sensors [43]. A prototype with four propellers and an Arduino microcontroller ran the avoidance algorithm. A fuzzy algorithm was used to determine the drone's reaction to its environment, while six ultrasonic sensors detected impediments. Sensor location is critical due to propeller-generated noise, as shown by an error rate exceeding 100% throughout the assessment. The sensors were then mounted 10 cm above the propeller for accurate measurements. The offline analysis shows a 1.81 percent mean error. When the impediment is far away, the sensor performs better due to the exponential drop in error with distance. Online mode increases sensor defects by 2.8%. The author published a proactive collision avoidance method for aerial robot navigation in unstructured urban and suburban areas. This method uses a 2D laser scan [44]. The open sector (OS) technique detects angle arcs in the scan where no range measurement is below a threshold and the arcs are large enough for the robot to travel safely. Modifying the target vector to include short-term memory of past actions creates a virtual target. A virtual target determines the best empty space, allowing the robot to quickly and smoothly cross complex barriers. Simulations and testing using an environmental monitoring quad-copter UAV verified the technique. The robot could travel outside areas without a structure at up to 3 m/s while maintaining a steady course. The open sector approach overcame possible barriers to field-based techniques.

The authors Yu et al. employed binocular stereo vision and an ultrasonic system to steer a tiny unmanned aerial vehicle (UAV) in avoiding obstacles [45]. This combination of senses enables us to perceive the surroundings and articulate strategies for circumventing obstacles. The stereo vision system utilizes the Rapidly-exploring Random Tree (RRT) algorithm to detect obstacles in close proximity to the UAV and determine an alternative path. Ultrasonic sensors rectify malfunctions in obstacle detection systems. This article outlines a method to enhance the automation of the flight control system's leveling capabilities. The obstacle avoidance experiments demonstrate the effectiveness of the technique and the performance of the UAV platform.

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2.5. Hexa-Rotor Drone

Hexacopters are six-propeller remote-controlled aircraft. This organism usually has a camera and ski-like legs. These skis stabilize the gadget during landing. Six propellers give this vehicle more agility and lift than a quadcopter. The aircraft is more stable than a quadcopter and can fly higher. Due of its better lifting capacity. Hexa-copter is used for transportation applications [46], [47], agriculture applications [48], monitoring crops [49], water quality measurements [50], surveillance systems [51] and energy harvesting [52].

David et al. revealed that the author built a hexacopter to find and recover a drone [53]. This scenario's key challenges include developing a manipulation design for efficiently gripping the target, quickly identifying items, and conserving battery life in an unknown and continuously changing environment. The author introduced a coverage path planning system that uses an image-based object detection algorithm to help the hexa-copter find a lost target. After finding the target, our hexa-copter can grab it with a unique gripper and transport it to a predetermined location. Additionally, it can avoid stationary and movable impediments. The hexa-copter has vision, LiDAR, and three sonar sensors on its front, left, and right sides. In [55], The author recommended using stereoscopic vision to identify and perceive objects and other aircraft for a multi-copter collision avoidance system. A ZED stereo camera on a DJI S900 Hexacopter UAS creates depth maps. NVIDIA Jetson TX1 boards handle depth maps and collision avoidance algorithms. The board uses XBee radios to communicate with the Pixhawk autopilot and ground control station. The ZED SDK can use camera depth maps for obstacle avoidance. The technique divides depth maps into many segments to find the image segment with the furthest objects. Because of its clearness, this stretch was chosen. The hexa-copter can go independently to that place and avoid obstacles.

The authors suggested the implementation of a LiDAR-based system to provide real-time collision avoidance for multirotor UAVs. This method enables unmanned aerial vehicles (UAVs) to autonomously examine structures without encountering restricted areas [54]. The collision avoidance technique underwent testing in a Gazebo simulation inside a diverse environment, involving a real UAV performing an external mission, a simulated obstacle, and LiDAR technology. This method allows for secure vehicle authentication without causing damage to delicate sensors such as LiDAR, and it may be tested in a lightweight unmanned aerial vehicle. Another author suggested a novel payload for unmanned aerial vehicles to do touch inspections on massive structures [55]. The hexacopter is equipped with LiDAR and ultrasonic sensors to detect objects. The payload was engineered to function autonomously from the flight controller. The device is strengthened by dual tubes, which enable seamless integration of the frame. The payload advances gradually towards the structure in order to prevent any potential rebounds. The image also displays a sturdy carbon fiber tube structure and a passive linear linkage featuring two rubber components. This connection serves to isolate the NDT sensor and structure from any vibrations produced by the unmanned aerial vehicle (UAV).

2.6. Octo-Rotor Drone

This aircraft has twice as many rotors as a hexacopter. It has eight working propellers. These are driven by eight motors. The aircraft climbs higher than quad- and hexa-copters. It combines quad- and hexa-copter agility, velocity, and elevation. They fly very steadily. Therefore, they can record steady, superb footage at any elevation. Professional filmmakers and adventurers prefer them. Eight rotors enable steady, elevated filming of wildlife, landscapes, and events. Octo-copter are used in inspection systems [56], agriculture applications [57], [58], monitoring systems [59], [60] and transportation applicaitons [61].

Chung and Son reported that the author recommended a multibody octo-rotor UAV to improve controllability and flight performance [62]. A typical multirotor is underactuated since it can only independently govern four rigid body dynamics states, although having more than four rotors. Pitch and roll are coordinated using x-y coordinates. Thus, the camera gimbal needs more actuators to position the camera. Multirotor UAVs have lower aerodynamic capabilities, such as flying speed, than fixed-wing UAVs. Aerodynamic drag increases because the multirotor's attitude must be adjusted to its speed. The research describes a multibody multirotor (MBMR) UAV that can decouple multirotor pitch angle control from main fuselage position control. This separation improves UAV control and aerodynamics. The multirotor can be partitioned into three frames utilizing rotating joints for pitch angle independence.

The author also suggested using linear model predictive control (LMPC) to develop a collision avoidance controller for MIMO plants to solve controller design issues [63]. Based on the collision cone concept, the design can improve flight controller efficiency by reducing PID loop computing load. The octo-copter's range detecting sensor locates obstructions accurately. This method is ideal for dealing with practical concerns including collision avoidance controller constraints and external disturbances. The simulation results show that an LMPC-based collision avoidance controller can mitigate progressive and fast disturbances. When applied to MIMO systems, LMPC appears to outperform PID control.

The author proposed a spraying agricultural drone. A 12-volt pump, 6-liter tank, four atomizing nozzles, an octo-copter frame, a landing frame, and eight Brushless Direct Current (BLDC) motors with propellers make up this mechanism. These motors can provide 38.2 KG of torque at 10 meters [57]. A First-Person View (FPV) camera and transmitter can be attached to the drone to monitor spraying and plant pests. Pesticide application takes less time, manpower, and money with this drone. Modifying the pump flow discharge allows this drone to distribute disinfectant liquids across structures, bodies of water, and densely populated areas.

A self-governing aerial aircraft that can carry a human passenger was also proposed [64]. First, a scaled-down multirotor aircraft was tested for design and flight characteristics. After the little drone is ready, we will build, assemble, and test a larger multirotor aircraft that can carry a similar-weight passenger. The smaller prototype's final design will be used. Creating an individual airborne transportation system will spark public debate about self-governing “air taxi” systems and spark STEM interest, including aeronautics.

As a summary, based on the research each type of drone has pros and cons. The tri-copter and quad-copter are cheap and light, so they're good for hobbyists and small tools. However, they can't carry heavy things. It's stable and can fly, even though one of the motors broke. This plane can go higher and carry more goods than the quadcopter. The octocopter is the strongest of the three drones because it can fly high and carry big things. But this drone costs the most and needs to be charged more often. The hexacopter is a good drone to think about because it has many uses and can be trusted to do important jobs. Compared to octocopters, they are cheap to build and keep up.

3. Perception: Obstacle Detection – Passive Sensors

Perception is the initial stage of every collision avoidance system. Drones need to have the ability to see their environment in order to accurately detect and recognize obstacles. In order to accomplish this, it requires one or more perception sensors [65]. Remote sensing systems necessitate the use of imaging sensors with diverse resolutions. The utilization of sensors varies based on the specific application. The observation sensors consist of LiDAR, visible cameras, thermal or infrared cameras, and solid-state or optomechanical devices [15], [66]. Sensors possess the capability to identify specific wavelengths of light and the electromagnetic radiation employed by remote sensing systems [21]. Multiple sensors are employed to identify obstacles, which can be categorized into two distinct groups: 1) Passive sensors refer to sensors that detect and measure physical properties without actively emitting any signals. 2) Active sensors, on the other hand, are sensors that emit signals and then measure the response to those signals in order to detect and measure physical properties. Passive sensors perceive and capture the energy released by objects or scenery. Passive sensors commonly used in sensing applications including optical, visual, thermal, and infrared (IR) cameras, as well as spectrometric instruments [67], [68]. Various camera types operate across a range of wavelengths including visible light, infrared (short-wave, near-wave, mid-wave, and long-wave), and ultraviolet.

