drones

Review

# Strategies for Optimized UAV Surveillance in Various Tasks and Scenarios: A Review

**Zixuan Fang** and **Andrey V. Savkin** *

School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, NSW 2052, Australia; zixuan.fang@unsw.edu.au
* Correspondence: a.savkin@unsw.edu.au

**Abstract:** This review paper provides insights into optimization strategies for Unmanned Aerial Vehicles (UAVs) in a variety of surveillance tasks and scenarios. From basic path planning to complex mission execution, we comprehensively evaluate the multifaceted role of UAVs in critical areas such as infrastructure inspection, security surveillance, environmental monitoring, archaeological research, mining applications, etc. The paper analyzes in detail the effectiveness of UAVs in specific tasks, including power line and bridge inspections, search and rescue operations, police activities, and environmental monitoring. The focus is on the integration of advanced navigation algorithms and artificial intelligence technologies with UAV surveillance and the challenges of operating in complex environments. Looking ahead, this paper predicts trends in cooperative UAV surveillance networks and explores the potential of UAVs in more challenging scenarios. This review not only provides researchers with a comprehensive analysis of the current state of the art, but also highlights future research directions, aiming to engage and inspire readers to further explore the potential of UAVs in surveillance missions.

**Keywords:** UAV path planning; UAV coverage planning; UAV applications; UAV optimization; UAV surveillance; UAV monitoring; aerial video surveillance; review; survey

check for updates

**Citation:** Fang, Z.; Savkin, A.V. Strategies for Optimized UAV Surveillance in Various Tasks and Scenarios: A Review. *Drones* **2024**, *8*, 193. https://doi.org/10.3390/drones8050193

Academic Editor: Abdessattar Abdelkefi

Received: 25 February 2024
Revised: 2 May 2024
Accepted: 8 May 2024
Published: 12 May 2024



## 1. Introduction

Surveillance tasks are typically classified by the type and number of objects to be monitored, as well as the significance of the task. In a standard surveillance task, the goal is to gather specific information about the targets, such as trajectory, status, number, and activity. Traditionally, surveillance tasks utilized ground-based video cameras or other sensors to capture information. However, due to their limitations, these devices often struggle to cope with complex environments in many scenarios [1,2]. With the development of Unmanned Aerial Vehicles (UAVs), computer vision and imaging technologies, stable and efficient UAV surveillance systems are gradually replacing these technologies and working autonomously in many applications [3–5].

Common UAV surveillance tasks include environmental monitoring, search and rescue (SAR), agricultural surveillance, target tracking, traffic flow monitoring, infrastructure inspection, etc. [6]. As shown in Figure 1, camera-equipped UAVs are capable of logistics, environmental surveillance, agricultural surveillance, and collaborative work with other units. These tasks greatly utilize the unique capabilities of UAVs, and give full play to the advantages of UAVs in terms of mobility and flexibility, and often reduce the cost of surveillance. Using sophisticated localization, navigation, data collection, and control algorithms, UAVs can achieve autonomous single-unit operation, or operate in the form of a cluster for data sharing and collaborative operations.

For surveillance missions, the use of a single UAV meets the need for cost control, and for missions that do not require coverage of large ranges or allow surveillance to be conducted sequentially, a single UAV can be used to achieve surveillance by designing path-planning algorithms. The surveillance range of a UAV is often correlated with its flight altitude, and even a single UAV can achieve greater coverage through altitude adjustment [7]. For some large-scale missions, it is sometimes difficult for a single UAV to efficiently fulfill the needs of the mission, and this is when the existence of a UAV network is necessary. The use of multiple UAVs to form a UAV network, using information sharing between UAVs, designing optimized allocation or deployment strategies, and planning the corresponding paths, can greatly enhance the efficiency of the mission [8].


**Figure 1.** Each UAV is equipped with a camera and performs different surveillance tasks such as environmental monitoring, search and rescue, agricultural surveillance, and urban surveillance for police security.

Some publicly available data also demonstrate the superiority of drones as a novel approach. According to DroneUp, work performed with UAVs identifies 20% more critical issues than traditional inspection methods using human labor or other sensor equipment. This is because UAVs can replace humans in carrying out monitoring tasks in some areas that are difficult to detect. Difficulties encountered in the past in the use of human beings to carry out monitoring tasks, such as difficulties in accessing some high-risk areas, difficulties in ensuring safety, the long time required for overhauling large areas and the weak data collection capacity, can be more easily accomplished with the help of UAVs. Additionally, UAVs can make field inspections up to three times faster, scan towers three times more efficiently than tower-climbing inspectors, bridge inspections require roughly 17% of the labor hours required for manual inspections and up to 87% reduction in labor and resources per mile of inspection [9]. The data shown in Figure 2 reveal the multifaceted benefits of UAVs in infrastructure inspections and highlight their significant potential to increase efficiency, reduce costs, and optimize resource use. These findings provide solid data support for the further integration and development of UAV technology in a variety of infrastructure inspection applications.

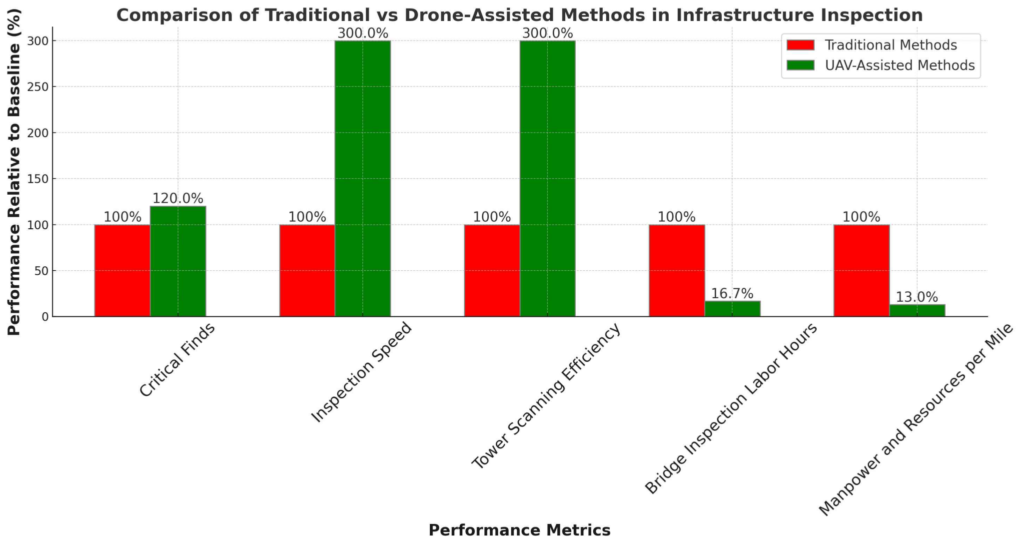


**Figure 2.** The chart comparing the performance of traditional and drone-assisted methods for infrastructure inspections, with the % percentage of each item indicating the improvement or savings compared to traditional methods [9].

Although many articles have been published on single UAVs and UAV clusters performing surveillance missions in different environments and under different mission conditions, the discussion on the optimal surveillance problem in complex environments is not specific enough, and an optimization-based review of the UAV surveillance problem has not yet been presented to the readers. Some of the current studies have investigated UAVs performing tasks in complex environments [10,11]. They studied the problem of executing optimal path planning for UAVs within a 3D unknown environment but did not address the study of the optimization problem and the exploration of the actual surveillance problem. The study [12] proposed a detailed UAV-UGV (Unmanned Aerial Vehicle-Unmanned Ground Vehicle) surveillance scheme and presented its solution to the optimal path planning problem; however, this article focuses less on the visual information of surveillance and more on the synergy between different intelligences. In another study [13], the importance of UAVS (Unmanned Aerial Vehicle Surveillance) in SAR missions was carefully examined, the research was not focused on optimal deployment or optimal path planning but rather on how to use advanced algorithms to process and improve the quality of UAVS images.

Surveillance, as the core responsibility of UAVs' navigation task at this stage, deserves an in-depth discussion. This should further exploit the characteristics of UAVs, enhance the optimality of surveillance tasks, comprehensively study the behaviors of UAVs across various domains and environments, and analyze the challenges they face as well as the strategies to overcome them. To keep the researcher informed, our paper will also discuss several methods for optimizing surveillance tasks. As we mentioned above, there are not many publications on UAV mission execution in complex environments, and the literature that researchers can access is not focused enough. We will also specifically analyze the optimization tools and strategies for UAV mission execution in different complex environments.

As shown in Figure 3, we have four main types of surveillance tasks, namely, area security and target tracking-based surveillance, infrastructure retrieval-based surveillance, search and rescue-based surveillance, and environment and resource surveillance tasks. For these four types of surveillance tasks, our paper also analyzes the path planning and deployment strategies adopted by different researchers to optimize and solve the Path Planning Problem (PPP) and the Coverage Problem (CPP) arising from the corresponding surveillance tasks.


**Figure 3.** Different types of surveillance topics.

This survey will be organized as follows: Section 2 will focus on the analysis of UAV surveillance systems based on target tracking.In Section 3, we will review surveillance methods and strategies for infrastructure inspection. This section focuses on the navigation and deployment of UAVs, detailing how they achieve optimal processes and results in various environments, similar to the structure of Section 2. Search and rescue-based UAS surveillance will be reviewed in Section 4, providing a comprehensive assessment of the methods and strategies involved. Section 5 will present the application of UAV surveillance environmental, archaeological, and mining applications. For all the topics mentioned above, the limitations of the methods and strategies in existing research will be explained, possible solutions will be proposed, and the feasibility of future research will be envisioned in Section 6. Finally, a comprehensive summary of the paper is presented in the last section.

## 2. UAV Surveillance for Target Tracking

Surveillance mission for target tracking is one of the main responsibilities of UAVs, for target tracking we adopt a broad definition, for this task, UAVs need to monitor a specified target, which can be a person, an object, or an area, to obtain information about the object of interest, such as traffic information, activity trajectories, quantity changes, etc., depending on the environment with different Information Preference. A target-tracking task can be classified mainly based on the target, number of UAVs, problem type, and optimization goal, and a complete target-tracking task is a combination of these elements.

Figure 4 clearly shows the structure of our target-tracking oriented surveillance task in terms of target, number of UAVs, problem types, and optimization methods. For the Target item, common moving targets include transportation, wildlife, pedestrians, etc. [14–16], while stationary targets are commonly set as an area. The number of UAVs is an important metric in determining the efficiency and complexity of the task, more UAVs can perform the task at the same time, which greatly reduces the time required to complete the task, but this also poses a challenge to the researcher, the need to maximize the use of the UAV resources, which requires that the path planning and deployment strategy needs to be optimal. Tasks can in turn be decomposed into CPP, PPP, and their combined types to fit the needs of the mission.


**Figure 4.** Different elements of Target Tracking Surveillance.

For optimization studies of UAV surveillance, the physical model of the UAV often exists as a constraint in the optimization problem and cannot be ignored. However, in optimization problems, researchers focus more on optimization in deployment and planning rather than the UAV motion model itself, so proposing a more simplified physical model is beneficial to help solve and implement the optimization problem. In [17], a simplified dynamic model is presented as follows

$$\begin{cases} P(t) = (x(t), y(t), z(t)) \\ \dot{P}(t) = v(t)\omega(t) \end{cases} \tag{1}$$

$x(t), y(t), z(t)$ represents the UAV's location in 3D space, while $v$ and $\omega$ denote the speed and direction of the UAV's movement, respectively, where $v(t) \in R, 0 < v(t) \leq u_{max}$, $\omega(t) \in R^3, \|\omega(t)\| = 1\ \forall t, v_{max}$ is a given positive constant, and $\|\cdot\|$ is the Euclidean vector norm.

For target-tracking-oriented surveillance tasks, the quality of task accomplishment can be measured by several metrics: quality of Surveillance, surveillance time, and surveillance energy consumption. Quality of Surveillance is a human-set metric, which includes the clarity of the surveillance image, the distance between the UAV and the surveillance, etc., and requires different judgments according to different problems without a fixed definition. Surveillance time is an important metric in target tracking, and longer surveillance time often means richer information. Energy consumption is a commonly used metric to measure the level of path planning, and optimized paths can help UAVs minimize energy consumption while accomplishing their missions. Figure 5 clearly shows the classification of different optimization objectives for a surveillance task based on goal tracking.

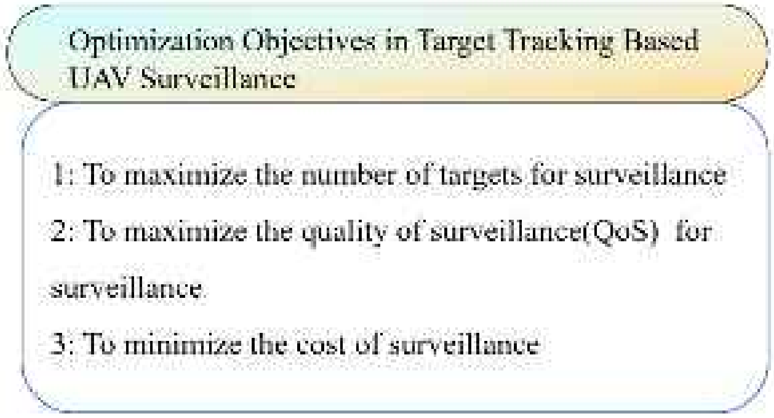


**Figure 5.** Optimization Objectives of Target Tracking Based UAV Surveillance.

*2.1. UAV Surveillance Methods Maximizing the Number of Observed Targets*

In a surveillance mission for target tracking, in the absence of a specific target of interest, the UAV conducts surveillance on a generic target, and the more targets the UAV monitors per unit of time, the more effective its surveillance is. Thus, maximizing the number of targets monitored is equivalent to maximizing the efficiency of UAV surveillance. Therefore, the optimization problem falls on maximizing the number of targets under surveillance. To achieve the goal of maximizing the number of surveillance targets, the path can be optimized by solving either the path-planning problem (PPP) or the coverage-planning problem (CPP). We will discuss both solutions separately and compare them.

In the study [18], the mission area is decomposed into several unit circles with waypoints within each unit circle, the coverage planning problem is transformed into a path planning problem based on the Traveler's Problem (TSP), and the sequence of connections of all unit circles is solved according to the shortest path principle, and a smooth coverage path is created using cubic Bessel curve fitting. The method effectively reduces the path length and optimizes the curvature, which helps to improve the efficiency of UAV flight paths, accurate area coverage, and the ability to cover the maximum number of all targets in the area. Although the method does not mention the involvement of a surveillance system, it can still be considered a viable PPP solution. The paper [19] develops effective navigation algorithms for teams of UAVs on ground surveillance missions by dividing the surveillance area into multiple convex subareas and planning a series of paths with parallel line segments for each UAV to achieve effective coverage of the entire area, solving the optimization problem of maximizing the number of area points to be regularly monitored.