The authors suggest utilizing acoustic waves to instantaneously track and locate automobiles [69]. The author utilizes noisy data to create enduring spatial features and sequential state estimation in order to generate the result. The author substantiates his method by employing empirical sound data from the real world. Monocular or stereo optical or visual sensors utilize the spectrum of visible light [70], [71]. Thermal or infrared cameras function within a wavelength range of 700nm to 14m, which is longer than the wavelength range of visible light. Visual cameras utilize the spectrum of visible light to capture and generate images, whereas thermal cameras employ infrared radiation. Unlike traditional cameras, infrared cameras excel in low light conditions [67]. Image processing is crucial for extracting valuable data from all camera images. Furthermore, the extraction of regions of interest necessitates additional processing resources, in addition to a technique for calculating obstacle range and other factors [72]. Visual cameras are influenced by various environmental factors such as lighting conditions, fog, and rain, as well as the camera's limited field of vision [73], [74].

3.1. Camera

Visual sensors like cameras collect data by taking pictures of things and surroundings. Monocular, stereo, and event-based visual cameras are prevalent [75]-[77]. Cameras' compactness, lightweight construction, low energy usage, adaptability, and easy installation are perks. However, these sensors are weather-dependent, have low image clarity, and are sensitive to illumination and backdrop color contrast. Since any of these variables degrade image quality, they significantly affect the output.

The other authors proposed a monocular camera-based ground robot obstacle recognition approach [78]. The lower picture is used for basic obstacle identification with enhanced Inverse Perspective Mapping (IPM) and a vertical plane model. This method works for robots moving at 1 m/s. The MRF framework segments barriers to calculate the robot's proximity to the nearest obstacle. A stereo camera approach was also suggested [79]. Stereo cameras use intrinsic and extrinsic features to accurately measure absolute depth, unlike monocular cameras. Stereo imaging requires more computational power. To reduce computing costs and handle complex systems with six degrees of freedom (6DoF), such as drones, the authors split obtained images into nine sections. To smooth the controller's response, a fuzzy controller is used. Falanga et al. propose an event camera-based obstacle avoidance algorithm for high-speed drones [80]. Event cameras employ less processing power than obstacle detection cameras, making them better for obstacle avoidance. An event camera only records environmental changes, avoiding the need to collect extraneous data.

3.2. Infrared

IR cameras are used as infrared sensors in low-light conditions. They can be used with visible cameras at night to overcome their limitations. Due to thermal camera output blurriness and distortion compared to RGB cameras, its data can be evaluated by extracting false control points and analyzing them to determine automatic image inclination or orientation [81]. Roomba, for instance, uses infrared and bump sensors to avoid obstructions. The bump sensor only detects barriers or items that touch the robot, which may cause damage.

4. Perception: Obstacle Detection – Active Sensors

Active sensors radiate and detect reflected radiation. An independent transmitter (source) and receiver/detector make up active sensors. A transmitter sends light, electricity, or sound that reflects off an object and is sensed by a sensor receiver. Most of these sensors operate in the microwave range, allowing them to infiltrate the environment under most situations. For detection, LiDARs [82], radars [83], sonar or ultrasonic sensors [84], [85], and active infrared sensors [86]. These sensors have fast response time, low processing power consumption, wide coverage, low weather and illumination susceptibility, and exact obstacle property measurements such distance and angle. They use millimeter wave (MMW) radar [87]. From radar signal reflections, they calculate the distance between an item and a vehicle. The things are detected and monitored at this distance. Performance is also evaluated in various weather and distance circumstances. Although radar-based solutions may sound appealing, they are too expensive or large for battery-powered UAVs [88], [89].

4.1. Radar

Radar sensors emit radio signals that are reflected back to the radar when they encounter an item. Measure the signal's reflection time to measure the item's distance from the radar. Airborne radar systems have been used for decades due to their weather tolerance. Airborne radar systems are expensive but used for data collection due to their precision. Radars use pulsed or continuous waves. Continuous-wave radar emits frequency-modulated linear signals. In contrast, pulsed-wave radar emits intense, brief signals, creating a blind zone [90]. In addition, radars measure object motion and velocity. When an object approaches the radar, the signal bounces back faster. The object's speed is calculated from this frequency variation [91]. Although weather-insensitive, microwave radar sensors operate at a lower frequency spectrum, limiting their angular resolution. Millimeter wave radar sensors are smaller and offer higher angular resolution, but they are very weather-sensitive [92]. The antenna's aperture limits angular resolution, however increasing frequency can help.

Due to their weather resistance, low-light and overcast capability, and wide coverage range, radars are ideal for outdoor applications. Radars can only identify obstacles due to their low output resolution. Replicating an object's proportions is impossible [93]. Other authors used a small radar system to determine distance instantly in varied weather situations [91]. A small radar sensor and obstacle collision avoidance system processor are included. OCAS calculates avoidance criteria using radar data including obstacle velocity, azimuth angles, and range and instructs the flight controller on how to avoid collisions. The system's performance showed that obstruction detection within the detection range approaches 90%. The collision avoidance technology was tested in four scenarios. The results showed that safety margins increase the likelihood of avoiding a collision by over 85%, even if radar data is inaccurate.

The authors thoroughly examine the benefits of using multichannel radar sensors with UAVs for obstacle recognition. They also study obstacle detection and computation, including velocity and angle. The number is 92. Empirical data show that forward-looking radars' simultaneous multitarget range capabilities may identify several targets throughout a 60-degree azimuth range. In their independent collision avoidance solution, Nijsure et al. used Ultra-Wideband (UWB) collocated MIMO radar [94]. Radar cognition can adjust the UWB-MIMO radar emission waveform to improve UAV detection and guidance. It also estimates collision points. Because radar systems are reliable in all weather and can precisely estimate distances and close speeds, the other author studies them for sense and avoid on UAVs [95]. This article covers S (3 GHz), Ka (35 GHz), and X (10 GHz) radar frequencies. It also weighs the pros and cons of each frequency. X-band was the best radar band for sense and avoid, according to the authors. This is because it can be easily integrated into the UAV frame without increasing its size and provides a cost-effective and accurate angular measurement solution. Moses et al. tested radar sensors and developed a compact, lightweight X-band radar sensor for UAVs. This was because radar sensors can accurately detect UAV targets and obstacles [96]. UAV propulsion causes Doppler shift, which is used to properly detect targets and optimize maneuvers to avoid collisions. Scientists say their vehicle detection and identification method can be scaled up for larger vehicles.

4.2. LiDAR

LiDAR sensors work like radar. In LiDAR sensors, an emitter emits laser pulses onto surfaces and a receiver detects their reflection. LiDAR sensors measure surface distance by monitoring pulse bounce time. Data capture with LiDAR is efficient and accurate. LiDAR systems have become cheaper during the past 20 years. LiDAR sensors have also shrunk in size and weight, making them suitable for small and micro UAVs [93], [97]. Cost-effective 1D and 2D LiDAR sensors outperform radar systems. Nanashibi and Bargeton used different laser scanners on a vehicle to demonstrate their new system's accuracy [82]. In 3D environments, 2-axis LiDARs are employed for mapping and obstacle detection [98]. The constant mobility and range of LiDARs cause motion warping in their data, making their use difficult. Adding sensors to LiDAR may solve this problem, according to Zhang and Singh [99]. Only 3D LiDARs can reliably locate and orient things. Tong et al. align intensity photographs from 3D LiDAR scans with visual features to correct motion-induced distortion [100]. LiDAR can detect tiny objects and create a monochromatic 3D image using a short wavelength. One shortcoming of LiDAR is its inability to detect optically clear glass. Adding an ultrasonic sensor to LiDAR may help overcome this constraint.

4.3. Sonar

Ultrasonic sensors measure distance by emitting sound waves and detecting their reflection [101], [102]. The ultrasonic sound waves span from 25 to 50 kHz, which exceeds human hearing [103]. The distance computation mechanism is similar to radars and LiDARs. Emitting a wave and measuring the time it takes the reflected wave to reach the object. Ultrasonic sensors are widely available and cheaper than most range sensors. Ultrasonic sensors are unaffected by transparency, unlike LiDARs. LiDARs struggle to distinguish transparent glass, but ultrasonic sensors are unaffected by color. However, if the item deflects the sound wave away from the receiver or absorbs sound, the sonic sensor results will be unreliable.

As a summary, an active sensor has a transmitter, a source of energy to emit a wave with a given wavelength range, and a receiver to read incoming waves reflected off environmental objects. A passive sensor only detects light or energy emitted or reflected by objects, requiring an external energy source. Cameras are passive sensors that need an external light source, while LiDAR is active and shoots laser pulses at the scene and reads the backscatter for processing. Camera data is limited by the quality and intensity of an external light source, but LiDAR data is not. Active sensors use more power than passive sensors that merely read data since they transmit and receive. However, active sensors gather directed data—reflected versions of their own signals—simplifying data processing. Passive sensors like visual cameras require a lot of computational power to filter and interpret raw image data to find significant points of interest. A camera-based collision avoidance solution has a high processing cost, making it challenging to deploy in situations demanding fast object recognition and decision making. However, given adequate illumination, it can provide more detailed environmental information than LiDAR, sonar, or radar. Range systems are better for collision avoidance than camera-based techniques due to their faster response times and greater tolerance for poor illumination and weather.