Another more widespread solution to the problem of optimizing for the maximum number of monitors is to choose to solve it in terms of a deployment strategy, which is generally a subclass of the CPP problem and the most widespread solution to the CPP problem. The paper [20] solves a deployment problem for UAV networks using a distributed coverage maximization algorithm for finding locally optimal positions of UAVs, aiming to maximize the coverage of surveillance and monitoring areas. The ability to achieve obstacle avoidance and efficient deployment by requiring only pre-computed probability densities and positions of other UAVs in the UAV cluster makes the algorithm easy to implement and highly practical. The study [21] proposes an optimization model to maximize the coverage surveillance quality and develops an algorithm to maximize the surveillance coverage, where each FR-BS operates independently and requires only local information to guide its movement and find a locally optimal solution, which makes it possible to maximize the quality of the coverage while satisfying all the constraints. The algorithm proposed in this research requires only local information, is computationally simple, can be performed in real-time, and successfully maximizes the quality of surveillance coverage. In other words, it maximizes the number of targets to be monitored in the area. The paper [22] presents a 3D localization algorithm designed to maximize energy efficiency while covering as many users as possible. Optimizing the position of the UAV in the vertical and horizontal dimensions, respectively, the deployment in the horizontal dimension is modeled as a circular placement problem and a minimum closed circle problem, achieving a wider coverage area and increasing the number of user targets to be covered and monitored.

This paragraph explores strategies to maximize the number of surveillance targets in unmanned aerial vehicle (UAV) surveillance missions using path planning problems (PPP) and coverage planning problems (CPP). In the absence of a specific surveillance target, the goal of a UAV is to cover as many targets or areas as possible to improve surveillance efficiency. The PPP solution focuses on optimizing the flight path by reducing the path length and optimizing the curvature to cover more targets. The CPP solution, on the other hand, focuses on deployment strategies that aim to find locally optimal positions for the UAV to maximize the coverage of the surveillance and monitoring area. Both approaches aim to achieve the goal of maximizing the number of surveillance targets.

### *2.2. UAV Surveillance Methods Maximizing the Quality of Surveillance (QoS)*

Quality of Surveillance (QoS) is derived from Quality of Service, a term widely used in telecommunications and computer networking, which was originally used to describe the quality and performance of data transmitted over a network but is now referred to as Quality of Surveillance (QoS). Surveillance measures the degree of effectiveness of a surveillance system, including surveillance coverage, surveillance accuracy, and data quality, and since surveillance behavior is often related to the behavior of users in communications, Quality of Surveillance (QoS) can also be thought of as a measure of UAV participation in related tasks.The paper [14] proposed a distributed navigation algorithm for UAV (Unmanned Aerial Vehicle) networks that independently determines the motion based on local information and is proposed for effective surveillance of targets moving along curved roads. The algorithm aims to maximize the Quality of Surveillance (QoS), which ensures the convergence of UAV positions by minimizing an integral measure of the distance between all targets and the nearest UAV for optimal surveillance. Another similar discussion on Quality of Surveillance (QoS), also referred to as Quality of Service, is presented in the study [23]. A three-dimensional deployment optimization strategy adapted to Unmanned Aerial Vehicle Base Stations (UAV-BS) maximizes the total number of user equipment (UE) covered within the surveillance range under the user's data rate demand and the capacity constraints of the UAV-BS, and the article also describes this process as QoS optimization. The relationship between air-to-ground (A2G) path loss and UAV-BS position (both horizontal and vertical dimensions) between UAVs and ground users is established, and then a 2D placement method based on genetic algorithms (GA) is proposed.

One aspect of UAV surveillance missions that require researchers to focus on is the surveillance of moving targets and how to optimize it. The variability and flexibility of moving targets require UAVs to conduct surveillance while also considering how to maintain the quality of surveillance and overcome the effects of the environment [24]. In [16], it allows UAV teams to dynamically adjust their flight paths through a decentralized control strategy to optimize the quality of surveillance of moving target groups. The core idea is to partition the path containing the target into subsets based on the current position of the UAV and compute the center of mass of the target density function in each subset. Each UAV updates its flight direction and speed based on the position of these centers of mass to ensure that it moves in the direction of improving surveillance quality, i.e., reducing the average distance to the target, and improving surveillance coverage and response speed by dynamically adjusting the flight path to cope with changes in the target movement or path. this approach of balancing local decision-making with global information allows the UAV to effectively respond to changes in target movement This balancing of local decision-making and global information allows the UAV to effectively respond to changes in target movement and maintain optimal surveillance. Another feasible optimization strategy incorporates a computer vision approach for feature extraction of moving targets. The method described in [25] uses machine learning models to recognize moving targets. For the surveillance task of the UAV Network, to improve efficiency and surveillance quality, a multi-target intelligent algorithm based on target location and UAV capability as well as mission urgency is used to improve the surveillance quality, while a path planning algorithm is used to ensure the comprehensiveness of the UAV's coverage and safe obstacle avoidance capability. For the problem that targets are difficult to track while moving, a multiple data source fusion method is proposed to estimate target speed and position.Advanced robust controllers can ensure that the generated paths can be implemented by the UAV, but this is beyond the scope of this paper [26,27].

This paragraph explores strategies for maximizing the Quality of Surveillance (QoS) in Unmanned Aerial Vehicle (UAV) surveillance missions. QoS includes surveillance coverage, accuracy, and data quality. The article discusses a series of algorithms designed to maximize the QoS of a UAV network under a variety of constraints. Some of the methods focus on maximizing the number of user devices covered within the surveillance range, while others focus on minimizing the distance between all targets and the nearest UAV to improve surveillance efficiency and quality.

### *2.3. UAV Surveillance Methods Minimizing the Cost*

Minimizing the cost of surveillance is very important in UAV surveillance missions, and reducing the cost of surveillance can lead to more sustainable operation of the UAS in long-term projects, thus improving the overall surveillance efficiency and performance. The cost of UAV surveillance mainly includes the consumption of energy and the impact of negative optimization terms.

The study [28] explores a three-dimensional deployment algorithm for Unmanned Aerial Vehicle (UAV) surveillance and monitoring. The goal of this algorithm is to maximize the overall Quality of Coverage (QoC) of a target covered by a UAV network, i.e., Quality of Surveillance (QoS). The QoS of the target is maximized by a population of UAVs deployed in a specific area, taking into account the navigation rules in both horizontal and vertical directions, while satisfying multiple constraints. It presents an optimization model that aims to maximize user coverage while minimizing the cost of communication between UAVs. The research [29] introduces a Voronoi diagram-based path generation (VPG) algorithm for the energy-constrained unmanned aerial vehicle (UAV) path planning and coverage problem, which solves the path planning problem of not being able to achieve complete coverage of an area due to the path length limitation caused by energy constraints, and maximizes the extent of the monitorable coverage.

Minimizing surveillance cost is important in unmanned aerial vehicle (UAV) surveillance missions, where the cost of UAV surveillance mainly includes energy consumption and the impact of negative optimization factors. Related studies have proposed various optimization models and algorithms that aim to maximize surveillance coverage and QoS while minimizing the communication cost and energy consumption between UAVs. Through these optimization strategies, the research endeavors to improve the effectiveness of UAV surveillance while minimizing the attrition associated with energy consumption and other related costs.

### *2.4. Research Gaps and Future Improvement*

For UAV surveillance for target tracking in a broad sense, current research has been able to cover most of the cases. However, it is worth mentioning that there are very few articles on the integration and research of AI techniques such as large models, neural networks, and reinforcement learning, which is because the model building and design is more complex, nevertheless, we can still be inspired by many studies.

Table 1 presents the current state-of-the-art optimisation strategies, classifies them for different optimisation objectives, and comprehensively describes the advantages and disadvantages of their optimisation strategies. The optimization strategies and solution methods involved in this table such as MILP, heuristic algorithms, distributed algorithms, etc. The main core of the UAV optimization problem is to deal with the optimization of specific optimization indexes under multiple constraints, and the above is of positive significance for solving the complex UAV surveillance optimization problem.

**Table 1.** The comparisons of UAV Optimization Methods and Objectives.

| Reference | Optimization Methods | Optimization Target | Advantages | Disadvantages |
|---|---|---|---|---|
| [14] | Distributed and Local Optimization | Minimising the expectation of the square of the average distance from all ground targets to the nearest UAV | Simple calculation, no global information required | Local optimum traps, high communication bandwidth dependence |
| [30] | Distributed, particle swarm optimization combined Bresenham algorithm | Minimize energy consumption, flight risk estimation and maximize surveillance areas | Simple implementation, low computational complexity, small parameter dimension | Local optimum traps and lower dynamic performance |
| [31] | Mathematical Modeling and numerical optimization | Minimise the number of UAVs needed for surveillance and maximize surveillance coverage | High efficiency and task-specific adaptability | Low generalisability, complex modelling, excessive parameter sensitivity |
| [32] | Mixed-integer linear programming(MILP) | Minimising total UAV energy consumption and maximising the amount of surveillance completed | High accuracy and complex problem solving | High computational complexity, unpredictable solution time, poor solution to non-linear problems |
| [33] | Heuristics Algorithm | Minimize data capture time and transmission delay | Simple to implement, strong NP problem-solving skills and low computational cost | No guarantee of a globally optimal solution, strong parameter dependence |

The study [34] develops a multi-agent deep reinforcement learning-based UAV surveillance system to optimize the coverage area while reducing overlapping and shaded areas, improve surveillance services and deal with a variety of uncertainties while providing an original deep reinforcement learning framework for guiding future UAV-based dynamic autonomous surveillance research.

## 3. UAV Surveillance for Infrastructure Inspection

In today's rapidly evolving technological era, Unmanned Aerial Vehicles (UAVs) have become a key monitoring and inspection tool, particularly in the area of infrastructure inspection. This chapter will provide an in-depth look at the use of UAVs in infrastructure inspections, highlighting their potential to increase efficiency, reduce costs, and enhance safety. We will provide an overview of the best current strategies and technologies and analyze their efficacy in dealing with complex environments and diverse tasks. This chapter will detail the use of drones in the inspection of bridges, power lines, pipelines, and other critical infrastructure elements, demonstrating their advantages in data collection, processing, and analysis. This chapter aims to provide a comprehensive view showing the diverse applications and challenges of drones in infrastructure inspections. We will also discuss the limitations of current technologies, as well as potential directions for future research to drive continued innovation and development in the field.

The use of UAVs to inspect infrastructure is a hot research direction and application direction that has emerged in recent years. In the past, the use of manual inspection was both dangerous and inefficient, and because the infrastructure to be inspected, such as power line towers, transmission lines, bridges, and so on, is quite large, it is difficult to detect specific details through manual inspection. Moreover, due to safety considerations and space constraints, dispatching more than one person to the same location for inspection is generally not allowed, making it hard to detect faults or hidden dangers in corners, which can be overlooked and lead to greater harm in the long term [35]. To solve the above problems, more flexible and autonomous inspection UAVs are widely used. These UAVs are configured with different cameras according to the actual needs of the work and can work in a network of UAVs while sharing information and discovering potential problems. For this type of surveillance aimed at infrastructure inspection, we classify two categories for discussion according to the different inspection objects: one is the inspection and surveillance of transmission lines, and the other is the inspection and surveillance of bridges [36]. Meanwhile, we classify the methods adopted by UAV surveillance systems into two categories (Figure 6). The first is vision-based methods, which include various cameras and algorithms, infrared light detection, and optical flow; these focus on enhancing UAVs' ability to surveil task objects, improve image quality, and detect hard-to-see problems. The second category is path planning-based approaches, which concentrate on deploying UAVs more efficiently to access and inspect facilities, commonly including transmission lines and photovoltaic farms [37].

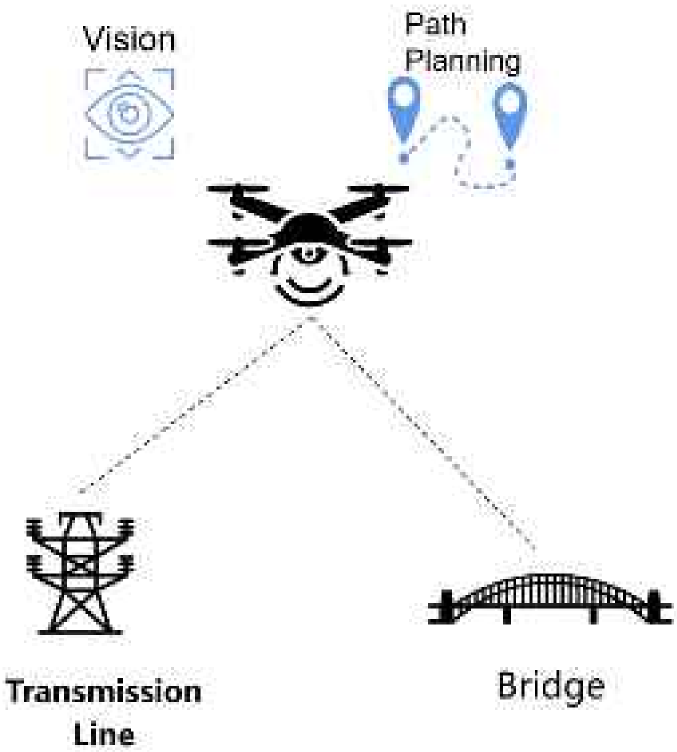


**Figure 6.** UAV Infrastructure Inspection Based Surveillance.

### 3.1. UAV Surveillance for Transmission Line Inspection

Before the large-scale adoption of drones for the inspection of overhead transmission lines, manual inspection was the only option. Units responsible for maintenance needed to send workers to configure a large amount of protective equipment and climb high towers to carry out work such as foreign object detection, equipment fault inventory, and localization [38,39]. The application of UAV technology in modern transmission line inspection and surveillance has become a revolutionary advancement [40–43]. In this section, we will focus on two key technologies of UAVs in transmission line inspection: vision scheme and path planning. We will explore vision schemes first, especially the application of computer vision technology in UAV inspection. Computer vision enables UAVs to capture images of transmission lines through high-resolution cameras and use advanced image processing algorithms to detect and identify potential trouble spots, such as line damage, unusual hot spots, or growth trends. This advanced image analysis not only improves the accuracy of inspections but also provides important visual data for preventive maintenance [36,44].

In the study [45], an autonomous navigation method for UAV power line inspection is proposed. A perspective navigation model is introduced for such complex visual tasks of grid tower and transmission line inspection and surveillance. By navigating the UAV, the perception of 3D orientation is enhanced with the help of perspective images. The proposed region-based convolutional neural network for tower detection, and tower tracking vision strategy via kernelized correlation filter, which is capable of accurately determining the flight heading after obtaining the vanishing point (VP), is evaluated in a real-world environment with satisfactory results [46,47]. The study has presented a comprehensive and novel technological framework, but the setting of optimal safety distances for UAVs is still not well articulated. According to previous studies, different voltage designs require different safety distances to be designed. Additionally, while the study generalizes some aspects, it is primarily limited to the inspection of grid towers; for transmission line inspections, it still faces limitations due to varying inspection components and purposes. The following study [48] proposed a navigation method for autonomous inspection of UAVs along the side of transmission lines, which utilizes transmission towers and lines to navigate the UAVs at the same time, relying on the PTZ camera (PTC) to assist visual guidance. The three closely related problems of tower localization, VP detection, and safety distance sensing are solved. The transmission tower can be regarded as a landmark for navigation, and a fast neural network (Tower R-CNN) is customized to accurately achieve reliable localization [49,50]. To navigate the UAV along the transmission line, an effective edge-based detection framework is also designed to compute and optimize the vanishing point (VP) of the PTL, and finally, the single-parameter uni-responsive optimization cost function is used to calibrate the Perspective image. Compared to the previous paper, this research improves on the lack of inspection functionality on transmission lines and pioneers the integration of neural networks and tracking algorithms, demonstrating good results in experiments.