5. Action: Collision Avoidance Controller

There are three main types of collision avoidance algorithms: 1) the “sense and avoid” approach makes collision avoidance easier to understand so that it costs less to run and responds faster. Each drone has to find and avoid obstacles and change its path when it needs to, regardless of what the other drones are planning. 2) Conflict resolution is the ability to see a problem coming, let a person know about it, and help them solve it. 3) Model predictive control predicts how the dependent variable will change in the system being modeled. The method figures out the best control inputs for a UAV model while keeping limits in mind to make a cost function as small as possible. The next step is to run the sequence's first control input. 4) Drones that are driven by ANN need computer vision to work. Drones can use this technology to find moving items and take pictures of them, as well as to analyze and store data from the ground. 5) A potential field function is set by the electric forces between charged things. Each unmanned aerial vehicle (UAV) node in a group of drones is like a charged particle, and the path is set by the forces that pull or push against obstacles. 6) Geometric guidance methods use the speeds and locations of the UAV and the object to figure out the distance between the agent and the obstacle. 7) Methods based on optimization find the best or almost best way for each drone to move and plan its path in relation to other drones and objects. These algorithms use the positions and sizes of stationary items to find the best way within a certain amount of time.

5.1. Sense and Avoid (SAA)

Sense-and-avoid approaches aim to reduce computational resources for fast response times. Simplifying collision avoidance to obstacle detection and avoidance achieves this. Thus, each drone in a swarm may manage its own route without knowing others'. Each drone's position in respect to the others is established, and the collision avoidance algorithm calculates specific routes for the drones to avoid collisions inside the group and with external barriers. The sense and avoid collision avoidance system is ideal for dynamic environments due to its fast response. This technique equips an agent/robot with LiDAR, sonar, and radar. Zheng et al. proposed scanning a point cloud with the RPLIDAR A2 to estimate UAV position [104]. RPLIDAR A2 has an 8-meter detection range, weighs 190 grams, scans at 10 Hz, has a 1° resolution angle, and produces a 360-point sequence after a single scan. Polynomial velocity estimation is used to estimate the LiDAR's position as it scans each point and correct the distorted point cloud. Cluster Based on Relative Distance and Density clusters point clouds with different densities. The experimental results show that this study's technique can properly cluster point clouds with non-uniform density and correct their displacement. It also shows that a little, inexpensive obstacle detection device can benefit the UAV.

A laser-based avoidance system for driverless vehicles was introduced [105]. The system used a two-wheeled robot. This system can swiftly receive barrier distance information, avoid obstacles, and decide a new direction and travel by processing data at the computation platform level. Faria et al. use a two-dimensional laser for three-dimensional exploration to save costs and payload weight [106]. Since the unmanned aerial vehicle (UAV)'s main goal is to collect surface data, the exploration procedure must address the non-beneficial viewpoint (NBV) problem to strategically position the sensor. The author proposes deterministic, autonomous 3D exploration. System uses 2D laser sensor and modular design. The frontier algorithm is used locally and globally. This method includes a surface neighborhood in the frontier surface idea. The Lazy Theta* algorithm builds safe paths during the expedition. The well-known A* method is modified to be angle-independent. The UAV can survey 93% of the search area in under 30 minutes. It does this by autonomously constructing a route that adapts to inner regions, irregular structures, and suspended objects. According to Moffatt et al., Velodyne VLP-16 LiDAR was used to construct a multi-copter UAV obstacle detection and avoidance system [107]. The absence of obstacle identification and avoidance skills and situational awareness has prevented UAVs from being widely used. This sensor was designed to identify and avoid obstructions. The UAV can map its surroundings. Deciphered LiDAR data was used to build a UAV path without obstacles using distance and azimuth statistics. LiDAR was the main visual sensor for the obstacle avoidance algorithm [108]. A mathematical model is constructed using System Identification (SI) for this system design, and field-test data is used to verify the USV model's accuracy. Next, we cover LOS-based navigation. The USV platform's modular GNC architecture integrates obstacle detection, path-following, and control. Two simulated and field-tested control scenarios are shown in the experimental results. These tests prove the GNC architecture's capabilities and performance. GNC algorithm accuracy is tested by exactly building the safety boundary box and reaching the last USV path waypoint. The line-of-sight (LOS) navigation system controls the unmanned surface vehicle (USV)'s velocity and heading.

Aakash and Manoj Kumar calculated the best route between LIDAR obstacle-detected waypoints [109]. The RPLIDAR (LiDAR) sensor created UAV paths in this investigation. The approach entails creating a 3D map with a gazebo and visualizing it with ROS rviz. This is done using a single LIDAR-reading plan. The unmanned aerial vehicle (UAV) went from the starting point to the destination area without any obstacles using the data. This technique works, as shown by experiments. Chiella et al. developed a GNSS-LIDAR navigation system for aerial robots in sparsely populated forests. This system is suitable places with ample flight space and intermittent GNSS reception [110]. Due to the difficulty of autonomous vehicle navigation in forests. Tree canopies may degrade or eliminate GNSS data in these situations. A complete ecological map is impossible due to the many obstacles. To combine LiDAR-based odometry with GNSS and AHRS data, RAUKF was used with the Unscented Kalman Filter (UKF). The motion control approach uses a vector field and optimal planner to avoid obstacles. The user may more easily strategize the vehicle's main goal, which is to precisely define a trajectory in three-dimensional space to navigate obstacles.

5.2. Conflict Resolution

The CD&R technology anticipates conflicts, alerts human operators, and sometimes resolves them. Multiple levels of subdivision exist within these three major processes. Any conflict—aircraft or otherwise—relies on decision-making. AUVs with fixed wings can avoid collisions with stationary and moving obstacles using the author's novel collision avoidance algorithm [111]. A safety-oriented control algorithm helps UAVs move from dangerous to safe states under certain conditions. For fewer UAV transitions between “safe mode” and “danger mode,” a conflict buffer is used to resolve conflicts and ensure a smooth transition. The appropriate criteria can be utilized to avoid collisions with static and dynamic barriers and internal vehicle collisions. The UAV outperforms static and dynamic barriers in obstacle avoidance. The three UAVs choose the best trajectory based on their positions and velocities. The author introduced Learning-to-Fly (L2F), a decentralized aerial collision avoidance technology in many UAS. UAS can autonomously plan and execute missions with Signal Temporal Logic-articulated spatial, temporal, and reactive objectives [112]. Mixed Integer Linear Programs (MILPs) are used to prevent UAS collisions while meeting mission goals. However, addressing this issue online is challenging. Instead, we designed L2F, a collision avoidance system with two stages: a learning-based decision-making scheme and a distributed, linear programming-based UAS control method. Our solution is 6000 times faster than MILP and is practical in real-time applications, according to the author. If maneuverable, the approach can resolve 100% of collisions. We also evaluate L2F against two other methods and show its suitability for quadrotor robots.

Mu et al. proposed a local information exchange algorithm/protocol to ensure agent unanimity [113]. A graph-based linear consensus mechanism is designed for switching topology construction control. The requirements for information consensus are given. Additionally, collision/obstruction avoidance is addressed. Also offered is a consensus mechanism with a switching topology and collision/obstacle prevention. Avoiding collisions and obstacles with the enhanced artificial potential approach prevents potential fields from interacting with a local minimum. Lyapunov theory supports the protocol's stability. Finally, numerical simulations demonstrate the approach's usefulness. When UAVs don't see impediments, simulations show formation is fast and constant. If a UAV senses an obstruction or the distance between UAV I and UAV j is less than dsafe, the formation will prioritize obstacle/collision avoidance over formation shape. After avoiding obstacles and crashes, the formation will be repeated. The author proposed expanded decentralized consensus-driven control for multi-agent systems [114]. With a decentralized consensus-based controller and complete system architecture, a single Ground Control Station operator could handle the entire swarm. The technique focuses on formation control, waypoint tracking, and static and dynamic obstacle avoidance. The number of UAVs connected does not alters these goals. The controller and system architecture are tested in MATLAB and verified in the real world using a hardware platform. The findings show that small on-board computers allow the construction of a decentralized controller, improving system redundancy and cost-effectiveness. Waypoint placement accuracy was 87% and virtual obstacle avoidance accuracy was 92% without UAV collisions.

Ren et al. examined the flight safety of a quadrotor UAV with a suspended payload approaching an obstruction [115]. Payload swing causes system instability and safety problems. Start with a detailed quadrotor UAV with a cargo system model. Once waypoints are collected, a cubic curve is used to create an urban reference trajectory. The Dubins trajectory approach is used in suburbs to create a smooth, continuous obstacle avoidance trajectory. Predictive control calculates the best path with lowest payload oscillation in real time while avoiding unknown impediments. The inner-loop regulates attitude and the outer-loop controls position using a PID controller in the trajectory tracking design. The simulations show that the predictive control optimization curve passes each waypoint. The drone can quickly avoid unfamiliar obstacles and restart its journey. We can see that the payload swing angle is maximal. Nonlinear quadrotor UAV models provide predictive control-based trajectory planning to meet requirements. Dubins' preferred suburban path can be calculated and followed by the UAV in real time.

5.3. Model Predictive Control

Model predictive control (MPC) is an advanced method of process control that is used to control a process while satisfying a set of constraints. It has also been used in recent years in power system balancing models and power electronics. Model predictive controllers are based on dynamic models of the process, which are typically linear empirical models obtained through system identification. The primary advantage of MPC is that it enables optimisation of the current timeslot while taking future timeslots into account. This is accomplished by optimising a finite time horizon but implementing only the current time slot and then optimising again and again, as opposed to the Linear-Quadratic Regulator (LQR). Additionally, MPC is capable of anticipating future events and taking control actions accordingly. PID controllers, on the other hand, lack this predictive capability. Although MPC is almost universally implemented as a digital control, research is underway to improve response times using specially designed analogue circuitry.

Lindqvist et al. developed a Nonlinear Model Predictive Control (NMPC) framework for path planning and obstacle avoidance that can handle dynamic obstructions [116]. The author also classified trajectories to forecast barrier placements. Results show that the safety distances between the avoiding UAV and the approaching UAV and obstacle are 0.45 m and 0.42 m for the two oncoming obstacles. As with a single obstacle, the avoidance maneuver begins immediately after the obstacle-UAV takes off, and the solver time peaks at 35 ms. By merging a linear model predictive controller (MPC) with non-linear state feedback, Baca et al. developed a unique trajectory tracking approach for UAVs [117]. A technique that can be smoothly integrated into a UAV control pipeline and used by an application layer as a trajectory tracker is the goal. Additionally, the goal is to simplify the design and security testing of advanced planning systems by simplifying the proposal process. Accurate trajectory monitoring allowed the autonomous landing on the moving automobile at 15 km/h. No rival landed faster than the MPC tracker (25:1 s). The team won the autonomous object collection competition with three unmanned aerial vehicles and the best score.

The author also used Distributed Model Predictive Control (DMPC) with Mixed Integer Quadratic Programming (MIQP) to improve the trajectory [118]. The collision avoidance system uses DMPC and trajectory tracking to limit collisions based on ICAO Right of Way regulations for human-piloted flights. Expressing the DMPC as a Mixed Integer Quadratic Programming optimization problem reduces computing load. When a collision is detected, the control algorithm slows down like humans. The MPC performs a turn maneuver if the aircraft cannot be decelerated and a collision is imminent. MPC optimizations on the receding horizon are often calculated in less than 0.2s, indicating that the method is ready for real-time implementations.

Huang et al. created a collaborative collision avoidance system for many UAVs to satisfy the need for independence for one [119]. This concept can prevent UAV collisions in shared airspace. Many unmanned aerial vehicles (UAVs) struggle to work together due to airspace issues. The author used a novel model predictive control (MPC) strategy to prevent UAV collisions. In addition, the Extended Kalman filter (EKF) predicts mobile obstacles or targets in confusing environments. The data reveal that the suggested technique reduces UAV task completion time, improves its performance metric, and ensures its ability to monitor the target, improving work fulfillment efficiency.

5.4. Artificial Neural Networks (ANN)

An Artificial Neural Network (ANN) programs robots to think and act like humans. Additionally, the term can be applied to any machine that can learn and solve issues like a person. AI-driven drones use computer vision mostly. This technology lets drones identify, photograph, and analyze and store data on the surface while in motion. UAVs are promising for agricultural plant protection. Unorganized fields with unknown objects increase the risk of crashes, threatening flying safety. The author proposes deep-learning-based object detection, image processing, RGB-D information fusion, and a task control system (TCS) to improve UAV intelligence and reduce operational safety and efficiency risks [120]. Deep learning and a depth camera help the UAV identifies impediments. It recognizes impediments and delivers category, profile, and three-dimensional geographical position information. Several experiments test the UAV's ability to identify and avoid obstacles. CNN has an average detection accuracy of 75.4% and processes a single image in 53.33 milliseconds. Additionally, the obstacle's closeness to the depth camera considerably affects its shape and location forecast. Depth, width, and height measurements from 4.5 to 8.0 meters have uncertainties of 0.53, 0.26, and 0.24 meters, respectively. The simulation flight trials showed that the UAV can independently pick the best way to avoid obstacles and design a flight path that minimizes distance using RGB-D sensor fused information.

Yang et al. used a lightweight probabilistic CNN to estimate depth and avoid obstacles in real time. This method targets a lightweight, energy-efficient drone [121]. The proposed probabilistic convolutional neural network (pCNN) accurately predicts depth map and confidence level for every video frame. The proposed pCNN's accuracy is considerably improved by using sparse depth estimate from visual odometry to guide dense depth and confidence inference. The estimation depth map is turned into Ego Dynamic Space (EDS) by incorporating the drone's dynamic mobility limits and spatial depth map confidence values. The EDS system calculates navigable waypoints and generates drone control commands. Our depth prediction method processes at 12Hz and 45Hz on TX2 and 1050Ti GPUs. This is 1.8 times faster and more accurate than current approaches for depth estimation. Extensive trials using public databases confirmed these conclusions. Dai et al. used CNNs to teach a quadrotor unmanned aerial vehicle (UAV) to autonomously navigate unfamiliar and chaotic environments and avoid obstacles [122]. To improve UAV robustness and decision-making, a two-stage end-to-end obstacle avoidance architecture is created. This architecture uses a single forward-facing monocular camera. Initial prediction uses convolutional neural networks. Depth-wise convolution, group convolution, and channel split efficiently forecast steering angle and collision probability in the model. The control system converts the steering angle into a UAV yaw angle command in the second stage. The grayscale system flew 368m on Road1 and at least 154m on Road2 in road tests. This shows that the suggested automated obstacle avoidance system can handle highway sceneries and adapt to straight and curved highways. The detailed trod test proves the UAV can fly independently over extended distances. However, lawns near the tread affect the obstacle avoidance mechanism. Grayscale imaging systems can seamlessly traverse a continuous fold line during continuous curve tests. In the forest flying test, the grayscale photo network found a better route. The system does a 45-meter fly after being trained with datasets under varied illumination conditions and outperforms other systems during the night test.

Back et al. developed a UAV approach that uses vision to follow bike tracks and avoid obstructions [123]. The Convolutional Neural Network guides the UAV to follow a course and stay near the center. CNN control instructions are held for a certain time to address disturbances like wind that deviates the UAV from its path or the camera failing to catch the trail. These commands fix the issues and resume normal operation. Using optical flow computed with an additional CNN, trails can be navigated safely. The UAV uses trail tracking, disturbance recovery, and obstacle avoidance to handle trail travel scenarios. The suggested technique performed well based on CNN classification accuracy, runtime, and GPU use. Trail navigation performance is assessed by evaluating the average distance from the trail center in simulations and experiments. Lowering the average trail distance with lateral offset control and longitudinal offset control has been proven. The disturbance recovery approach is tested using simulations. Evidence reveals that the UAV may return to its path after an unforeseen perturbation. Ultimately, the combined algorithm's efficacy is assessed by examining UAV trajectories in various settings. Another study suggested employing deep reinforcement learning (OA) for UAV obstacle avoidance [124]. Partial observability—UAVs' ability to receive and store environmental structure data—is the foundation of this method. They can make more accurate navigation selections in future operations. This research created and tested a Deep Recurrent Q-Network with Temporal Attention. A deep reinforcement learning robotic controller uses this network to help UAVs avoid obstacles in congested and unfamiliar environments. Current monocular vision UAV obstacle avoidance methods rely significantly on environmental data, like the previous approach. These controllers fail to use the copious environmental data to make judgments. The results show that the approach has a high inference rate and transferability, making it ideal for intelligent robotics. Our solution only works for avoiding obstacles and can be effortlessly integrated with a path planner that determines the route from the initial to the final place.

5.5. Potential Field Function

Force-field methods, sometimes called potential field methods, use a repulsive or attractive force field to push or pull an agent/robot. This technique relies on the robot's movement, geometry, and obstacle geometry; hence it requires accurate obstacle position and form knowledge. Dynamic obstacles have unknown properties. Yamaguchi and Tamagawa developed a collision-prevention waypoint navigation method using artificial potential with random priority [125]. A multi-robot navigation system that can perform many tasks must prevent collisions by transmitting information about each robot's course. Robots have an autopilot system with waypoint navigation, but using it for collision avoidance is harder than creating a course. We developed a new waypoint adjustment method for path planning. This approach uses random-priority artificial potential. We also suggested using k-nearest neighbor and Delaunay triangulation to increase the velocity of the artificial potential method. The testing results show that random priority improves speed by nearly 80%. Additionally, the random priority technique is identical to slotted ALOHA wireless circumstances. Muhammad et al. developed a new obstacle avoidance planning method for local minimum. This method enhances the artificial potential field algorithm [126]. This issue's principal downside is the local minimum and target unattainability when obstructions are close. The updated artificial potential field (APF) technology ensures the robot avoids stationary impediments and reaches the destination efficiently. This method lets the robot reach the objective without obstacle avoidance issues. Unlike the APF algorithm, this technique does not imprison the robot in the local minimum. Simulations show that the improved artificial potential field technique helps the robot avoid collisions and reach the destination.