Table 2 has proposed unique solutions, and these innovative approaches have inspired more innovative research by providing new ideas and possible research directions for future research. By comparing different studies, it is possible to get a comprehensive picture of the technological progress of UAVs in the field of power line inspection. Demonstrating applications ranging from basic computer vision to complex deep learning algorithms, these studies reflect the depth and breadth of technological development in the field and provide directions for future work, such as improving the accuracy and robustness of the algorithms, optimizing the UAV's navigation and surveillance strategies, and how to effectively integrate multiple technologies to enhance inspection efficiency and safety.

**Table 2.** The comparisons of UAV Transmission Line Inspection Methods from Five Studies.

| Feature/Method | Paper 1 [51] | Paper 2 [48] | Paper 3 [52] | Paper 4 [53] | Paper 5 [54] |
|---|---|---|---|---|---|
| **Main Technology** | Detecting-Tracking Visual Strategy (DTVS) | Monocular-Based Navigation with Neural Network | Neural Network-Based Line Segmentation and VP Optimization | Fusion of Deep Learning and Real-Time Tracking | Machine Learning and Computer vision |
| **Tower Localization & Tracking** | Faster R-CNN and KCF | Tower R-CNN and Fast Smooth Tracking | Neural Network and Line Segment Detector (LSD) | Faster R-CNN and Kernelized Correlation Filters (KCF) | MLP Neural Network and Hierarchical Tracking |
| **Navigation Strategy** | Perspective Model | Vanishing Point Detection and Distance Perception | Vanishing Point Detection and Line Filtering | Vanishing Point Detection and Multi-View Triangulation | Detection by Registration |

The focus of the above research is on improving the surveillance and detection of objects, while other studies on transmission lines take a more global approach. The upcoming research focuses more on groups of detected objects and developing efficient methods for system-wide detection, primarily through path planning strategies [55,56]. Several studies have proposed sampling-based path planning, such as RRT, RRT*, PRM algorithms, etc., which have the advantage of being able to quickly cover the formulated scope of work and converge to have a solution [57–59]. The proposed algorithm can distinguish between tower and line monitoring based on transmission line inspection content. Considering the UAV safety distance as well as designing a reasonable inspection path using the Genetic Algorithm (GA), a combination of the Genetic Algorithm and Genetic Simulated Annealing (GSA) algorithm is used to obtain an effective inspection path. Genetic algorithms have strong global search ability and can find the optimal result quickly. Although the algorithm can find the optimal value in a wide-range search, it does not specify how to retrieve specific components in transmission lines. Also, it failed to conduct comparative experiments to demonstrate the algorithm's superiority. In the process of UAV inspection, many optimization items need to be considered, the first and foremost being the energy source of the UAV and the number of grid facilities that can be retrieved. Therefore, some studies have proposed UAV inspection path planning for different optimization items after optimizing different items. In the study [60], a novel path planning algorithm is proposed that considers optimizing stringent energy availability constraints and achieving energy-efficient inspections. optimized for the energy consumption of UAV swarms during inspection operations, the proposed algorithm efficiently solves the inspection path planning problem in polynomial time, yielding significant performance gains in terms of minimizing overall inspection time and energy. A joint approach based on Bessel curves and Particle Swarm Optimization (PSO) is also proposed in the publication [61] to solve the problem of UAV road inspection of large PV farms, which fully takes into account the flight attitude, the limitations of the camera setups and the path lengths, and improves the efficiency and reliability of the inspection system.

The UAV path planning approach provides a fast solution for signal tower retrieval, but this solution focuses more on a single objective and is less well thought out in the face of a multi-objective task. A feasible approach is to combine path planning with an optimization problem, considering the impact of constraints on the overall task, and completing the specified task as best as possible within the constraints. In the study [62], a composite optimization problem based on a stochastic rapid exploration random tree (RRT) algorithm is proposed to maximize the number of grid inspections, maintaining the same quality of service (QoS) while ensuring line-of-sight (LoS) connectivity and enabling obstacle avoidance.The research utilizes an optimization model to enhance UAV-based inspections of Power Grid Towers (PGTs) in mountainous regions. It aims to maximize successful inspections across a set of PGTs denoted as $P_k$, assuming uniform Quality of Service (QoS) requirements. To formalize the inspection process, the research introduces the function $\alpha(p_k)$, where $k$ denotes the index of the PGT. This function serves as an indicator, assuming a value of $k$ upon successful completion of inspection and 0 in case of failure, where

$$\begin{aligned} &\text{maximize} \sum_{k=1}^{K} \alpha(p_k) \\ &\text{subject to} \\ &\qquad d_{\min} \le d_k \le d_{\max}, \forall k \in 1,2,\ldots,K \\ &\qquad z_{min} \le z_d \le z_{\max} \end{aligned} \tag{2}$$

$d_k$ represents the distance between the UAV and the $k$th PGT, and $z_d$ signifies the altitude of the UAV, ensuring it operates within predefined boundaries.The objective function $\sum_{k=1}^{K} \alpha(p_k)$ tallies the count of successfully visited base stations by the UAV, encapsulating the core aim of the optimization endeavor.By solving this optimization problem, UAV can finalize the inspection tasks in a highly efficient and safe way while considering all the constraints in a well-organized operation.

### *3.2. UAV Surveillance for Bridge Inspection*

After exploring the insights of UAVs in transmission line inspection, we now turn our attention to the emerging technology applications in the field of bridge inspection. Bridges are key nodes in urban and rural transportation networks, and their maintenance and safety monitoring are crucial for ensuring public safety and smooth transportation. With the acceleration of urbanization and the rapid development of transportation infrastructure, the safety and stability of bridges, as key links connecting cities, are particularly important. However, traditional bridge inspection methods are usually time-consuming, costly, and risky. Against this backdrop, UAV technology has emerged to revolutionize bridge inspection. With their unique mobility and efficient data collection capabilities, UAVs offer a whole new perspective on bridge inspections. They can easily reach all corners of a bridge, including those areas that are difficult or impossible to reach for human inspectors. With high-definition cameras and other sensors, UAVs are not only able to work around the clock but also provide accurate data that helps engineers identify and assess potential structural problems promptly. This section will delve into the use of UAVs in bridge inspections, demonstrating the important role UAVs play in the maintenance of modern urban infrastructure.

The traditional method of using manual labor to inspect bridges has similar flaws as manual labor for transmission line inspections, i.e., inefficiency and insecurity. UAVs are capable of accomplishing bridge inspections faster and more effectively. UAVs are capable of remotely extracting information on the structural health condition of bridges at different angles and orientations with the help of non-destructive or non-contact methods under emerging technologies such as photogrammetry, laser scanning technology, infrared thermography, sensors, machine vision, etc., either in a single or a networked composition [63,64]. For UAVs, the surveillance focus during bridge inspections is to detect safety hazards, such as structural cracks. This includes performing geometric measurements to determine the dimensions and positions of elements from a distance. Subsequent general inspections can involve defect quantification, moisture ingress identification, delamination detection, damage localization, displacement measurements, spalled surface identification, risk assessment, and progress logs maintenance. All these tasks can be efficiently executed by UAVs [65]. Since the focus of the research in this paper is to demonstrate the feasibility of UAV surveillance of bridges, no specific distinction will be made between the differences in surveillance effectiveness and associated planning between bridge sites and elements of bridges. In the subsequent content, the discussion will mainly focus on visual-based surveillance planning, which includes infrared light surveillance, machine vision, and sensor surveillance.

LiDAR plays an important role in bridge surveillance and inspection, and most UAVs inspecting bridges are equipped with LiDARr systems. UAVs using LiDAR systems can collect and analyze point cloud data to conduct surveillance and inspection of bridges [66–68]. Focusing on Genetic Algorithms (GA) and A* algorithms to solve the Traveling salesman Problem (TSP), this paper presents a 3D path planning approach for bridge inspections using UAVs equipped with Light Detection and Ranging (LiDAR) scanners. Potential locations of bridge surface defects (e.g., cracks) are considered to maximize flight time optimization while achieving maximum visibility. A well-demonstrated design solution for UAV path planning based on surveillance inspection [69]. In a previous paper, the authors explained the reason for using the A algorithm, since A produces shorter UAV paths compared to RRT, and shorter paths represent lower work time in a walk-through inspection task, since the object being inspected is known [70]. The study [71] uses a sampling-based RRT algorithm to traverse the full path searching and solving a convex optimization problem and proposes a fast and efficient path planning scheme for optimizing the computational complexity, and the path planning method is very practical in bridge inspection and power tower inspection, and shows scalability in terms of the computation time and the size of the inspection target. Considering smoothness and scalability, the Traveling Salesman Problem (TSP) is replaced with a new traversal path search, and the Art Gallery Problem (AGP) steps are replaced using sequential convex optimization to ensure detailed inspection and complete coverage of the objective. Besides these, in [72], an intelligent inspection method for transmission line UAVs based on LiDar technology is proposed to optimize the position between the current frame and the reference frame based on the distance and azimuth angle of the target that can be returned by the LiDar, on top of the positional attitude that has been modeled and estimated by the UAV for dynamics modeling. This LiDar-based transmission line inspection method ensures the real-time spatial position of the UAV and eliminates the effects of lagging visual positioning information. The study optimizes a key issue in power inspection and improves the quality of inspection, but does not propose a complete framework for the overall inspection task. In [73], it discusses the issue of standardized protocols for LiDar-equipped UAVs in transmission line inspection, which includes four data analysis steps, i.e., point cloud classification, critical point extraction, path generation, and fault detection, using LiDAR's ability to acquire high-precision spatial information to identify the location of each power line component to guide the UAV's route planning for inspection, and also validating the formulated concepts using a dataset,. and successfully achieved efficiency and cost optimization, providing a more feasible framework for LiDAR-based surveillance for transmission line inspection.

### *3.3. Research Gaps and Future Improvement*

In these sections, we explore in detail key technologies and algorithms for UAVs in bridge surveillance and inspection, innovations that demonstrate not only the sophistication of UAV technology but also its great potential in modern infrastructure maintenance. By integrating high-precision imaging technologies and complex and advanced planning algorithms, UAVs have become an efficient, safe, and economical method for bridge inspection and maintenance.

After an in-depth discussion of UAV technologies and algorithms for bridge surveillance and inspection, it is worthwhile to further reflect on future enhancement directions as well as gaps in current research. First, although UAV technology has made significant progress in the field of bridge inspection, there are still several key areas that require further research and development. For example, exploring the mode of multi-drone cooperative work, which can carry out bridge inspection in a wider range and more dimensions, and improve the inspection efficiency and coverage. Meanwhile, as bridge inspection requires large-scale data collection, efficient data processing, and analysis methods become increasingly important as the amount of data collected by UAVs increases [74,75]. Research should also focus on how to more quickly and accurately extract useful information from large amounts of image and sensor data. Finally, combining machine learning techniques to quickly identify hidden problems in bridges through data accumulation and learning is another critical area [76]. As technology continues to advance and innovate, the role of drones in bridge inspections will become more prominent and their capabilities more comprehensive. From increased levels of automation to enhanced data analytics, from multi-drone collaboration to increased adaptability and durability, these advances will provide more efficient and safer solutions for drones to perform infrastructure retrieval and surveillance tasks.

## 4. UAV Surveillance for Safety

### *4.1. UAV Surveillance for Search and Rescue (SAR)*

Time is of the essence when faced with natural disasters, emergencies, and search and rescue missions. This chapter focuses on analyzing and discussing the use of Unmanned Aerial Vehicles (UAVs) in Search and Rescue (SAR) oriented surveillance missions, highlighting their importance as an advanced technology in emergency response and personnel location. We will explore current strategies, technological innovations, and how UAVs operate in complex and challenging environments [77,78].

UAVs from DJI have already played an important role in many international rescue events [79]. Starting with an overview of the basic requirements of search and rescue missions, the chapter will provide insights into how UAVs can overcome limitations when it comes to large-scale disasters and complex scenarios, particularly in terms of rapid deployment, efficient surveillance, and precise positioning in hard-to-reach areas. The chapter aims to show the potential of UAVs to improve search efficiency, reduce rescue time, and enhance the safety of rescue operations. In addition, we will discuss the current challenges faced by these technologies, as well as possible directions for future developments aimed at further enhancing the role of UAVs in search and rescue missions.

The SAR approach is based on surveillance planning for path planning. This type of SAR process can be inspired by the herding behavior in agropastoralism, where in a herding scenario, we can simply divide the objects into two types: herders and animals. The herdsman creates a path to the destination for the animal by driving, shouting, guiding, etc., and the herdsman monitors the animal's behavior throughout the process and keeps the animal moving on the planned path. UAVs are gradually taking the place of herders for autonomous grazing [80,81]. We discuss UAV grazing behavior here to further inspire researchers to use similar ideas to solve the problem of realizing the UAV rescue of disaster victims in the framework of path planning. We can model the disaster victims as a similar movement model as animals and consider the evacuation point or safe zone as a grazing area, thus equating the two problems. Surveillance of targets to be rescued while planning a path for them to a safe zone reconstructs the surveillance problem into one that balances monitoring target dynamics with evacuation and rescue.

The study [82] describes a collision-free motion control algorithm for grazing large-scale populations of animals, capable of surveillance and navigating animals randomly scattered in a map to a target area, and based on the algorithms involved in sliding-mode control capable of path planning at animal boundaries. This type of behavior is similar to the framework we have designed for the search and rescue of disaster victims by UAVs and can be directly applied to search and rescue missions. The article describes the dynamic of animal flocking by boids model based on Reynolds' rules. This can be similarly applied to the modeling of disaster victims. In a disaster scenario, the group behavior of disaster victims conforms to four basic principles of collision avoidance, velocity matching to nearby members, the desire to be near the centre of the nearby members, and hazard avoidance. members and hazard avoidance [83,84]. Figure 7 shows this transferable method applied in human beings' search and rescue tasks. The blue star is used to represent destinations.