F. Wang et al. developed a graph theory and artificial potential field theory-based distributed formation control method. This method solves UAV self-collision, obstacle avoidance, and formation communication architecture challenges. This method is described in [127]. The Artificial Potential Field technique is prone to hesitating and trying to solve problems that are impossible due to obstructions. The UAV formation can evade obstacles while following the control plan, attain the appropriate speed and formation quickly, and maintain stability while traveling to the objective. Fu et al. created a consensus-based collaborative control law for UAV swarm maintenance and reconstruction [128]. The author also used an artificial potential field and a consensus mechanism to maintain and rebuild swarm structure while avoiding impediments. The swarm formation transformation approach's fixed UAV deployment in the target formation is a negative. CBBA is used to allocate positions from the initial formation to the target formation, making formation transformation more flexible and efficient. Simulations show that the UAV swarm can quickly establish, sustain, and recreate the intended configuration while avoiding obstacles. Pre-assignment does not produce a V-shape, but CBBA position allocation does.

Another researcher developed a flexible collision avoidance method for various unmanned aerial vehicles [129]. Modifying the APF function utilizing communication topology and weights optimizes communication information flow and ensures primary member safety. A repulsive potential based on the UAV's relative velocity to the obstacle improves obstacle avoidance in the multi-UAV. Because the APF technique places little importance on communication topology and weights, this strategy is used to ensure the primary safety of critical formation members. A weakly rigid geometric arrangement cannot be sustained indefinitely by most collision avoidance algorithms. Mathematics and execution are simple in the collision avoidance strategy. Three-dimensional flight simulations using five six-degree-of-freedom unmanned aerial vehicles (UAVs) indicate that the flexible collision avoidance technique can quickly avoid collisions while maintaining a stable geometric formation. Multiple algorithms were used to avoid obstacles in Zheng et al.'s UAV flight path planning system. The UAV's movements are tracked by a revolving vector field [130]. Repulsion between UAVs takes into consideration distance and target-directed gravity to control them. UAVs are guided to the target using the artificial potential field method while avoiding obstacles. A rotating vector field approach for avoiding convex polyhedral obstacles is also offered. The smoothing approach is combined with vector field rotation to ensure a safe and smooth trajectory. Simulations show that the subsequent rotation vector field can design UAV collision avoidance and address “dead zone” and “jitter”. This allows UAV trajectory planning in difficult situations to be more flexible.

5.6. Geometric Guidance

Geometric techniques use form features to maintain minimum agent distances, such as UAVs. The time to collision is calculated using UAV distances and velocities. The author developed TRACE to train quadrotor UAV models using a unique cooperative collision avoidance technique [131]. The author created a mathematical model of coordinated operations, including speed and direction changes, to prevent UAV collisions. A strategy was developed to optimize these actions by minimizing energy expenditure while considering flight dynamics. The author created a learning model that can swiftly and reliably switch two UAVs' relative states to their ideal reciprocal behaviors when a collision is detected. This model will be optimized and run on UAVs. Thus, optimized direct current (DC) operations were more effective across a wider range of UAV approach angles. The energy difference between moves and no maneuvers was less than 2.5%. In training and evaluating 425 new cases, the classifier had 87.5% accuracy. The action models' prediction accuracy over the optimal values was always over 90%. More investigation of performance under new situations revealed a 95.3% collision-avoiding rate.

To prevent multiple unmanned aerial vehicles (UAVs) from colliding with moving and stationary objects, C. Y. Tan et al. developed the 3D velocity obstacle methodology. Their publication outlined this method [132]. The multi-UAV system's main goal is to complete tasks without colliding with airspace impediments. A tridimensional collision avoidance system that helps automobiles perform safely is the goal. The author suggested improving 3-D velocity obstacle (VO) approach. They also suggested using the pyramid cone technique to create a stationary obstacle-compatible collision avoidance system. Thus, the unmanned aerial vehicle avoided the immovable impediment and completed its objective. A collision is avoided, and the goal is achieved. The trajectory data shows the UAV avoided the stationary barrier. Unmanned aerial vehicle minimum distance from barrier is 0.3521 m.

The other author hypothesized that kinematic decomposition helps the UAV avoid collisions and sustain speed [133]. Collission-avoidance vector fields, a novel type of local parameterized guidance vector field, enable spontaneous movement around obstacles in the proposed technique. These vector fields are formed by studying UAV kinematics and modifying velocity based on proximity. The suggested UAV kinematic decomposition incorporates collision avoidance and constant-speed mobility. Harmonic potentials and navigation function parameter adjustments are computationally expensive, making them difficult to apply on real-time systems. They only work for obstacle replanning. CAVF-based motion plans incorporate stationary and moving impediments with minimum processing complexity, making them suitable for real-time applications. The suggested controllers also give trajectories that exactly follow these motion plans within constraints.

According to K. Wang et al., this practical obstacle avoidance path planning method should contain geometrical features [134]. Agricultural UAV coverage paths are determined using obstacle avoidance path planning. Agriculture UAVs must be operated by remote control pilots in fields with trees, poles, or cabins for safety. In a broad expanse with limited visual perception, this could be problematic or dangerous. Data suggests the field is a concave polygon with three obstacles. The field crosses one obstacle and passes two nearby. Obstacle polygons intersect field polygons, trimming them. The outcome will cover the field. Evidence shows the technique is efficient and feasible.

5.7. Optimisation Based

Optimisation uses geographic data to construct an avoidance trajectory. Probabilistic search algorithms use limited and uncertain data to find the best search areas. To reduce the computational cost of these algorithms, ant-inspired algorithms, genetic algorithms, Bayesian optimization, gradient descent-based approaches, particle swarm optimization, greedy methods, and local approximations have been developed. Y. Hu et al. developed a distributed technique that accounts for UAV velocity and collision avoidance. This technique is designed for mass UAV motion planning [135]. UAVs often have only localized awareness of the network, and their limited sensing and communication capabilities make it hard to receive information from other UAVs. To avoid problems, unmanned aerial vehicles (UAVs) must foresee dangers and take precautions. This work showed motion planning in 2D and 3D environments. The work examined using the velocity-aware A* algorithm, collision prediction approach, and collision avoidance algorithm in rotor UAV swarm applications with fundamental kinetic control logics. Despite longer real path lengths and higher time costs, the recommended technique has a good success rate. Path and time expansion depend on the situation, especially the starting and ending points, but a broader area and more UAVs will quickly increase path complexity and mission duration. UAVs have an average velocity of 0.65, which can change with acceleration and deceleration.

J. W. Hu et al. developed a distributed formation control and collision prevention system. This method uses Voronoi partitioning and a standard artificial potential field [136]. Voronoi partition theory divides space into zones for collision prevention. These task zones limit UAV movement. Popular artificial potential fields are used to develop the motion control law. Two UAVs on the verge of colliding often stop at a local optimum because the repulsive force equals the attracting force. When quadrotors collide, destinations are swapped. It prevents collisions between UAVs that are farther than the safe distance. The Fast-Geometric Avoidance algorithm (FGA) by the author combines geometric obstacle avoidance with optimal start time. This depends on kinematics, collision probabilities, and navigation [28]. Fast Geometric Avoidance (FGA) uses kinematics, collision probability, and navigation restrictions to determine the best start time after geometric obstacle avoidance. Simulations of several mission situations reveal that this strategy avoids many barriers better than earlier methods. Monte Carlo simulations and aircraft simulator flight missions verify the algorithms' efficacy. According to Y. Wu et al., the improved consensus algorithm (ICA) should align the UAVs' three degrees of freedom (DOFs) with their relative positions. Conventional consensus can contain formation information with this change [137]. The suggested minimal adjustment method addresses UAV maneuverability restrictions. Use particle swarm optimization (PSO) to avoid obstacles. The ICA-PSO technique handles static barriers, whereas the MPC-PSO strategy handles dynamic ones. These algorithms can be combined to handle more complex situations. The simulation findings show that the ICA can build UAVs with diverse initial conditions that meet all criteria. The obstacle avoidance algorithm provides UAV formation flight safety and efficiency.

Krishnan and Manimala devised a Particle Swarm Optimization-based Collision Avoidance algorithm (PSO-CA) to create escape maneuvers around obstacles and suggest new waypoints for UAV route dynamically modification [138]. The author suggested using a “obstruction sense and avoid” algorithm and a logical decision-making mechanism to help the UAV change flight routes if it finds an obstacle. A 10-kilometer radar system detects impediments, and the unmanned aerial vehicle (UAV) adjusts its movements to the radar information, making it suited for new terrain. The suggested technology will autonomously guide the UAV away from traffic. The algorithm's durability was shown by gradually increasing obstacles and successfully guiding the UAV along the safest trajectory numerous times. The graphical results show that the system works in complex situations and may be used in all unmanned aerial vehicles (UAVs) for real-time autonomous flight. Another author described UAV path planning and obstacle avoidance for cage culture assessment [139]. The proposed technology automatically inspects cage farms, saving manpower and money. It's like the traveling salesperson. Genetic algorithms work for TSP and cage culture analysis. Along with path planning, IPSO is employed to avoid cage collisions. IPSO works in static or dynamic environments with impediments. The suggested IPSO outperforms others. The shortest route to the goal. IPSO's path has less changes in direction and turn angles. IPSO chooses the best path length when the UAV faces several obstacles.

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As a summary, the research shows a trade-off between computational time, complexity, optimal solution requirements, pre-mission path planning, and static and dynamic adaptability. The proper algorithm must be chosen depending on operational requirements, or one can merge various collision avoidance approaches or two-layered collision avoidance strategy. For local static/dynamic barrier avoidance, sense and avoid approaches, the simplest and most resilient with minimum data overheads and response times, are safe in all scenarios. To avoid local minima and reach the goal without collisions, it must be paired with a more efficient path planning algorithm. Because the sense and avoid approach is not reliant on external communications, reacts instantly to environmental changes, has quick response times, and low data overheads, it can be used as a failsafe/standalone approach to ensure UAV safety, especially in highly dynamic environments where adaptability and flexibility are needed.

6. Sensor Fusion

Sensor fusion reduces uncertainty by combining sensor data from numerous sources. Integrating video camera data with WiFi localization signals improves indoor object location accuracy. Increased precision, completeness, and reliability may be included in uncertainty reduction. Or, it may be a new perspective like stereoscopic vision, which calculates depth by integrating two-dimensional images from two cameras with slightly different angles. Fusion data sources need not be same. Fusion might be direct, indirect, or output. Direct fusion uses soft sensors, past sensor data, and comparable or dissimilar sensors to integrate data. However, indirect fusion combines environmental knowledge and human input. Grid Map, Kalman Filter, Particle Filter, SVM, CRF/MRF, Deep Learning, Fuzzy Logic, and Evidence Theory are sensor fusion algorithms.

The Sock et al. Grid Map is 2D probabilistic. Our method uses 3D-LIDAR and camera. Robotic applications leverage LIDAR and camera data for their benefits [140]. This approach builds traversability maps for each sensor assuming unique data. The visual sensor traversability classifier updates automatically. 3DLIDAR assesses terrain crossability using inclines. Combining Bayes' rule and two probability maps increases detection. Sensor responsibilities vary by approach. The author used a UGV in tough terrain to test the method. Mapping aids navigation, planning, and manipulation. Tran et al. propose a fusion architecture that builds a 3D map without a scanner or visual processing using 2D LIDAR and 3D ultrasonic sensors [141]. Two sensor models are suggested for map updates. Our fusion approach supports 2D/3D maps. We compare probability combining methods and study strategy selection. Real-ground robot research indoors. We employ 2D and 3D maps to better reflect the environment. Sensor fusion saves resources and improves environmental and ego-pose assessments. Cheap 3D ultrasonic sensors improve the robot's environment perception. Robots with limited resources require this.

Kalman Filter provides object tracking for autonomous vehicle vision systems. Ego-vehicles predict object placements and plan motions via tracking. These methods frequently use RGB or LIDAR sensor data. Combining 2D-RGB camera images with 3D-LIDAR data is beneficial. An algorithm by Park et al. identified and estimated airborne object positions for BVLOS UAV safety [142]. LiDAR and vision detect objects. The YOLOv2 architecture recognizes 2D pictures. We cluster LiDAR point clouds to detect things. Sensor properties affect detection rate. Inaccurate detection algorithms need another sensor. Kalman filters increase single-sensor detection. Sensor data was blended to improve detection. The 3D position of an object is computed from its pixel and LiDAR distance. We tried fusion in the Gazebo simulator. Obstacle recognition, dynamic state evaluation, and avoidance technique are covered in the thesis. Buchholz assessed SAA's viability in static and dynamic operations [143]. This study uses dynamic simulation and data post-processing. 3D LIDAR, visible cameras, and 9 DOF IMU sensor suites enable autonomous UAS Situational Awareness and Analysis in urban areas. Fusion of inertial measurements and LIDAR point clouds localizes and improves obstacle data, producing encouraging results. The data fusion method and SAA guidance system need improvement.

Particle Filters are utilized in many fields to reconstruct sparse signals. Liu and Sun create the probability function of a particle filter tracker that integrates color visual and thermal data for object tracking using joint sparse representation [144]. On both modalities, sparse representation is calculated jointly and tracking results are pooled using a minimum coefficient procedure. Update modality reference templates and improve tracking robustness using co-learning. The suggested fusion methodology outperforms previous methods in the OTCBVS database. Industrial uses in places with poor satellite communications are increasing for unmanned aerial robots. A three-dimensional method by Carrasco et al. can find airborne robots in difficult settings [145]. These adaptive platforms must be trustworthy to add value. A 3D laser scanner, radio sensors, a previous map, and input odometry are used in the probabilistic solution. The aerial platform can estimate posture with this. The experiments show the method is accurate, durable, and computationally efficient.

SVM requires consideration of real-world metropolitan driving conditions while using perception sensors without position information. Li et al.'s autonomous driving system uses LIDAR and visual data for real-time optimal-drivable-region and lane recognition [146]. This multimodal method covers the most passable areas ahead of a vehicle. We recommend merging LIDAR and vision data at the feature level to find the best drivable area. A conditional lane identifying method is then selected based on the best driving area. This strategy works on surfaced and unsurfaced roads. Multiple experiments prove system efficacy and durability.

Häselich et al. examine CRF/MRF 3D laser range finder data [147]. The neighboring landscape is a two-dimensional grid with obstacles and paths. Markov random fields show terrain cell interactions. Grid cells may carry contextual information to avoid sensor noise or ambiguity misclassification. Camera photos add color and visual details to the point cloud, complementing laser range data. Classification uses 3D points and camera pictures. Innovative online landscape categorization uses Markov random fields with camera and laser data. The proposed technique can recognize highways and obstacles with 90% recall for an autonomous mobility robot. Camera and LIDAR data help Xiao et al. improve the conditional random field (CRF) model [148]. The author labeled pixels and LIDAR points using a hybrid energy function after alignment. A boosted decision tree classifier predicts pixel and LIDAR point unary potentials. The hybrid model's paired potentials represent picture, point cloud, aligned pixels, and LIDAR point contextual coherence. This method probabilistically blends sensor data to enhance information usage. To extract road sections with graph cuts, optimize the hybrid Conditional Random Field (CRF) model. In KITTI-ROAD benchmark dataset empirical study, the recommended strategy beats existing methods.

For Deep Learning, Ku et al. propose AVOD, an Aggregate View Object Detection network. This method is for Deep Learning [149]. Subnetworks share features using LIDAR point clouds and RGB images in the proposed neural network design. The proposed road scene Region Proposal Network (RPN) leverages a novel architecture for multimodal feature fusion on high-resolution feature maps. These suggestions enable the second-stage detection network predict three-dimensional object size, direction, and categorization. This architecture performs well on the real-time KITTI 3D object identification benchmark with low memory usage. This makes it perfect for driverless vehicles. When cameras and LiDAR fail, several modalities raise environmental awareness. Sonar and radar are hard to integrate since traditional sensor techniques don't adapt to these environmental representations. Balemans et al. employ modality prediction to keep current operations and decouple an autonomous agent's sensory system from navigate stack [150]. The author forecasted LiDAR point clouds using eRTIS, our 3D in-air acoustic ultrasonic sensor. To safely navigate with variable and imperfect visual signals, the author tested current algorithms with predicted data.

Industrial vehicles use LiDAR and a single-color camera to detect passive beacons in Wei et al.'s Fuzzy Logic demarcation method. Space-limited vehicles use model-predictive control to circumvent limitations [151]. Beacons are orange traffic cones with reflective poles. In addition to beacons, LiDAR may misidentify shiny surfaces like worker safety jackets. Deep learning to map camera beacons onto LiDAR space lowers false positives, says the author. The Mississippi State University Center for Advanced Vehicle Systems (CAVS) concluded that the proposed strategy decreases false positives and preserves accuracy. Due to imprecision and ambiguity, sensory data extraction is difficult. Data collection is complicated by multiple sensors. Majumder and Pratihar used fuzzy clustering and prediction techniques to fuse multi-sensor data [152]. Data was categorized and a fuzzy reasoning-based forecasting tool created using entropy-based fuzzy C-means clustering. Clusters in this piece are tiny and unique. It also introduces cluster-based reasoning. We tested the method with two multi-sensor data categories. The new method outperformed older ones on both data sets. This method uses similarity-based fuzzy clustering to search the dataset and develop a fuzzy reasoning tool.