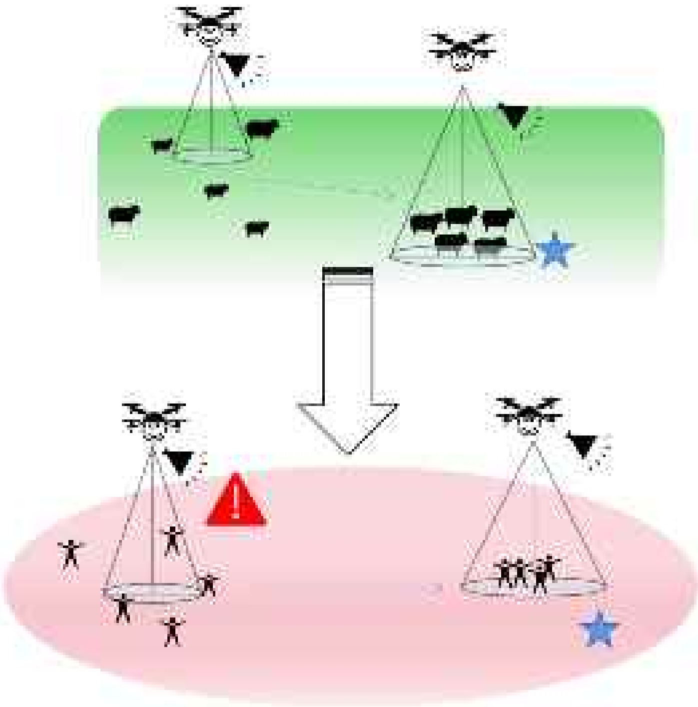

**Figure 7.** Herding Inspired Search and Rescue.

The UAV assigns positions to minimize the maximum distance between the animal and the centroid in the shortest possible time, and the extended fence vertices corresponding to the target animal are selected as the optimal positions of the UAV for guiding the target animal close to the centroid. These corresponding extended fence vertices are referred to as guidance points at which animals are efficiently gathered and can be surveilled by UAVs. In the second phase, a barking UAV configured with a broadcasting system is used to drive the animals under surveillance to the designated sites. The study [85] introduces path path-planning algorithm based on multi-objective optimization for SAR tasks.The study divides the task into multiple levels, minimizes the time to find the target and the time to establish a communication path, and plans to obtain the optimal path. By forming a link path to the target, the ground personnel are guided to perform the rescue. This research innovatively proposes algorithms that can be adjusted according to coverage or connectivity, which is fruitful in search and rescue missions. The drawbacks include insufficient discussion on the timeliness of the system and a lack of research on deployment in emergencies. However, in terms of coverage area, the study did prove the feasibility of its algorithm. Additionally, combining UAV and UGV for search operations is a promising avenue for future research. The paper [86] proposes a search and rescue system consisting of an aerial robot and a ground robot to perform search and rescue missions for unknown environments where obstacles are present, the aerial robot first surveils the area of interest and multiple targets, and then the ground robot is guided by the aerial robot to reach the target location. The combination of the two forms its proposed search and rescue system. This study fills the gap of polymorphic unmanned systems in the above studies, but its optimality has not been fully elaborated. A good demonstration of timeliness and obstacle avoidance capability is obtained, but coverage is lacking. Focusing on the application of search and rescue (SAR) for maritime accidents, the paper [87] transforms the SAR mission into a layered two-phase SAR mission. In the first phase, a UAV is used to perform grid-based zoning, which transforms a large spatial area and greatly reduces the resources required for the search. In the second phase, a mixed-integer linear programming problem is formulated to solve the optimal path to achieve optimal coverage of the area. In terms of coverage performance, the study achieves certain results with optimality, which is an excellent case of applying UAVs to SAR-based surveillance missions.

### *4.2. UAV Surveillance for Policing*

UAVs are used in a wide range of search and rescue missions, including searching vast areas, monitoring disaster sites, providing medical assistance, and delivering critical supplies. These missions require highly coordinated operations and rapid decision-making, with UAVs' real-time data transmission and visual information providing invaluable assistance. Meanwhile, police missions face similar challenges, requiring surveillance of criminal activity, tracking suspects, maintaining public order, and providing emergency support. Police surveillance missions often require rapid response, real-time information, and extensive surveillance coverage, and UAVs play a key role in policing. UAVs can also reduce risk to law enforcement officers, increase efficiency, and reduce costs, as well as provide critical intelligence and visual data.

The study [88] proposes a police UAV surveillance scheme that grids the area under surveillance to achieve dynamic surveillance over a large area, with the size of the grid depending on the surveillance and reconnaissance capabilities of the police UAV. The deployment of UAVs is differentiated according to the different needs of the grid attributes, and multiple UAVs are deployed for the monitored area to perform police search and surveillance by performing regional full-coverage path planning for undetected areas. In addition to the familiar police forces on duty in the city, police forces on the highway also need UAVs for police surveillance collaboration. Surveillance of moving targets is a great challenge to UAV surveillance performance, how to achieve high-quality surveillance and police collaboration is a problem to be solved at this stage of UAV highway police surveillance. The paper [89] shows the study for the police forces on duty in the city, police forces on the highway also need UAVs for police surveillance collaboration. Surveillance of moving targets is a great challenge to UAV surveillance performance, and how to achieve high-quality surveillance and realize police collaboration is a pending issue for UAV highway police surveillance at this stage. In the research, a set of UAV formation strategies with alternate leaders are designed based on different scenarios, where UAVs monitor and track moving units based on GPS information, share the data to the ground base station, and provide information to highway law enforcement police friction to help them track and intercept. Unlike the previous research, those focus more on the quality of surveillance [90,91]. In the paper [92], the UAV surveillance activity also considers the ability of covertness. The importance of covertness in UAV surveillance is especially critical when performing police missions, where exposing one's position information will alert the target under surveillance and cause the surveillance mission to fail [93,94]. The stealthy surveillance algorithm proposed in this study allows the UAV to change the angle and distance between the UAV and the target as frequently and drastically as possible during surveillance so that when the target tries to search for the surveillance UAV visually with the naked eye, the UAV can maintain a reasonable distance between the UAV and the target, which also makes it difficult for the UAV to be detected. At the same time, the algorithm also ensures the quality of surveillance by keeping the UAV on the target at all times with an optimal function and using the dynamic programming approach [95,96].

### 4.3. Research Gaps and Future Improvement

When using UAVs for surveillance missions for SAR purposes, most of the current research remains in simple environments and is mostly aimed at surveillance of natural disaster occurrences, while neglecting SAR surveillance in other complex environments, such as urban, marine, and mountainous environments. The review paper [97] describes the major shortages of UAVs in urban rescuing. One is the lack of autonomy in complex environments; traditional UAVs typically require external infrastructure for navigation and communication, and these may not be available in a disaster scenario. The second is limited energy, UAVs have energy constraints and are constrained in terms of flight performance, sensor capabilities, and computational resources. Third, there is a lack of reliable indoor and outdoor navigation, which prevents seamless indoor and outdoor navigation. The high computational demands for simultaneous tasks such as stereo processing, visual ranging, and laser ranging are a great challenge for UAVs.To solve this problem, more advanced perception and online planning algorithms can be used, using a combination of laser and stereo vision, planning optimization path to control energy loss distributed computing, etc. [98–100]. The paper [101] specializes in UAVs (Unmanned Aerial Vehicles) in maritime SAR. The need for efficient implementation of SAR at sea was emphasized, as fast and effective search and rescue operations are crucial when faced with disasters such as shipwrecks. The robustness of the UAV is also very important, as both wind and rain can affect the use of the UAV at sea. Battery capacity and flight time limitations of UAVs are major limitations. Therefore, effective energy management strategies are an important part of the equation, and improving the UAVs themselves by employing solar-powered UAVs to extend their operating hours is also a viable enhancement strategy [90,102,103]. The above two points mainly focus on the emergency response capability, coverage, sustainment, and robustness of UAV rescue missions. Another topic that has not been extensively studied yet is the collaborative rescue between UAVs and ground units such as unmanned vehicles and mobile robots, where UAVs are used to conduct surveillance and search and to issue commands for the unmanned vehicles to carry out rescue missions. In addition to the research, [86], which we have already mentioned above, research work has explored the possibility of UAVs and vehicles performing SAR-oriented surveillance missions within cities [104]. Using communication UAVs to monitor road events to plan the fastest path while considering road constraints. Efficiently providing information to rescue services takes into account the high mobility and limited energy capacity of UAVs. In addition to event monitoring, energy consumption can be balanced between UAVs, which communicate in an ad-hoc manner with existing vehicles on the ground to ensure rapid rescue by rescue teams. The resulting issue of SAR in urban scenarios is also worth discussing, and how UAVs can be used to better monitor unplanned events will also be a point of interest [105].

Overall, in UAV surveillance missions for SAR purposes, there is a need to focus on coverage capability, sustained operation capability, emergency response capability, the system's robustness, and expandability. As well as how UAV performs SAR surveillance in different scenarios such as field, mountain, city, ocean, etc., and how to overcome the effects of surveillance effect and SAR capability brought by these environmental factors. These are the core issues that deserve in-depth study in future research in realizing UAV SAR surveillance.

## 5. UAV Surveillance for Environmental, Archeological and Mining Applications

In this section, we will delve into the key role of UAVs in the field of environment, archeological, and mining applications and how they provide new perspectives on sustainable development and resource management. With global environmental and resource management increasingly becoming a key challenge, the use of innovative technologies has become critical. UAV technology has come to the fore, offering new possibilities and opportunities for environmental and resource surveillance.

The role of UAV's surveillance capability in the environment and resources field is mainly reflected in a more comprehensive perspective and the ability to fuse data, and the superiority of its surveillance capability demonstrates a level of technology that goes beyond over-mapping.

UAVs have become versatile in the field of environmental and resource surveillance, not only providing new tools but also creating solutions that contribute to scientific research, sustainable resource utilization, and environmental protection. In the next sections, we will review UAV surveillance for archaeology, ocean coast mapping and marine activities, wildlife, smart agriculture, geology, mining, and studying volcanoes.

### *5.1. UAV Surveillance for Archaeology*

In recent decades, UAV surveillance has changed the face of archaeology in different cultural, geographic, and climatic situations, providing archaeologists with a new powerful research tool. UAVs are capable of covering vast territories with ease, providing high-resolution imagery and maps. We will delve deeper into the key applications of UAVs in archaeology, describing how drones have improved the methodology of archaeological research and providing specific case studies demonstrating how UAVs have We will also provide specific case studies that demonstrate how drone surveillance has helped archaeology in different cultural, geographic, and climatic contexts.

The survey paper [106] provides a comprehensive overview of the evolution in archaeology from sensor detection to the use of UAVs for detection surveillance. The article reviews the technologies used in UAV archaeology and discusses how different sensor systems such as LiDAR sensors, Near-Infrared and multi-spectral Cameras, hyperspectral cameras, ground-penetrating radars, and how different sensor systems can be configured to perform archaeological surveillance tasks on UAVs [107–110]. Due to the unique morphology, stratigraphy, topography, and archaeological features of each archaeological site, the automation of historical site detection is undoubtedly a complex and challenging task, and due to the need for increasingly accurate data acquisition and data generation, the use of sophisticated processing and analytical techniques derived from UAV sensing allows for a promising future in the direction of UAV-aided archaeological exploration, detection, and surveillance research.

As mentioned above, because of the difference in morphology, stratigraphy, topography, and archaeological features of each archaeological site, UAVs performing archaeological missions will be deployed differently depending on the location, and therefore a discussion of UAV archaeological operations in different regions, cultures, historical stages, and states is necessary. In the paper [111], UAVs are applied at the Chalcolithic archaeological sites in the Mostistea Basin and Danube Valley (Southern Romania). The area lays the foundation for defining two iconic prehistoric cultures of the Northern Balkans - the Boian and Ancient Melnica cultures. The full surveillance coverage of the area of interest by the UAV through path planning algorithms and the subsequent 3D reconstruction of the area through data integration, orthophotography, digital elevation modeling, and 3D modeling, the UAV used for the mapping, recording, and monitoring of the archaeological sites, helps archaeologists to follow up close the process of transformation of the archaeological sites and landscapes, which brings a new step forward in the program of the study of the sites of the Red Bronze Age in the target area. Other articles [112–114] similarly used UAVs to perform a multi-data sensor fusion of topographic information from archaeological remains, demonstrating the efficiency of UAVs for mapping and data integration of archaeological remains.

In addition to the use of surveillance ability in modeling and data collection of natural environments in historical sites, UAVs play an important role in the archaeology of man-made structures. The research [115] focuses on the process of mapping the rocky city of Vardzia, carved into the steep tuff slopes of the Erusheti Mountains, based on advanced remote sensing techniques and UAV-based digital photogrammetry [116,117], to map the potential hazards of the rock complex, after meticulous deployment, the UAV helped archaeologists to obtain high-resolution orthophotos of the Vardzia escarpment and the overlying slopes, as well as a complete 3D digital models, which can be effectively applied to detect protection criticalities affecting the Vardzia rock monastery complex, to detect slope criticality on a large scale, and also in hazardous areas that are difficult to access, while ensuring the safety of the operators.

In addition to facing large-area and large-scale mapping tasks, an important direction of UAV application in archaeology is the use of lasers or vision cameras for data acquisition and 3D reconstruction of archaeological targets. The study [118] uses photogrammetry to generate 3D models of ancient Phrygian lion tombstones. It uses UAV flight surrounds to process irregular and overlapping aerial image data to generate geo-referenced 3D point clouds that allow researchers to analyze surface features such as color, moss, and cracks from the results of UAV surveillance. The paper [119] has inspired more archaeologists to discover the UAV's capabilities in 3D reconstruction and use it to rebuild past work methods of monitoring archaeological targets with manual photo compositing. In another paper around refining the structural challenges of ancient buildings and the challenges of reconstruction to achieve improvements in accuracy. A new method of 3D reconstruction of ancient buildings combining 3D laser scanning and tilt photogrammetry is proposed, which utilizes a feature point matching algorithm to achieve accurate fusion of multi-source data, collects and constructs a complete 3D model of the inside and outside of the ancient buildings, and performs relative median error calculations, which restores the traditional ancestral temple architectural information and models. It greatly improves the modeling efficiency and can provide important technical support for the restoration and protection of ancient architectural cultural heritage.

### *5.2. UAV Surveillance for Coast Mapping and Marine Activities*

Coastal areas are usually rich in geographic diversity, which makes it difficult for traditional ground-based mapping and remote sensing methods to obtain comprehensive and accurate coastline data, while UAVs can capture detailed coastline images and provide more accurate geographic information data with outstanding video surveillance ability, and can also carry out a combination of multiple types of mapping data to provide more comprehensive coastline information to cope with a more complex geographic environment and to give full play to the high resolution of UAV technology, flexibility and low cost. Coastline mapping and monitoring marine activities is one of the key applications of UAV surveillance, offering unprecedented opportunities for marine resource management, ecological protection, and climate research. The high altitude view and flexibility of UAVs make them a powerful tool for monitoring and protecting the marine environment as well as people engaged in activities at sea [120]. UAV surveillance provides unprecedented accuracy and efficiency in shoreline mapping. From shoreline geography to land-use planning, UAVs can capture extremely detailed shoreline imagery, helping to better manage coastal resources and ecosystems.

In the paper [121], UAV photogrammetry and GNSS techniques combined with surveillance were utilized to study natural and human-induced morphological changes in coastal areas. Unlike the single topographic observation and remote sensing techniques commonly used in the past [122,123], this study employs UAV-mounted 3D photogrammetry and fused GNSS techniques to generate 3D models to understand and quantify geomorphic changes through trajectory interpolation for comparison and validation, while orthophotos are used to highlight changes in the coastal shoreline. UAVs have dramatically improved accuracy and efficiency over past manual or photographic approaches. Another research [124] utilized UAV remote sensing to detect shoreline changes, using UAVs to collect both LiDAR and image data; the UAVs were able to achieve greater and more uniform ground coverage and higher point densities in different geomorphic environments than traditional methods, combining long-distance mapping with LiDAR and overcoming the lack of flexibility in mapping in the past [125–127].

In addition to being able to utilize the superiority of UAVs in coastline mapping, environmental monitoring missions targeting the offshore can also see UAVs in action. Ecological monitoring is an area of interest for UAV surveillance, especially in the marine environment, where changes in the environment directly affect biodiversity and fisheries-related activities, and where marine monitoring is one of the most challenging types of UAV surveillance deployment missions due to the presence of wind and waves [128]. The importance of monitoring the marine environment for early warning and assessment of meteorological conditions and ecosystem disasters was emphasized. The limitations of existing marine monitoring platforms, such as offshore platforms, ships, or buoys, in terms of low spatial resolution and high cost of data acquisition were noted. Autonomous unmanned platforms, such as UAVs and UGVs had the advantages of being easy to deploy, intelligent, flexible, mobile, and cost-effective in data acquisition, allowing for the rapid acquisition of data with fine spatial resolution and real-time monitoring of marine pollution and risks [129]. Traditional methods use cursors for monitoring, but this method lacks flexibility, while using UAVs would not be able to cover the vast marine environment due to energy constraints, so using a hybrid sensor surveillance network that combines the two is a good alternative [130,131]. A hybrid sensor network combining a UAV and a cursor is used in the paper [132], which uses a swarm of drifting buoys as the main environmental sensors to cover a wide coastal area and a UAV as a data receiver and a dynamic network router, providing transmissions that are below background noise and are also highly resistant to external interference.

In addition to surveillance of the marine environment, UAVs are also capable of monitoring human activity within the waters. A novel application scenario is the surveillance of human and shark activities in the ocean to protect offshore safety. This topic has generated a lively discussion in recent years because past means of repelling sharks have not been responsive enough and can also cause unnecessary harm to sharks [133–135]. UAVs can now be used to form a network of sensors that, in combination with acoustic devices, frequency transmitters, and cameras, can be used for shark activity prevention and control using broadcasting, frequency banding, and visualization, while at the same time protecting the safety of those who are active offshore [136]. A novel UAV shark protection scheme incorporating complex algorithms has been proposed [137], where shark interception algorithms are designed to guide UAVs to reach predicted intersections to stop sharks using multiple UAVs in formation and surveillance, to achieve the pursuit and surveillance of sharks, and to do no harm to the sharks.

### *5.3. UAV Surveillance of Volcanoes*

The use of UAVs in volcano monitoring combines volcanology and advanced UAV technology to better understand and monitor volcanic activity [138]. Volcanoes are one of the most dynamic and unpredictable geological phenomena on Earth, and eruptions can pose a significant threat to nearby people and the environment. Therefore, understanding the active state and behavior of volcanoes is critical to protecting public safety. The introduction of UAVs has provided a new means of volcano monitoring by allowing them to fly over hazardous areas and capture high-quality images and data, playing a key role in protecting neighboring communities, studying volcano activity, and providing real-time monitoring. Many studies are currently utilizing UAVs to map and monitor volcanic terrain, to obtain topographic and geothermal data in complex volcanic areas with limited information, to assess and predict volcanic activity, and to achieve disaster mitigation and prevention [139–141]. The challenge before the volcano surveillance UAV is how to overcome the difficulty of surveillance in complex terrain, where traditional camera-based surveillance methods are unsustainable in high-temperature and high-pressure environments. This research article proposes the use of magnetic field measurements by UAVs in addition to making visible and infrared measurements. The method has shown excellent results in mapping structural contacts between different ages or types of strata, as well as deep thermal anomalies and intrusive systems, demonstrating that low-altitude measurements are particularly relevant to clearly imaged magnetic anomalies and their changes over time in the volcanic context and that it is possible to use UAVs to efficiently monitor the dynamics of the volcano, while also maintaining the robustness of the system, which is better in efficiency compared to previous methods [142]. Another application scenario for volcano surveillance is surveillance after an eruption, where the use of UAVs enables rapid, low-cost surveillance and mapping of the altered volcanic terrain. Satellite remote sensing is slow and has a long response period for mapping post-eruption terrain, and smoke due to volcanic eruptions can also have a significant negative impact on satellite remote sensing. Therefore, UAVs are needed for rapid post-disaster response, and the study [143] uses UAVs to map the terrain, detect changes, and analyze the volume of a post-eruption volcano to help with rapid response in post-disaster management.

### *5.4. UAV Surveillance of Wildlife*

Wildlife is vital to the maintenance of ecological balance and biodiversity, and UAV surveillance has become a powerful tool for scientists. UAV surveillance records and analyzes the behavior of wildlife, tracking animal migration, breeding behavior, foraging habits, and so on, providing valuable data for behavioral ecology studies to help them track animal abundance and behavior, as well as protection and conservation efforts. Wildlife conservation is another important area for UAV surveillance. UAVs can monitor offenses such as illegal hunting, poaching, and wildlife trade, which can help law enforcement agencies combat wildlife crime. In addition, UAVs can help track injured wildlife and provide rescue and medical help. UAV surveillance also focuses on the coexistence of humans and wildlife. They can monitor the impact of human activities on wildlife habitats, help manage conflicts, and promote sustainable development [144]. Different types of animals have different living environments and activity patterns, and the use of UAVs for surveillance will often be adapted to the characteristics of the target according to different animals. Many studies have been conducted on whales, monkeys, wildebeests, and other organisms that have been subjected to surveillance and abundance measurements using UAVs [145–152].

Covert surveillance is a topic worth exploring, especially in animal surveillance missions. The application of UAVs in animal surveillance has been introduced above, and with the development of technology and the advancement of concepts, minimizing the impact on animals during surveillance is one of the current topics worth discussing. One feasible idea is to use covert methods for surveillance, of which there are many covert methods, such as using navigation methods, using special equipment, and adopting strategies for optimal deployment [153,154]. The primary concern during the surveillance of animals is solid quality, and generally speaking, the imaging is better when the UAV is closer to the animal under surveillance, but this can also pose a huge problem in terms of the impact and injuries caused when the UAV trespasses on the animal's territory [155,156]. To solve this problem, when conducting surveillance on animals, in addition to ensuring the quality of surveillance, it is also necessary to avoid affecting the living conditions of the animals as much as possible. The research from the paper [157] introduces a navigation method for covertly observing a group of animals and their habitats, based on the law of navigation in sliding mode, which guides the UAV to minimize the maximum change of orientation and continuously adjusts the bit position during the close observation mission to reduce the monitored animals and realize the purpose of covert surveillance. This type of dynamic smoothing regulation is of greater interest when compared to the commonly used method of reducing the impact of surveillance by simply expanding the distance to the monitored animal [158–160]. Derived from the inspiration of carnivores, which engage in a range of covert behaviors when hunting. Around this, the paper [161] developed a biomimetic (biologically inspired) motion camouflage-based UAV navigation algorithm for covert surveillance of moving targets. The proposed UAV navigation mimics a stealth behavior typical for some predators such as dragonflies or hunting falcons. The key feature of the algorithm is that it relies only on azimuthal measurements and does not require the speed or distance information of the target. In the research [162], a bionics-based study of UAV Network surveillance is presented, combining the hybrid grey wolf optimization algorithm with bionic localization to propose a new clustering (BIC) scheme, which greatly improves the utilization of the clusters and reduces the latency. A new algorithm is proposed for optimizing the propulsive power and 3D trajectory of a solar-powered fixed-wing UAV in camouflage tailing and video surveillance missions [163]. The algorithm is validated for its superiority in terms of visual camouflage and power efficiency concerning the existing schemes and also extends the surveillance mission's Duration. In the paper [164], the use of solar-powered UAVs for covert surveillance of a single target is discovered. This approach strikes a balance between maintaining visual camouflage and efficient energy management. The trajectory of the UAV is optimized to remain undetected by the target for optimal surveillance efficiency and energy efficiency.

### *5.5. UAV Surveillance for Mining*

UAVs play a vital role in exploration, mining, reclamation, and resource management in the mining sector UAV surveillance can provide high-resolution geological imagery, laser scanning, and thermal infrared data, which can help geologists to better understand the composition and distribution of underground deposits and provide more accurate exploration and resource assessments, thus improving the efficiency and feasibility of mining. UAVs can also be used to monitor mineral extraction activities in mining areas, capture the progress of mining works in real-time, check safety and environmental protection measures in mining areas and provide response support in case of emergencies, as well as monitor the state of mining, land use, water management, and environmental impacts, among other things, which can help to formulate sustainable mining plans and protect ecosystems. This is essential for balancing resource development and environmental protection [165–167]. The surveillance capability of UAVs is firstly utilized in the stage of mining exploration, in the research [168], a method of using autonomous flying robots to explore underground tunnel environments and build 3D maps is proposed, the navigation algorithm used, by measuring the minimum distance to obstacles and measuring the horizontal scan of obstacles in front of the UAV for navigating the robot searching in tunnels to avoid collisions with the tunnel walls, and in mine The process of exploration kind of 3D mapping, providing a scalable solution for mine exploration navigation and monitoring. The purpose of underground surveillance is to remove obstacles and hazards, build a relatively safe environment, and collect relevant data to help engineers improve efficiency [169,170].

In the research [171], a low-altitude UAV using a surveillance system was investigated in acquiring high-resolution images to reconstruct the geometry of an open pit mine. A comparison of DSM generated from UAV point clouds and DSM generated from Terrestrial Laser Scanner (TLS) data was evaluated and fairly accurate data was obtained. Other studies [172,173] have utilized different types of UAVs to topographically survey different open pit mines and obtain surveillance photographs of the study area. The study [174] utilized sky bottom and inclined aerial photographs obtained by UAV surveillance system as a means of reconstruction of the quarry topography.

### *5.6. UAV Surveillance in the Arctic*

The extreme environments of the polar regions and their sensitivity to global climate change make continuous monitoring of the region critical, and we will explore the use and importance of Unmanned Aerial Vehicles (UAVs) for surveillance in polar environments. Low temperatures, strong winds, and remote geographic locations present special challenges for UAV operations. This section begins with a background on polar surveillance and its requirements for UAV technology and will focus on how UAVs can overcome the technical challenges of effective surveillance in extreme climatic conditions, providing an in-depth analysis of the use of UAVs in Arctic surveillance [175,176].

In the era of rapid global and regional climate change, the use of UAVs to monitor subtle changes in polar regions and ice shelves is essential in environmental protection and resource utilization. In polar terrain, the main objects monitored by UAVs include glacial calving, crevasses, surface subsidence, ice landforms, atmosphere, plants and animals [177–181]. Limitations in temporal and spatial resolution, weather conditions that can also interfere with satellite remote sensing data, and restrictions on authorized aerial operations due to security and resource constraints are all challenges for UAV surveillance missions in polar environments. Many studies have been conducted to propose optimized solutions based on the functional characteristics of video surveillance [182–184] Arctic regions are rich in undeveloped mines and natural gas fields, but due to the complexity of the terrain and the instability of the climate, most of them are dispersed over a wide area, making the monitored space quite fragmented. Traditional remote sensing and mapping platforms require a lot of manpower and resources for monitoring, nowadays UAVs are used instead of manpower to monitor the movement of deformations on the surface of tailings deposits due to subsidence, and to better carry out the task of mining surveillance in subarctic climates, and the results of the surveillance will help the managers and the companies to carry out the reservoir management operations and to track the surface displacements within the decimeter range, for better planning and safety precautions [185]. In video surveillance of polar environments, UAVs provide a key solution in the study of polar terrain such as rift valleys, crevasses, and subsidence, overcoming the lack of resolution of satellite observations. UAVs can repeat the collection of high-precision data based on previous meteorological surveys, helping researchers to accurately characterize the ice surface. This also supports the future integration of UAV video surveillance with other technologies such as LiDAR solutions, GNSS, and fused sensor solutions [186–189].

At the same time, the biological status of the polar regions can also be extensively monitored using UAVs to learn about the behavioral status and abundance of animals, and UAV video surveillance can be accurately and widely applied to assess the ecological status of organisms and appropriately minimize the incursion of human activities into animal territories [190–193]. It is worth noting that animals are less responsive to UAVs than humans, and their reactions are gentler. Concealment is quite important when using UAVs for animal surveillance, which is described more specifically in another section.

### *5.7. Existing Research Gaps and Future Research Directions*

UAV surveillance has already made significant progress in environmental protection, ecological research, and resource management, but we also see many potential research gaps and opportunities that deserve further exploration and exploitation.

In future research, we need to look more deeply into sensor technology and data integration to obtain more comprehensive and high-resolution environmental and ecological data [194–197]. Meanwhile, intelligence and autonomy are key areas that need to be continuously improved in the field of UAV surveillance to adapt to the complex and changing natural environment and mission requirements. Real-time data analytics and decision support will continue to evolve to better support emergency response, resource management, and environmental protection decisions. At the same time, compliance and privacy protection issues will continue to be of concern, and solutions will need to be found to ensure the legal and ethical use of data.

Multi-modal and multi-environmental applications are an important trend for the future, and UAV surveillance will play a greater role in areas such as ocean monitoring and wildlife protection [198,199]. These diverse applications will require more research to adapt to different environments and mission requirements. On top of that, the addition of AI makes the task more interesting, with more flexibility and better adaptability of the AI-driven UAVs as the arithmetic ability increases [200].

Research on integrating sensor networks to enable data collection will also greatly assist in the development of the above research topics [201,202]. In archaeological surveillance and geographic and mining surveillance, the integration of virtual reality and augmented reality technologies [203], as well as site reconstruction and 3-D modeling technologies that drive UAV automation [204,205], will provide archaeologists with additional tools and methods for more in-depth study of archaeological sites in different cultures, geographies, and climates. The field of UAV surveillance holds great potential for environmental, ecological, and resource management, but also presents numerous challenges and opportunities. Future research and innovation will continue to advance the field and provide new solutions to the complex problems facing the planet.

## 6. Future Research and Challenges of UAV Surveillance

The utilization of Unmanned Aerial Vehicles (UAVs) in surveillance applications has witnessed remarkable growth, driven by advancements in technology and an expanding range of use cases. This section delves into the emerging frontiers and the multifaceted challenges in UAV surveillance. For UAV surveillance missions, the challenges faced come from several main sources. One is the coordination and co-working of multiple UAV networks, as well as the synergy between UAVs and other devices such as unmanned vehicles, ground base stations, and sensors [206,207]. The construction of the UAV surveillance network brings more freedom, which enables UAVs to better fulfill their missions with the help of the capabilities of other units while conducting surveillance and thus can come up with composite missions based on surveillance. However, when there is more intelligence in the network, the control also becomes more complex, so how to design the surveillance network will be one of the key issues that future researchers need to focus on [164,208]. Secondly, the impact of complex environments on UAV surveillance tasks. In the past, research often focused only on the ideal environment for UAVs to perform surveillance tasks, but in reality, UAVs often need to perform surveillance tasks in mountainous areas, cities, forests, etc. The complex environment not only creates a great challenge for surveillance but also creates a lot of difficulties for UAVs' autonomous obstacle avoidance as well as path planning. Researchers need to judge the complex environment and design the optimal path or optimal deployment for UAVs to ensure the quality of surveillance [209,210]. The third challenge is the integration of UAV surveillance with AI [4]. Machine learning, neural networks, and generative AI are now the focus of attention in both the scientific and engineering communities, and these AI tools will greatly assist UAVs in their surveillance tasks, finding optimal methods, and even allowing UAV surveillance to autonomously developing unique strategies for specific targets and situations. The last challenge addresses the UAV's energy issues, as it is well known that the range of a UAV limits its surveillance capabilities. UAVs have limited batteries, and replacing UAVs, replacing batteries, or designing strategies for rotating UAVs will waste some time and increase costs. One possible direction is to configure surveillance UAVs with hybrid energy sources to extend their range [211].