Evidence Theory says Advanced Driver Assistance Systems (ADS) help drivers complete challenging jobs and reduce risk. The automobile uses sensors to create and maintain an internal environment model. Vehicle perception ties it to static and moving obstacles in space and time. Chavez-Garcia recommended SLAM for stationary components and DATMO for mobile components [153]. In some cases, perceptual output is used to determine the ideal driving behavior. System reasoning and control require exact environmental imitation. An effective object tracking system must classify moving objects accurately. Intelligent cars use sensors. multiple sensor fusion has been investigated for a long time since it requires combining input from multiple perspectives to generate an accurate model. Duplicate environmental measurements do this. Multiple perception stages fuse. Author tested recommended methods. The author compared pedestrian (cyclist) recognition, categorization, and monitoring using real driving data. A composite representation at multiple perceptual test levels yields good results. Starr and Lattimer suggest sensor fusion could improve smoke-obstructed rangefinding. LWIR stereo vision and spinning LIDAR would be combined [154]. This method uses LIDAR's precise measurements and LWIR cameras' perceptual abilities in translucent and foggy environments. Multiple-resolution voxel-domain sensor data was integrated using the Dempster-Shafer theory of evidence. LIDAR data was evaluated for intensity and distance to distinguish returns with high and moderate attenuation. High-attenuation LIDAR return data was used to model a sensor. LIDAR low-attenuation returns and LWIR stereo vision points were used to generate accurate occupied and open space sensor models. The fusion method was tested in a naval fire in a room and hallway with different smoke densities. Room-hallway assessments were compared to baseline rangefinding in trials. During occupancy, fusion is 5-10% more accurate than LIDAR in good weather. LIDAR cannot work in dense fog. LIDAR performed 40% worse in haze than fusion. Fusion and LIDAR performed comparably in clear conditions, differences of less than 5%.

7. Discussions and Conclusions

The previous sections reviewed unmanned vehicle collision avoidance technologies and tactics in detail. Conventional classification is shown in Table 1. Both passive and active sensors were investigated for obstacle detection in Table 2. Analysis covered sense and avoid, conflict resolution, model predictive control, AI, potential field function, geometric guiding, and optimization-based collision avoidance systems. Table 3 summarizes and assessed the pros and cons of various approaches.

Instead of vertical lift rotors, fixed-wing drones generate lift with wings. They are more efficient since they just need energy for propulsion, not aerial position. Thus, they may travel farther, explore wider areas, and watch their target longer. Gas engines are efficient and power sources. Many fixed-wing UAVs can fly for 16 hours due to fuel's higher energy density. The inability of fixed-wing aircraft to hover makes them unsuitable for aerial photography. Due to their size, these objects require a runway or catapult launcher for propulsion and a runway, parachute, or net for safe retrieval. Only small fixed-wing drones can hand launch and belly land in a field. In addition, learning to fly fixed-wing drones is expensive and complicated.

The fixed-wing hybrid VTOL seamlessly transitions between multi-rotor platforms and drones. Military and commercial pilots can use fixed-wing VTOL drones. These drones can fly vertically without a launcher or runway. So, they can work nearly anywhere. Compared to multi-rotor UAVs, fixed-wing UAVs can fly faster, further, and longer, covering more ground. VTOL fixed-wing drones increase coverage and data collecting for large farms. Producers can quickly analyze crop health and other indicators, saving pesticide and fertilizer costs. Moist and dry regions can be identified by a thermal camera payload. VTOL fixed-wing drones educate decision-makers in real time, boosting pre-planning, control, and emergency reaction while reducing operator risk.

Single-rotor drones exhibit superior efficiency compared to multi-rotor drones and can be powered by a gas motor to achieve extended flight durations. According to aerodynamics, a larger rotor blade rotating at a lower speed is more efficient. Quadcopters are more efficient than octocopters due to certain reasons, and certain long-range quadcopters are equipped with large propellers. A single-rotor drone can be equipped with elongated blades that bear a resemblance to rotating wings rather than traditional propellers, thereby enhancing its effectiveness. Drawbacks of these systems encompass intricacy, expense, fluctuation, and the potential hazard posed by their sizable rotating blades. A multi-rotor propeller has the potential to inflict significant harm, while the likelihood of causing additional damage is low. Tampering with the elongated, razor-edged blades of a solitary rotor drone could result in more severe harm. Single-rotor drones are of intermediate difficulty, positioned between multi-rotor and fixed-wing aircraft. Hovering enables a gradual initiation and progression. These gadgets exhibit insufficient stability and lack the capacity to compensate for poor landings. Their intricate mechanical design necessitates meticulous maintenance.

A tri-copter drone consists of three robust motors, three controllers, four gyros, and one servo. Motor and location sensors are positioned at the furthest ends of three arms. Adjust the throttle lever to increase the altitude of the tri-copter. The gyro sensor will rapidly transmit the signal to the controller, which will regulate the rotation of the motor. A variety of traditional sensors and technical components are utilized to ensure that a tri-copter remains stable during its flight. Variable-angle propellers are advantageous for three-rotor aircraft. The aircraft's ability to yaw is facilitated by the rear propeller, which provides tailplane-like characteristics and allows for controlled counter-rotation forces. Tri-rotor boats have superior stability and maneuverability compared to multi-rotor boats, but necessitating an additional servo and control hardware and software. The configuration employs a reduced number of propulsion motors, hence enhancing energy efficiency. The increased rotor spacing enables the use of larger propellers and provides a clear camera field of vision.

Quad-copter drones have a greater lifting capacity compared to helicopters of the same size. The quadcopter's rotors provide enough lift to counteract its weight. In comparison to a helicopter of equivalent dimensions, it has a greater capacity for transporting cargo. This technology is utilized in both military and commercial unmanned aerial vehicles (UAVs). The craft's four rotors enable it to effortlessly elevate substantial loads without requiring any modifications to its engineering. Therefore, the ship is economically efficient and has a greater carrying capacity. Quad-copters possess a high level of agility. They effortlessly levitate and maneuver in any orientation. Nevertheless, it possesses a lower level of power compared to hexa- and octo-copters. This suggests that it is incapable of lifting as much weight as the other two boats. Contrary to hexa- and octo-copters, the quad-copter experiences a crash in the event of motor failure.

A hexacopter has the ability to remain airborne even if one of its propellers is damaged or not functioning. The propellers are equipped with motors that have a 120-degree angle. If one engine fails, the remaining five engines are capable of sustaining the flight of the jet. The drone will descend smoothly, ensuring the safety of the camera. This spacecraft is capable of safely landing even if two propellers are lost. There are four quadcopters. Indeed, it possesses the ability to fly. Hexacopters have the ability to achieve more altitude than quadcopters because they are equipped with six propellers. Propellers generate more lift than quadcopters. This drone surpasses quadcopters in terms of speed. As a result of having additional propellers. Quadcopters often have a lower weight compared to hexacopters. It has a greater capacity than a quadcopter. Thus, it can hold a high-performance hexacopter camera. Building quadcopters is cheaper than hexacopters. Extra rotors cost more. Additionally, they outgrow quadcopters. This diminishes their density. Changing hexacopter rotors is more expensive.

Octocopters fly rapidly with eight propellers. The vessel gains considerable lifting power and acceleration. Octocopters outperform quadcopters and hexacopters. Agility does not compromise mastery. The pilot controls the plane precisely with numerous rotors. Octo-copters fly amid rain and strong gusts. Even without a motor, this ship can fly. Octo-copters may fly with two or three broken components. Flying with four or five engines is the vessel's principal benefit. Airborne pay is safeguarded. Excellent engine control, stability, and hovering. Extreme heights are possible. Moving fast and agilely. Octo-copters film movie scenes. Octocopters carry plenty. Big enough for cameras and batteries. Additionally, it can transport commodities. This device is huge. Large eight-rotor plane. Its construction and operation are costly. Large power output makes rotor acquisition expensive. Breakage replacement may be expensive. Octo-copters are energy-hungry. Its flight time is short.

According to the literature, each drone model has pros and cons. The tri-copter and quad-copter are economical and lightweight, making them suited for hobbyists and small equipment, but they cannot carry big loads. Despite motor failure, the hexa-copter is stable and can fly. This plane outperforms the quad-copter in altitude and cargo. The octo-copter can fly high and carry heavy loads, making it the most powerful of the three drones. However, this drone is the most expensive and requires frequent charging. Due to its benefits and reliability in critical tasks, the hexa-copter is a good drone to consider. Compared to octocopters, manufacture and maintenance are cheap.

Active sensors have a transmitter that emits a wave within a predetermined wavelength range using its own energy source and a receiver that detects and analyzes waves reflected by environmental objects. An external energy source is needed for a passive sensor to detect light or energy emitted or reflected by objects. Cameras need an external light source to function, while LiDAR sensors actively generate laser pulses onto the scene and analyze the reflected signals. LiDAR data is not limited by the quality and intensity of an external light source, unlike camera data.

Active sensors require more power than passive ones since they send and receive. Data processing is simplified by active sensors' focused data—reflected copies of their own signals. Passive sensors like visual cameras must filter and process raw image data to discover and evaluate relevant points of interest, which needs heavy processing. Camera-based collision avoidance is computationally expensive and difficult to use for rapid object recognition and decision-making. It can deliver more accurate environmental data than LiDAR, sonar, or radar in the right lighting. Range systems beat camera-based collision avoidance due to their lower processing requirements, faster response times, and ability to handle severe sunshine and weather.