We commence with an exploration of integrated UAV surveillance networks and sensor fusion, emphasizing the synthesis of heterogeneous data sources to enhance situational awareness. In addressing the challenges of UAV surveillance in complex environments, we confront the intricacies of operating in varied and often unpredictable terrains. The role of AI-based Methods in enhancing the intelligence and autonomy of UAV systems is then examined, showcasing how artificial intelligence is revolutionizing UAV capabilities. Lastly, we turn our attention to hybrid energy source UAV surveillance, underscoring the need for sustainable and efficient energy solutions to extend UAV operational longevity. Together, these subsections provide a comprehensive overview of the current state and future trajectory of UAV surveillance technology, laying the groundwork for continued innovation in this dynamic field.

### *6.1. Surveillance Network of Cooperating Unmanned Vehicles*

The importance of UGV-UAV synergistic control lies in the complementary nature of their respective unique capabilities and limitations. UGVs specialize in ground-based missions such as navigation and physical interaction, while UAVs can quickly cover vast areas and conduct surveillance from the air. When these two systems work effectively together, they can overcome the limitations of a single system and achieve wider surveillance coverage, more efficient data collection, and greater mission adaptability. By using appropriate optimization strategies, it is possible to ensure that UGVs and UAVs achieve optimal path planning and decision-making when performing common tasks, thus improving the performance of the entire surveillance network [212–215]. In our previous content, we mentioned that UAVs need to consider optimization metrics such as optimal coverage, optimal quality of surveillance coverage, or quality of surveillance service (QoC/QoS) when performing surveillance tasks, which is a relatively well-solved problem for single UAVs, whereas for multiple UAVs, more constraint variables and optimization complexity pose more challenges, and in the surveillance process must also consider obstacle avoidance, thus requiring researchers to propose new feasible algorithms. The paper [21] proposes a passive obstacle avoidance algorithm to help UAVs adjust their position while surveillance, taking into account both horizontal and vertical motion navigation strategies, and the algorithm ultimately converges to be optimal for the metric of Quality of Surveillance Coverage (QoC).In the research [216], UAV perceptive mobile networks that simultaneously consider sensing coverage, noise perturbation, and communication capabilities are proposed. This UAV network is able to achieve comprehensive surveillance of the area and interaction with the base station, which is of positive significance for the design of smart body network in the future 6G smart city, challenging the problem of being deployed in limited locations when UAVs form a surveillance network in the past, and realizing comprehensive surveillance in the perceptive state. The value lies in the exact consideration of dynamic and static constraints on the collision and deployment positions of UAVs in practice to achieve surveillance optimization. The network structure composed of UAVs and unmanned vehicles is also a major direction for future development, and often they combine different tasks. UAVs are responsible for space surveillance, while UAVs can provide surveillance help on the ground or perform other tasks, making the entire network present an autonomous, intelligent, t and hierarchical operation structure that greatly enhances the scalability of the system.UAVs can monitor traffic and communication information from an aerial perspective, capture target dynamics, and share them with unmanned vehicles, which can perform tasks based on the information provided by the UAVs [217,218]. Using the above design to solve problems and challenges in UAV networks will increase its effectiveness and utility in multiple application scenarios.

In addition to the UAV surveillance network, which consists of clusters of UAVs, UAVs can be used to form a more comprehensive surveillance network with unmanned ground vehicles (UGV) and unmanned underwater vehicles (UUV) [219,220]. In the paper [221], A UAV-USV-UUV network for collaborative underwater target surveillance and search, an energy-optimal oriented target hunting model incorporating the DQN algorithm, is proposed. For the multi-intelligentsia collaborative problem, it is crucial to coordinate the communication between them, in this paper the connection between UAV and USV is based on the EM channel, and the acoustic channel is used for signaling between UUV and USV.USV operates as a wireless communication relay. The system proposed in the article is well implemented for target monitoring and capturing and always finds an optimized path to search the target quickly with minimum energy. In addition to underwater collaborative networks, another meaningful collaborative network is a forest wildfire surveillance network combination of UAVs and UGVs. The paper [222] proposes an unmanned surveillance network of UAVs and UGVs that allows for autonomous collaboration and wayfinding to monitor burn sites. The UAV monitors the area following a forest fire from the air, providing navigation for the UAV to inspect the burn sites, and the UGV patrols the points marked in the UAV surveillance along the path with centimeter-level accuracy. In the research [223], the UAV IoT solution for wildfire detection is proposed to optimize the fire monitoring probability of UAVs for the deployment density and the number of UAVs, to achieve the maximum probability of fire monitoring and discovery under constraints, and to incorporate a Markov chain to analyze the probability of surveillance and the probability of failure, which suggests a flexible and efficient processing solution for future wildfire monitoring.

*6.2. UAV Surveillance in Complex Environments*

We focus on surveillance of complex environments such as uneven terrain, mountains, forests, and cities, with special attention to optimizing strategies and algorithms. These environments pose special challenges for the effective deployment and operation of UAVs due to irregular terrain, dense vegetation, and complex urban structures. Our goal is to analyze and demonstrate how advanced algorithms and strategies can be used to optimize the performance of UAVs or UAV networks to improve the efficiency and accuracy of surveillance missions [224–227]. Uneven terrains and other complex environments, such as mountainous and rugged areas, can obscure the surveillance process, while surrounding objects can challenge the UAV's navigation and stabilized flight when performing surveillance missions, requiring the UAV to have efficient obstacle detection and avoidance capabilities, and requiring more advanced environmental awareness capabilities and autonomous decision-making solutions to ensure the reliability of the UAV system in a variety of complex environments as well as the surveillance quality of surveillance in various complex environments.

In the research [228], an effective navigation algorithm is proposed that takes into account the time when the sight distance between UAVs and ground vehicles is not obscured by the uneven terrain and the distance between UAVs and vehicles as seen from these UAVs, and improves the quality of the video surveillance by maintaining the sight distance between UAVs and vehicles for as long as possible as well as by navigating the UAVs to keep the distance to the ground vehicles as short as possible to improve the quality of the video surveillance and to overcome the negative effect of the uneven plane on the problem of video surveillance by a group of UAVs on multiple ground vehicles moving on uneven terrain is solved. This type of method seeks to maximize the effective surveillance time and minimize the proportion of affected parts, thus maximizing the ratio of surveillance quality to surveillance time. In the paper [229], two distributed algorithms based on Virtual Force and Local Voronoi are proposed to allow UAVs to change their surveillance angle and surveillance projection area through vertical and horizontal displacement, reorganize the multi-UAV surveillance network according to the terrain, overcome the line-of-sight loss of surveillance brought by the uneven environment, and realize the hole-free full coverage of the target area. To deal with path planning problems in complex and uneven surfaces, in [230], a reactive path planning algorithm that does not rely on a priori knowledge is proposed. It gives the coordinate conversion matrix $D$ as:

$$D = \begin{bmatrix} \sin\alpha\cos\beta & \cos\alpha\cos\beta & \sin\beta \\ -\sin\alpha & \cos\alpha & 0 \\ -\sin\alpha\sin\beta & -\cos\alpha\sin\beta & \cos\beta \end{bmatrix} \tag{3}$$

They introduce $\alpha$ to represent the angle between the $x_0$ axis and the $x_1$ axis, while $\beta$ represents the angle between the $x_1$ axis and the $x_2$ axis and conver them between the resulting coordinate system and the initial coordinate system is given by:

$$\begin{bmatrix} P_i \\ 1 \end{bmatrix} = \begin{bmatrix} {}^u_g D & {}^g P_{st} \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} {}^u P_{g0} \\ 1 \end{bmatrix} \tag{4}$$

where $P_i = [x_{st}, y_{st}, z_{st}]^T$ represents the point in the original coordinate system, and ${}^u P_{g0} = [x, y, z]^T$ is the point after the conversion.Then the matrix can transfer the obstacles and terrains' location into UAV's coordinates.Then the navigation method shown as follows

$$\begin{cases} \beta^i(t) = \alpha^i(t) \pm \alpha_{\text{safe}}, \\ \angle L1(t) = \cos\big(\beta^i(t)\big), \\ \angle L2(t) = \sin\big(\beta^i(t)\big), \\ \triangle V(t) = V_{\max} - \|v_x(t)\|, \\ l^i(t) = \triangle V(t)[\angle L1(t), \angle L2(t)]. \end{cases} \tag{5}$$

This adaptability to complex environments and the ability to handle navigation over uneven ground is not common in previous UAV navigation methods, usually those methods either rely on pre-calculated map data or are deficient in handling altitude changes and dynamic obstacles. This method is able to quickly respond to changes in the environment without the need for a predefined environmental model, thus maintaining stable and safe flight in unknown or dynamically changing complex environments. This capability is important for increasing the value of UAV applications in complex missions such as disaster response and environmental monitoring.

In addition to this, the challenges of UAVs performing missions in different weather need to be looked at. The fundamental challenge is the impact of unpredictable perturbations and noise on stability in UAV planning, such as preventing flights on the original route, instability in transit, and damage to the UAV system. How to plan surveillance missions for UAVs in windy and rainy environments and the path planning designed to enable surveillance is a topic of discussion because of the unpredictability of weather conditions, UAVs need more robust algorithms and planning to cope with the challenges posed by weather [231,232]. In [233], a solution to the UAV mission planning problem considering weather forecasting and energy consumption constraints is proposed, by proposing a declarative framework that makes it possible to build a reference model to analyze the relationship between the structure of a given UAV supply network and the potential behavior, which in turn generates a sequence of submissions that follow the requirements, taking into account collision avoidance, weather variations, and energy consumption constraints, and develops specific UAV routing and scheduling problems. This study has positive implications for future research on robust mission planning for UAVs in extreme weather conditions. Future research could go further and explore further in terms of different mission types, and different levels of disturbance, i.e., the drasticness of the climate, and different models.

Overcoming the challenge of uneven terrain and weather has significantly improved the operational efficiency and safety of UAVs in complex environments, expanding their areas of application and meaning that UAV technology is now able to more reliably carry out a variety of missions, such as target surveillance, communications monitoring, and search and rescue operations, even in previously inaccessible areas. This drives further innovation and development of UAV technology, laying a solid foundation for future applications in more diverse and challenging environments.

### *6.3. UAV Surveillance Using AI Technology*

AI algorithms can help UAVs quickly process large amounts of surveillance data and make accurate decisions in changing environments, planning optimal paths or optimal deployment locations, and machine-learning UAVs can achieve surveillance faster and more accurately [234]. At the same time, AI can also help UAVs perform complex tasks more autonomously and adapt to different environments and situations, improve UAV flight safety, and reduce the risk of accidents through better obstacle detection and avoidance systems. Currently, AI-integrated UAVs have had good results in several fields, such as communications, navigation, and urban flight navigation [4,235–237].

In [238], it transforms the real-time path planning and communication control problem for Unmanned Aerial Vehicles (UAVs) into an AI-learning task that can be solved by DRL. Two DRL agents are proposed and trained, respectively, to make these two models for UAVs in real-time navigation agents follow the best energy-efficient trajectories with maximum ALoS links, considering three factors UAVs practice signal surveillance and communication process energy consumption, collision avoidance safe flight and communication performance, solving the highly random and dynamic mobile vehicular networking problem when UAVs perform surveillance and communication tasks in the city and the navigation through obstructed high-density areas, showing better performance and significant savings in computational stress. The navigation and communication task of a

UAV is defined as an optimization problem that maximizes the quality of communication coverage provided by the UAV while considering energy consumption, flight time, and dynamic environmental factors. It chooses deep deterministic policy gradient (DDPG) as the DRL algorithm to self-optimize based on well-defined reward signals [239–241]. The DDPG algorithm updates the policy network by a gradient ascent method to maximize the expected reward of learning the flight and communication control policies that perform optimally in a given task. Typically, model construction for DDPG requires the following.

$$\begin{gathered} S \subseteq \mathbb{R}^n \\ A \subseteq \mathbb{R}^m \end{gathered} \tag{6}$$

Equation (3) defines state space, action space, and reward function. The state space defines all possible states of the environment, which in the scope of our discussion is the set of all situations that can be observed by the UAV. For example, the current position of the UAV, its speed, or information about its surroundings. The size and complexity of the state space directly affect the difficulty of the learning task. The action space, on the other hand, contains the set of all possible actions that the agent can take. For a UAV, actions include moving in different directions, changing speed, etc., and defining how to interact with the environment. The reward function is key in reinforcement learning and defines the immediate reward for taking a particular action in a given state. If the drone achieves the goal, he will receive a positive reward and vice versa.

Additionally,

$$J(\pi) = \mathbb{E}_{\tau\sim\pi}\left[\sum_{t=0}^{T} \gamma^t R(s_t, a_t)\right] \tag{7}$$

$J(\pi)$ is the objective function, representing the expected return under policy $\pi$; $R(s_t, a_t)$ is the immediate reward received at time $t$, in state $s_t$ after taking action $a_t$; $\gamma$ is the discount factor, used to calculate the present value of future rewards; $\mathbb{E}_{\tau\sim\pi}$ denotes the expectation over all possible trajectories $\tau$ under policy $\pi$. The objective function defines in the DDPG algorithm the goal that the agent needs to optimize, expressed as the maximization of the expected cumulative rewards obtained through the agent's interaction with the environment from the current state, and it can be combined with the optimization problem to provide a complete framework. Where the discount factor $\gamma$ is used to regulate the importance of future rewards. And DDPG utilizes an "actor-critic" architecture, where actors are responsible for learning strategies and critics evaluate actions. Strategies and value functions are optimized through gradient ascent (for actors) and gradient descent (for critics).

$$\begin{gathered} \nabla_{\theta^\pi} J \approx \mathbb{E}_{s_t\sim\rho^\beta}\left[\nabla_a Q(s, a|\theta^Q)|_{s=s_t, a=\pi(s_t)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)|_{s_t}\right] \\ \nabla_{\theta^Q} L = \mathbb{E}_{s_t, a_t, r_t, s_{t+1}\sim\rho^\beta}\left[(r_t + \gamma Q(s_{t+1}, \pi(s_{t+1})|\theta^Q) - Q(s_t, a_t|\theta^Q))^2\right] \end{gathered} \tag{8}$$

This set of formulas respectively guides the actor-network to learn how to change its action strategy to choose better actions in a given state in anticipation of higher long-term rewards and helps the critic network to more accurately assess the benefits of taking a particular action in a given state, thus providing the actor-network with accurate feedback to guide its strategy optimization. Through the interaction of these two networks, the DDPG algorithm can learn effective strategies for achieving specific goals in complex environments. For future research, DDPG, as a reinforcement learning algorithm based on deep learning, can find approximate solutions to NP-Hard optimization problems, such as path planning, through continuous trial-and-error and learning, and can also effectively deal with high-dimensional spaces, thus providing effective strategy learning and decision-making capabilities to further improve solution efficiency and effectiveness.In the paper [242], a path-planning optimization problem is transformed into a Markov Decision Process (MDP) with parameterized states, permitted operations, and detailed reward functions. Dueling

Double Deep Q-Networks (D3QN) are proposed to learn the decision-making strategies of a typical UAV to collect as much data as possible from the surveillance of multiple IoT nodes under realistic constraints. This model does not need to know the a priori environment with other intelligence and can run on a single UAV and scale to a multi-UAV Network.