Table 2 shows that each sensor has pros and cons, implying that no one sensor can solve collision avoidance. Using many sensors covers a larger region and mitigates places outside their range. By using the strengths of other sensors, combining them can overcome their weaknesses.

Table 2 shows that active sensors are more accurate than passive ones. Passive sensors use less power than active ones. Because active sensors transmit the signal before capturing the data for calculation. Passive sensors broadcast and read the signal from an external power source like sunlight or the object's source. Processing level is also important. Active sensors' data is focused and targeted, unlike cameras', and does not provide extraneous information. Processing active sensor data is easier than passive. Active sensors require less computational power to evaluate data than passive sensors, which raises another concern. Cameras involve complicated calculations for image processing and deleting extraneous data, making them more computationally intensive than LiDAR sensors.

Table 2 offers another thought-provoking look at how noise, weather, and light sensitivity affect data. Active sensors are less susceptible to noise than passive sensors because they can regulate data and generate transmission waves. LiDAR and ultrasonic sensors work in various environments, even in daylight, while cameras need optimal lighting to take pictures.

A passive sensor for obstacle detection may fail to distinguish between many objects in the surroundings, resulting in collisions. In one unfortunate event, a Tesla vehicle's collision avoidance technology failed to distinguish between a well-lit sky and a tractor trailer [155].

Collision avoidance strategies can be assessed from several angles and utilizing different criteria [156]. Evaluation metrics are usually depending on the algorithm's use case goals and platform constraints. Each collision avoidance algorithm has pros and cons and different evaluation measures to determine its viability for a certain application. Table 3 summarizes the pros and cons of the most widely utilized methods in the field. To compare numerous elements of the algorithms, we classed them independently using seven evaluation criteria. This table explains these criteria:

The first metric is complexity: In terms of algorithm design, the geometric, model predictive control, conflict resolution, and force-field methods are the most complicated (computational cost). In this comparison, the optimisation-based and artificial intelligence methods are of medium complexity, while the sense and avoid approaches are the least difficult.

The second metric is communication dependence: Sense and avoid approaches do not rely on communication because they operate locally and make judgments without involving other UAVs or systems. Some of the force-field literature reviewed relies on communication with other UAVs, while most of the other work does not, demonstrating that force-field approaches are not overly reliant on communication and that it depends on the model and implementation. Other methods, on the other hand, rely on interaction with other nodes/UAVs.

The third metric is pre-mission planning: Sense & avoid, conflict resolution, and artificial intelligence do not require it. The collision cone and the velocity obstacle are used in geometric approaches to plan the path. Pre-mission path planning is required for optimisation and force-field methods to work at their best.

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

The fifth metric is 3D compatibility: Methods such as sense and avoid, geometric, artificial intelligence, and optimisation have a lot of experience with 3D surroundings. Many academics, on the other hand, are working on determining the viability of applying force-field approaches, model predictive control, and conflict resolution in 3D dynamic environments.

The sixth metric is real-time performance: Sense and avoid, geometric, artificial intelligence, and model predictive control all perform better in real-time than force-field, conflict resolution, and optimisation methods, because sense and avoid do not require excessive processing to avoid changes in the environment, such as approaching obstacles. Additionally, geometric approaches are quick and computationally efficient. However, the drawback of geometric approaches over sense & avoid is that the time required to compute, and the complexity of the algorithm are greatly reliant on the algorithm implementation.

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

Research shows that computing time, complexity, optimal solution requirements, path planning before a mission, and ability to adapt to stationary and dynamic environments are all trade-offs. To meet deployment operational requirements, choose the right algorithm or combine different collision avoidance methods, such as a two-layered strategy [157]. Detect and avoid techniques, the simplest and most resilient strategy with little data requirements and short response times, are safe for dodging stationary or moving hazards in close proximity. To avoid getting stranded in a local minimum and reach the target without collisions, it must be integrated with a better path planning algorithm. Additionally, the sense and avoid approach responds quickly to environmental changes and operates independently of external communications. Its fast response times and low data overheads make it a reliable and self-sufficient UAV protection system.

Table 1. Performance comparison between UAV devices

Types of UAV	UAV Device	Speed	Control & Stability	Overall Payload	UAV Safety	UAV Size	Range	Battery Life
Multi-rotor drone	Tri-copter	Low	High	Low	None	Very small	Close-range	Medium
	Quad-copter	Medium	High	Low	None	Mini	Close-range	Medium
	Hexa-copter	Medium	Medium	Medium	√	Medium	Close-range	Low
	Octo-copter	Medium	Medium	Medium	√	Medium	Close-range	Low
Single-rotor drone		Medium	Medium	Medium	None	Medium	Short-range	Medium
Fixed-wing drone		High	Low	High	None	Large	Mid-range	High
Fixed-wing Hybrid VTOL		High	Low	High	None	Large	Mid-range	High

Table 2. Sensor attribute comparison for obstacle detection: short (0-100 m), medium (100 - 1000 m), long (> 1000 m)

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

Table 3. Performance Comparison between State-Of-The-Art Collision Avoidance Approaches

CA Approach	Complexity	Communication Dependence	Pre-mission Planning	Robustness	3D Compatibility	Real-time Performance	Escape Trajectories
Sense & Avoid	Low	x	x	√	3D	√	Local/Run-time
Conflict Resolution	High	√	x	√	2D	√	Negotiation protocol
Model Predictive Control	High	√	√	√	2D	√	Hybrid systems
Artificial Intelligence	Medium	√	x	√	3D	√	Optimised
Potential Field Function	High	x	√	√	2D	√	Force-field based
Geometric Guidance	High	√	√	√	3D	√	Protocol based
Optimisation Based	Medium	√	√	√	3D	√	Pre-defined

Avoiding flying collisions with LIDAR data to optimize UAV system settings is understudied. In this study, optimal collision avoidance parameter sets are automatically adjusted. LiDAR data detects obstacles and incursions in Miao et al.'s ALORID approach. This method assists collision avoidance controllers [158]. Ponte et al. use LiDAR sensor input parameter and Kalman Filter estimation to monitor obstacles and trespassers, hover, and land the drone [159]. Using LiDAR distance measurements alone, an automated system for recognizing and avoiding obstacles has not been developed. This could degrade the algorithm, obscuring the UAV's trajectory. Thus, this research will focus on improving collision avoidance controllers for real-time intelligent systems. UAV collision avoidance controllers with LiDAR sensors could increase autonomous flight and collision avoidance. To reduce collisions, a detect and avoid system with sensor fusion optimization needs more research.

8. Future Recommendations

According to the literature, there are three components that can be enhanced. The hexa-X rotor arrangement of the UAV is determined by its payload, which in turn determines the construction of the hexa-copter. The UAV payload is essential for ensuring stability, maneuverability, and flight endurance [160]. Once the 3D virtual model has been created using SolidWorks, it is necessary to do stress analysis using the finite element method. Therefore, it is necessary to analyze the hexa-copter's structure using finite elements and analytical load calculations specifically for landing and takeoff [161]. It is essential to perform this step in order to accurately determine the weight of the hexa-copter without any extra weight, which must not above 3.5 kilograms.

An additional enhancement that might be used in this study is the integration of sensor fusion, specifically utilizing LiDAR, sonar, and radar. The author is not aware of any sensor fusion technique that combines these sensors for the purpose of recognizing objects in UAVs. In addition, prior studies have predominantly concentrated on integrating multiple sensors, such as LiDAR, vision sensors, magnetic and inertial measurement units, visual inertial ranging, and GPS, with UAVs for sensor fusion purposes [162]-[166]. Upon realizing that the strengths of one sensor may surpass the deficiencies of the others, many sensors were employed collectively. The objective of sensor combinations is to surpass the performance of individual sensors by enhancing the proportion of desired signal to unwanted noise, reducing uncertainty and ambiguity, and enhancing dependability, durability, precision, accuracy, and other attributes.

Enhancements can be made to a hybrid system designed for an effective collision avoidance controller. An optimized data output for new path planning can be achieved by utilizing a hybrid system that combines Sense & avoid with an optimization technique. This optimizes the integration of sensor fusion data [167]. Sang et al. utilized an enhanced artificial potential field (APF) to develop their deterministic approach called multiple sub-target artificial potential field (MTAPF). The course was planned using an artificial potential field and an enhanced heuristic A* algorithm. By rotating the target locations, Unmanned Surface Vehicles (USVs) are able to avoid becoming stuck in local minimums when using the Multi-Target Assignment and Path Finding (MTAPF) algorithm [168]. Patel et al. developed a collision-prevention system by combining an Artificial Neural Network with a proportional-derivative controller. This controller acquires knowledge about the dynamics of the system and corrects faults that occur during high-speed and agile flight, motor malfunctions, and safe landings [169]. Hence, there is a requirement for a hybrid system that can effectively prevent collisions in diverse situations while simultaneously ensuring optimal real-time speed, scalability, safety, and efficiency.

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