Integrating machine learning techniques into UAV navigation and surveillance tasks significantly improves the accuracy and efficiency of UAVs in different tasks, improves the effectiveness of decision-making, and also saves a lot of time and resources [243–248]. In addition, it enhances the UAV's ability to respond to emergencies, while also providing opportunities for the development of UAVs in a wider range of applications.

### *6.4. UAVs for Mars Exploration*

As technology advances, human expectations for the exploration of other planets in space are increasing, with two of the most notable targets being the exploration of Mars and the Moon. The communication delays between Mars and Earth mean that robots must have a certain degree of autonomy, able to make decisions and operate without real-time commands, and at the same time, the complex and changing terrain of Mars poses a challenge to the robot's navigation capabilities [249–253]. The past idea of simply using unmanned vehicles for exploration appears to be inadequate in the face of these challenges, which calls for an increase in the synergy between UAVs and unmanned vehicles in the Mars This calls for increased synergy between UAVs and UAVs in the Mars exploration process to address these issues. This is because UAVs can fly over hard-to-reach areas such as cliffs, gullies, and mountains, thus providing a wider range of exploration than ground-based robots. UAVs can cover large areas quickly, collecting topographic, meteorological and geological data and sharing it with unmanned vehicles, increasing exploration efficiency [254–259]. In the papers [260–262], the collaboration of UGVs and UAVs on Mars exploration missions is discussed. Key issues include energy constraints for UAVs and UGVs. When UGVs are unable to take pictures of cliff edges, UAVs can provide aerial views for terrain monitoring. When the UAV cannot reach a target point that is too far away due to energy constraints, the UGV will carry the UAV to a specific location, which the UAV then explores and can recharge at the UGV. This UGV-UAV collaboration paradigm is based on a coordinated multi-phase strategy to solve different isolated parts of the problem, namely analyzing the Martian terrain and environment and identifying exploration target points. An initial path is then generated based on the environment and goals, optimized by an algorithm in which the energy constraints of the UGV and UAV are taken into account while ensuring that the UGV and UAV can efficiently avoid obstacles and be safe during the exploration process. Finally, the collected data is fused. Although the article is limited to a single UGV-UAV framework, its scalability can be expected in the future.

## 7. Conclusions

This paper provides an in-depth discussion of the applications and techniques of using Unmanned Aerial Vehicles (UAVs) to perform a wide range of surveillance missions in different scenarios and objectives. Not only do we discuss typical problems of UAVs in terms of path planning, deployment optimization, and multi-intelligence collaboration, but we also specifically select representative publications for categorized discussion, which are classified according to the target of interest. Specifically, we review UAV applications for general surveillance, instructions inspection, and search and rescue. We also discuss gaps and future directions in related research areas, presented in the form of limitations of existing approaches and possible solutions. Through this review paper, we hope to provide all relevant researchers and technicians working on UAV surveillance with review papers that will benefit their research. We also hope to continuously improve the robustness, optimality, and coordination with other intelligent units of UAVs in surveillance tasks to comprehensively improve the performance of UAVs in surveillance.

Future research will focus on improving the autonomy, reliability, and efficiency of UAV systems while exploring integration with other technologies such as artificial intelligence and big data analytics. These efforts will greatly advance the use of UAV technology in surveillance and security, further enhancing our ability to respond to diverse missions in complex environments. In addition, as technology advances and applications expand, related legal, ethical, and privacy issues should be emphasized and studied accordingly.

**Author Contributions:** Conceptualization, Z.F. and A.V.S.; methodology, Z.F.; software, Z.F.; validation, Z.F. and A.V.S.; formal analysis, Z.F.; investigation, Z.F.; resources, Z.F.; data curation, Z.F.; writing—original draft preparation, Z.F.; writing—review and editing, Z.F. and A.V.S.; visualization, Z.F.; supervision, A.V.S.; project administration, Z.F. and A.V.S.; funding acquisition, A.V.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the Australian Research Council. This work also received funding from the Australian Government, via grant AUSMURIB000001 associated with ONR MURI grant N00014-19-1-2571.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| UAV | Unmanned Aerial Vehicle |
| UGV | Unmanned Ground Vehicle |
| UAVS | Unmanned Aerial Vehicle Surveillance |
| PPP | Path Planning Problem |
| CPP | Coverage Planning Problem |
| RRT | Rapid Random Tree |
| PRM | Probabilistic Roadmap |
| QoS | Quality of Surveillance |
| QoC | Quality of Coverage |
| GA | Genetic Algorithm |
| GSAG | Genetic Simulated Annealing |
| PSO | Particle Swarm Optimization |
| TSP | Traveling Salesman Problem |
| AGP | Art Gallery Problem |
| LiDAR | Light Detection and Ranging |
| SAR | Search and Rescue |
| RIS | Reflective Intelligent Surfaces |
| VP | Vanishing Point |
| GNSS | Global Navigation Satellite System |
| D3QN | Dueling Double Deep Q-Networks |
| DQN | Deep Q Learning |
| USV | Unmanned Surface Vehicle |
| UUV | Unmanned Underwater Vehicle |
| MDP | Markov Decision Process |
| DDPG | Deep deterministic policy gradient |
| IoT | Internet of Things |

## References

1. Dande, B.; Chang, C.Y.; Liao, W.H.; Roy, D.S. MSQAC: Maximizing the surveillance quality of area coverage in wireless sensor networks. *IEEE Sens. J.* **2022**, *22*, 6150–6163. [CrossRef]
2. Fei, Z.; Li, B.; Yang, S.; Xing, C.; Chen, H.; Hanzo, L. A Survey of Multi-Objective Optimization in Wireless Sensor Networks: Metrics, Algorithms, and Open Problems. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 550–586. [CrossRef]

3. Elmokadem, T.; Savkin, A.V. Towards fully autonomous UAVs: A survey. *Sensors* **2021**, *21*, 6223. [CrossRef]
4. Rezwan, S.; Choi, W. Artificial intelligence approaches for UAV navigation: Recent advances and future challenges. *IEEE Access* **2022**, *10*, 26320–26339. [CrossRef]
5. Bai, Y.; Zhao, H.; Zhang, X.; Chang, Z.; Jäntti, R.; Yang, K. Towards autonomous multi-UAV wireless network: A survey of reinforcement learning-based approaches. *IEEE Commun. Surv. Tutor.* **2023**, 25, 3038–3067. [CrossRef]
6. Li, X.; Savkin, A.V. Networked Unmanned Aerial Vehicles for Surveillance and Monitoring: A Survey. *Future Internet* **2021**, *13*, 174. [CrossRef]
7. Wang, J.Y.; Su, D.P.; Feng, P.; Liu, N.; Wang, J.B. Optimal Height of UAV in Covert Visible Light Communications. *IEEE Commun. Lett.* **2023**, *27*, 2682–2686. [CrossRef]
8. Lin, S.; Liu, A.; Wang, J.; Kong, X. A review of path-planning approaches for multiple mobile robots. *Machines* **2022**, *10*, 773. [CrossRef]
9. 5 Surprising Statistics about Drones in Infrastructure. 2022. Available online: https://www.droneup.com/2022/05/24/5-surprising-statistics-about-drones-infrastructure (accessed on 18 May 2022).
10. Margraff, J.; Stéphant, J.; Labbani-Igbida, O. UAV 3D path and motion planning in unknown dynamic environments. In Proceedings of the 2020 International Conference on Unmanned Aircraft Systems (ICUAS), Athens, Greece, 1–4 September 2020; pp. 77–84. [CrossRef]
11. Batinovic, A.; Goricanec, J.; Markovic, L.; Bogdan, S. Path Planning with Potential Field-Based Obstacle Avoidance in a 3D Environment by an Unmanned Aerial Vehicle. In Proceedings of the 2022 International Conference on Unmanned Aircraft Systems (ICUAS), Dubrovnik, Croatia, 21–24 June 2022; pp. 394–401. [CrossRef]
12. Wu, Y.; Wu, S.; Hu, X. Cooperative Path Planning of UAVs & UGVs for a Persistent Surveillance Task in Urban Environments. *IEEE Internet Things J.* **2021**, *8*, 4906–4919. [CrossRef]
13. Mishra, B.; Garg, D.; Narang, P.; Mishra, V. Drone-surveillance for search and rescue in natural disaster. *Comput. Commun.* **2020**, *156*, 1–10. [CrossRef]
14. Savkin, A.V.; Huang, H. Navigation of a UAV Network for Optimal Surveillance of a Group of Ground Targets Moving Along a Road. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 9281–9285. [CrossRef]
15. Huang, H.; Savkin, A.V.; Huang, C. Decentralized Autonomous Navigation of a UAV Network for Road Traffic Monitoring. *IEEE Trans. Aerosp. Electron. Syst.* **2021**, *57*, 2558–2564. [CrossRef]
16. Huang, H.; Savkin, A.V. Navigating UAVs for Optimal Monitoring of Groups of Moving Pedestrians or Vehicles. *IEEE Trans. Veh. Technol.* **2021**, *70*, 3891–3896. [CrossRef]
17. Savkin, A.V.; Ni, W.; Eskandari, M. Effective UAV Navigation for Cellular-Assisted Radio Sensing, Imaging, and Tracking. *IEEE Trans. Veh. Technol.* **2023**, *72*, 13729–13733. [CrossRef]
18. Hanyu, Q.; Huang, L.; Bing, X. Unit Circles Decomposition-based Coverage Path Planning for UAV. In Proceedings of the 2022 34th Chinese Control and Decision Conference (CCDC), Hefei, China, 21–23 May 2022; pp. 3259–3264. [CrossRef]
19. Savkin, A.V.; Huang, H. Asymptotically Optimal Path Planning for Ground Surveillance by a Team of UAVs. *IEEE Syst. J.* **2022**, *16*, 3446–3449. [CrossRef]
20. Savkin, A.V.; Huang, H. A Method for Optimized Deployment of a Network of Surveillance Aerial Drones. *IEEE Syst. J.* **2019**, *13*, 4474–4477. [CrossRef]
21. Huang, H.; Savkin, A.V. An Algorithm of Reactive Collision Free 3-D Deployment of Networked Unmanned Aerial Vehicles for Surveillance and Monitoring. *IEEE Trans. Ind. Inform.* **2020**, *16*, 132–140. [CrossRef]
22. Alzenad, M.; El-Keyi, A.; Lagum, F.; Yanikomeroglu, H. 3-D Placement of an Unmanned Aerial Vehicle Base Station (UAV-BS) for Energy-Efficient Maximal Coverage. *IEEE Wirel. Commun. Lett.* **2017**, *6*, 434–437. [CrossRef]
23. Zhong, X.; Huo, Y.; Dong, X.; Liang, Z. QoS-Compliant 3-D Deployment Optimization Strategy for UAV Base Stations. *IEEE Syst. J.* **2021**, *15*, 1795–1803. [CrossRef]
24. Oh, H.; Kim, S.; Shin, H.S.; Tsourdos, A. Coordinated standoff tracking of moving target groups using multiple UAVs. *IEEE Trans. Aerosp. Electron. Syst.* **2015**, *51*, 1501–1514. [CrossRef]
25. Gu, J.; Su, T.; Wang, Q.; Du, X.; Guizani, M. Multiple Moving Targets Surveillance Based on a Cooperative Network for Multi-UAV. *IEEE Commun. Mag.* **2018**, *56*, 82–89. [CrossRef]
26. Mystkowski, A. Implementation and investigation of a robust control algorithm for an unmanned micro-aerial vehicle. *Robot. Auton. Syst.* **2014**, *62*, 1187–1196. [CrossRef]
27. Espinoza-Fraire, T.; Saenz, A.; Salas, F.; Juarez, R.; Giernacki, W. Trajectory tracking with adaptive robust control for quadrotor. *Appl. Sci.* **2021**, *11*, 8571. [CrossRef]
28. Huang, H.; Savkin, A.V. Deployment of Heterogeneous UAV Base Stations for Optimal Quality of Coverage. *IEEE Internet Things J.* **2022**, *9*, 16429–16437. [CrossRef]
29. Jensen-Nau, K.R.; Hermans, T.; Leang, K.K. Near-Optimal Area-Coverage Path Planning of Energy-Constrained Aerial Robots with Application in Autonomous Environmental Monitoring. *IEEE Trans. Autom. Sci. Eng.* **2021**, *18*, 1453–1468. [CrossRef]
30. Ahmed, N.; Pawase, C.J.; Chang, K. Distributed 3-D Path Planning for Multi-UAVs with Full Area Surveillance Based on Particle Swarm Optimization. *Appl. Sci.* **2021**, *11*, 3417. [CrossRef]
31. Al-Turjman, F.; Zahmatkesh, H.; Al-Oqily, I.; Daboul, R. Optimized Unmanned Aerial Vehicles Deployment for Static and Mobile Targets' Monitoring. *Comput. Commun.* **2020**, *149*, 27–35. [CrossRef]

32. Huang, H.; Savkin, A.V. Aerial Surveillance in Cities: When UAVs Take Public Transportation Vehicles. *IEEE Trans. Autom. Sci. Eng.* **2023**, *20*, 1069–1080. [CrossRef]
33. Scherer, J.; Rinner, B. Multi-UAV Surveillance with Minimum Information Idleness and Latency Constraints. *IEEE Robot. Autom. Lett.* **2020**, *5*, 4812–4819. [CrossRef]
34. Yun, W.J.; Park, S.; Kim, J.; Shin, M.; Jung, S.; Mohaisen, D.A.; Kim, J.H. Cooperative Multiagent Deep Reinforcement Learning for Reliable Surveillance via Autonomous Multi-UAV Control. *IEEE Trans. Ind. Inform.* **2022**, *18*, 7086–7096. [CrossRef]
35. Rakha, T.; Gorodetsky, A. Review of Unmanned Aerial System (UAS) applications in the built environment: Towards automated building inspection procedures using drones. *Autom. Constr.* **2018**, *93*, 252–264. [CrossRef]
36. Luo, Y.; Yu, X.; Yang, D.; Zhou, B. A survey of intelligent transmission line inspection based on unmanned aerial vehicle. *Artif. Intell. Rev.* **2023**, *56*, 173–201. [CrossRef]
37. Molina, A.A.; Huang, Y.; Jiang, Y. A Review of Unmanned Aerial Vehicle Applications in Construction Management: 2016–2021. *Standards* **2023**, *3*, 95–109. [CrossRef]
38. Zhao, Z.; Qi, H.; Qi, Y.; Zhang, K.; Zhai, Y.; Zhao, W. Detection Method Based on Automatic Visual Shape Clustering for Pin-Missing Defect in Transmission Lines. *IEEE Trans. Instrum. Meas.* **2020**, *69*, 6080–6091. [CrossRef]
39. Chen, D.Q.; Guo, X.H.; Huang, P.; Li, F.H. Safety Distance Analysis of 500kV Transmission Line Tower UAV Patrol Inspection. *IEEE Lett. Electromagn. Compat. Pract. Appl.* **2020**, *2*, 124–128. [CrossRef]
40. Wang, Z.; Gao, Q.; Xu, J.; Li, D. A review of UAV power line inspection. In Proceedings of the Advances in Guidance, Navigation and Control: Proceedings of 2020 International Conference on Guidance, Navigation and Control, ICGNC 2020, Tianjin, China, 23–25 October 2020; Springer: Berlin/Heidelberg, Germany, 2022; pp. 3147–3159.
41. Li, Z.; Zhang, Y.; Wu, H.; Suzuki, S.; Namiki, A.; Wang, W. Design and application of a UAV autonomous inspection system for high-voltage power transmission lines. *Remote Sens.* **2023**, *15*, 865. [CrossRef]
42. Xu, C.; Li, Q.; Zhou, Q.; Zhang, S.; Yu, D.; Ma, Y. Power line-guided automatic electric transmission line inspection system. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 1–18. [CrossRef]
43. Ma, W.; Xiao, J.; Zhu, G.; Wang, J.; Zhang, D.; Fang, X.; Miao, Q. Transmission tower and Power line detection based on improved Solov2. *IEEE Trans. Instrum. Meas.* **2024**, *73*. [CrossRef]
44. Foudeh, H.A.; Luk, P.C.K.; Whidborne, J.F. An advanced unmanned aerial vehicle (UAV) approach via learning-based control for overhead power line monitoring: A comprehensive review. *IEEE Access* **2021**, *9*, 130410–130433. [CrossRef]
45. Hui, X.; Bian, J.; Zhao, X.; Tan, M. Vision-based autonomous navigation approach for unmanned aerial vehicle transmission-line inspection. *Int. J. Adv. Robot. Syst.* **2018**, *15*, 172988141775282. [CrossRef]
46. Khac, C.N.; Choi, Y.; Park, J.H.; Jung, H. A Robust Road Vanishing Point Detection Adapted to the Real-world Driving Scenes. *Sensors* **2021**, *21*, 2133. [CrossRef] [PubMed]
47. Kong, H.; Sarma, S.E.; Tang, F. Generalizing Laplacian of Gaussian Filters for Vanishing-Point Detection. *IEEE Trans. Intell. Transp. Syst.* **2013**, *14*, 408–418. [CrossRef]
48. Bian, J.; Hui, X.; Zhao, X.; Tan, M. A Novel Monocular-Based Navigation Approach for UAV Autonomous Transmission-Line Inspection. In Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Madrid, Spain, 1–5 October 2018; pp. 1–7. [CrossRef]
49. Nguyen, V.N.; Jenssen, R.; Roverso, D. Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning. *Int. J. Electr. Power Energy Syst.* **2018**, *99*, 107–120. [CrossRef]
50. Ren, S.; He, K.; Girshick, R.; Sun, J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In Proceedings of the 28th International Conference on Neural Information Processing Systems—Volume 1, Cambridge, MA, USA, 7–12 December 2015; NIPS'15, pp. 91–99.
51. Hui, X.; Bian, J.; Yu, Y.; Zhao, X.; Tan, M. A novel autonomous navigation approach for UAV power line inspection. In Proceedings of the 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO), Macau, China, 5–8 December 2017; pp. 634–639. [CrossRef]
52. Bian, J.; Hui, X.; Yu, Y.; Zhao, X.; Tan, M. A robust vanishing point detection method for UAV autonomous power line inspection. In Proceedings of the 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO), Macau, China, 5–8 December 2017; pp. 646–651. [CrossRef]
53. Hui, X.; Bian, J.; Zhao, X.; Tan, M. Deep-learning-based autonomous navigation approach for UAV transmission line inspection. In Proceedings of the 2018 Tenth International Conference on Advanced Computational Intelligence (ICACI), Xiamen, China, 29–31 March 2018; pp. 455–460. [CrossRef]
54. Martinez, C.; Sampedro, C.; Chauhan, A.; Campoy, P. Towards autonomous detection and tracking of electric towers for aerial power line inspection. In Proceedings of the 2014 International Conference on Unmanned Aircraft Systems (ICUAS), Orlando, FL, USA, 27–30 May 2014; pp. 284–295. [CrossRef]
55. Claro, R.M.; Pereira, M.I.; Neves, F.S.; Pinto, A.M. Energy Efficient Path Planning for 3D Aerial Inspections. *IEEE Access* **2023**, *11*, 32152–32166. [CrossRef]
56. Jordan, S.; Moore, J.; Hovet, S.; Box, J.; Perry, J.; Kirsche, K.; Lewis, D.; Tse, Z.T.H. State-of-the-art technologies for UAV inspections. *IET Radar Sonar Navig.* **2018**, *12*, 151–164. [CrossRef]
57. Gammell, J.D.; Strub, M.P. Asymptotically Optimal Sampling-Based Motion Planning Methods. *Annu. Rev. Control. Robot. Auton. Syst.* **2021**, *4*, 295–318. [CrossRef]

58. Karaman, S.; Walter, M.R.; Perez, A.; Frazzoli, E.; Teller, S. Anytime Motion Planning using the RRT*. In Proceedings of the 2011 IEEE International Conference on Robotics and Automation, Shanghai, China, 9–13 May 2011; pp. 1478–1483. [CrossRef]
59. Karaman, S.; Frazzoli, E. Sampling-based Algorithms for Optimal Motion Planning. *arXiv* **2011**, arXiv:1105.1186.
60. Cui, J.; Zhang, Y.; Ma, S.; Yi, Y.; Xin, J.; Liu, D. Path planning algorithms for power transmission line inspection using unmanned aerial vehicles. In Proceedings of the 2017 29th Chinese Control And Decision Conference (CCDC), Chongqing, China, 28–30 May 2017; pp. 2304–2309. [CrossRef]
61. Luo, X.; Li, X.; Yang, Q.; Wu, F.; Zhang, D.; Yan, W.; Xi, Z. Optimal path planning for UAV based inspection system of large-scale photovoltaic farm. In Proceedings of the 2017 Chinese Automation Congress (CAC), Jinan, China, 20–22 October 2017; pp. 4495–4500. [CrossRef]
62. Fang, Z. Optimized UAV Navigation Overcoming LoS Obstructions for Maximized Power Grid Tower Inspections in Mountainous Terrains*. In Proceedings of the 2023 IEEE International Conference on Robotics and Biomimetics (ROBIO), Samui, Thailand, 4–9 December 2023; pp. 1–6. [CrossRef]
63. Puente, I.; Solla, M.; González-Jorge, H.; Arias, P. NDT Documentation and Evaluation of the Roman Bridge of Lugo Using GPR and Mobile and Static LiDAR. *J. Perform. Constr. Facil.* **2015**, *29*, 06014004. [CrossRef]
64. Seo, J.; Duque, L.; Wacker, J. Drone-enabled bridge inspection methodology and application. *Autom. Constr.* **2018**, *94*, 112–126. [CrossRef]
65. Feroz, S.; Abu Dabous, S. UAV-Based Remote Sensing Applications for Bridge Condition Assessment. *Remote Sens.* **2021**, *13*, 1809. [CrossRef]
66. Bolourian, N.; Soltani, M.M.; Albahri, A.; Hammad, A. High Level Framework for Bridge Inspection Using LiDAR-Equipped UAV. In Proceedings of the 34th International Symposium on Automation and Robotics in Construction (ISARC), Taipei, Taiwan, 27–30 June 2017; pp. 683–688. [CrossRef]
67. Hinks, T.; Carr, H.; Laefer, D.F. Flight Optimization Algorithms for Aerial LiDAR Capture for Urban Infrastructure Model Generation. *J. Comput. Civ. Eng.* **2009**, *23*, 330–339. [CrossRef]
68. Laefer, D.F.; Truong-Hong, L.; Carr, H.; Singh, M. Crack detection limits in unit based masonry with terrestrial laser scanning. *NDT E Int.* **2014**, *62*, 66–76. [CrossRef]
69. Bolourian, N.; Hammad, A. LiDAR-equipped UAV path planning considering potential locations of defects for bridge inspection. *Autom. Constr.* **2020**, *117*, 103250. [CrossRef]
70. Zammit, C.; van Kampen, E.J. Comparison between A* and RRT Algorithms for UAV Path Planning. *Unmanned Syst.* **2022**, *10*, 129–146. [CrossRef]
71. Shi, L.; Mehrooz, G.; Jacobsen, R.H. Inspection Path Planning for Aerial Vehicles via Sampling-based Sequential Optimization. In Proceedings of the 2021 International Conference on Unmanned Aircraft Systems (ICUAS), Athens, Greece, 15–18 June 2021; pp. 679–687. [CrossRef]
72. Zhang, Y.; Dong, L.; Luo, J.; Lu, L.; Jiang, T.; Yuan, X.; Kang, T.; Jiang, L. Intelligent Inspection Method of Transmission Line Multi Rotor UAV Based on Lidar Technology. In Proceedings of the 2022 8th Annual International Conference on Network and Information Systems for Computers (ICNISC), Hangzhou, China, 16–19 September 2022; pp. 232–236. [CrossRef]
73. Guan, H.; Sun, X.; Su, Y.; Hu, T.; Wang, H.; Wang, H.; Peng, C.; Guo, Q. UAV-lidar aids automatic intelligent powerline inspection. *Int. J. Electr. Power Energy Syst.* **2021**, *130*, 106987. [CrossRef]
74. Phillips, S.; Narasimhan, S. Automating data collection for robotic bridge inspections. *J. Bridge Eng.* **2019**, *24*, 04019075. [CrossRef]
75. Perry, B.J.; Guo, Y.; Atadero, R.; Lindt, J.W.v.d. Streamlined bridge inspection system utilizing unmanned aerial vehicles (UAVs) and machine learning. *Measurement* **2020**, *164*, 108048. [CrossRef]
76. Aliyari, M.; Droguett, E.L.; Ayele, Y.Z. UAV-Based Bridge Inspection via Transfer Learning. *Sustainability* **2021**, *13*, 11359. [CrossRef]
77. Arafat, M.Y.; Moh, S. Location-Aided Delay Tolerant Routing Protocol in UAV Networks for Post-Disaster Operation. *IEEE Access* **2018**, *6*, 59891–59906. [CrossRef]
78. Arafat, M.Y.; Moh, S. Localization and Clustering Based on Swarm Intelligence in UAV Networks for Emergency Communications. *IEEE Internet Things J.* **2019**, *6*, 8958–8976. [CrossRef]
79. DJI. Rescue Services. 2024. Available online: https://enterprise.dji.com/public-safety/rescue-services?site=enterprise&from=nav (accessed on 3 April 2024)
80. Lien, J.M.; Rodriguez, S.; Malric, J.; Amato, N. Shepherding Behaviors with Multiple Shepherds. In Proceedings of the 2005 IEEE International Conference on Robotics and Automation, Barcelona, Spain, 18–22 April 2005; pp. 3402–3407. [CrossRef]
81. Pfeifer, R.; Blumberg, B.; Meyer, J.A.; Wilson, S.W. Robot Sheepdog Project achieves automatic flock control. In *From Animals to Animats 5: Proceedings of the Fifth International Conference on Simulation of Adaptive Behavior*; MIT Press: Cambridge, MA, USA, 1998; pp. 489–493.
82. Li, X.; Huang, H.; Savkin, A.; Zhang, J. Robotic Herding of Farm Animals Using a Network of Barking Aerial Drones. *Drones* **2022**, *6*, 29. [CrossRef]
83. Strömbom, D.; Mann, R.P.; Wilson, A.M.; Hailes, S.; Morton, A.J.; Sumpter, D.J.T.; King, A.J. Solving the shepherding problem: Heuristics for herding autonomous, interacting agents. *J. R. Soc. Interface* **2014**, *11*, 20140719. [CrossRef]
84. Reynolds, C.W. (~) ~ ComputerGraphics, Volume 21, Number 4, July 1987. Available online: https://graphics.stanford.edu/courses/cs448-01-spring/papers/reynolds.pdf (accessed on 7 May 2024).

85. Hayat, S.; Yanmaz, E.; Brown, T.X.; Bettstetter, C. Multi-objective UAV path planning for search and rescue. In Proceedings of the 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, 29 May–3 June 2017; pp. 5569–5574. [CrossRef]
86. Shen, C.; Zhang, Y.; Li, Z.; Gao, F.; Shen, S. Collaborative air-ground target searching in complex environments. In Proceedings of the 2017 IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR), Shanghai, China, 1–13 October 2017; pp. 230–237. [CrossRef]
87. Cho, S.W.; Park, H.J.; Lee, H.; Shim, D.H.; Kim, S.Y. Coverage path planning for multiple unmanned aerial vehicles in maritime search and rescue operations. *Comput. Ind. Eng.* **2021**, *161*, 107612. [CrossRef]
88. Wenguang, L.; Zhiming, Z. Intelligent surveillance and reconnaissance mode of police UAV based on grid. In Proceedings of the 2021 7th International Symposium on Mechatronics and Industrial Informatics (ISMII), Zhuhai, China, 22–24 January 2021; pp. 292–295. [CrossRef]
89. Rabahi, F.Z.; Boudjit, S.; Bemmoussat, C.; Benaissa, M. UAVs-Based Mobile Radars for Real-Time Highways Surveillance. In Proceedings of the 2020 IEEE 17th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), Delhi, India, 10–13 December 2020; pp. 80–87. [CrossRef]
90. Huang, H.; Savkin, A.V.; Ni, W. Energy-Efficient 3D Navigation of a Solar-Powered UAV for Secure Communication in the Presence of Eavesdroppers and No-Fly Zones. *Energies* **2020**, *13*, 1445. [CrossRef]
91. Li, A.; Wu, Q.; Zhang, R. UAV-Enabled Cooperative Jamming for Improving Secrecy of Ground Wiretap Channel. *IEEE Wirel. Commun. Lett.* **2019**, *8*, 181–184. [CrossRef]
92. Huang, H.; Savkin, A.V.; Ni, W. Online UAV Trajectory Planning for Covert Video Surveillance of Mobile Targets. *IEEE Trans. Autom. Sci. Eng.* **2022**, *19*, 735–746. [CrossRef]
93. Lei, H.; Wang, D.; Park, K.H.; Ansari, I.S.; Jiang, J.; Pan, G.; Alouini, M.S. Safeguarding UAV IoT Communication Systems Against Randomly Located Eavesdroppers. *IEEE Internet Things J.* **2020**, *7*, 1230–1244. [CrossRef]
94. Savkin, A.V.; Huang, H.; Ni, W. Securing UAV Communication in the Presence of Stationary or Mobile Eavesdroppers via Online 3D Trajectory Planning. *IEEE Wirel. Commun. Lett.* **2020**, *9*, 1211–1215. [CrossRef]
95. Salgado, M.E.; Goodwin, G.C.; Graebe, S.F. Control System Design. 2001. Available online: http://caaelotel.elo.utfsm.cl/home/wp-content/uploads/Control-System-Design-SalgadoGoodwinGraebe.pdf (accessed on 7 May 2024).
96. Savkin, A.V.; Evans, R.J. *Hybrid Dynamical Systems: Controller and Sensor Switching Problems*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2002.
97. Tomic, T.; Schmid, K.; Lutz, P.; Domel, A.; Kassecker, M.; Mair, E.; Grixa, I.; Ruess, F.; Suppa, M.; Burschka, D. Toward a Fully Autonomous UAV: Research Platform for Indoor and Outdoor Urban Search and Rescue. *IEEE Robot. Autom. Mag.* **2012**, *19*, 46–56. [CrossRef]
98. Surmann, H.; Kaiser, T.; Leinweber, A.; Senkowski, G.; Slomma, D.; Thurow, M. Small Commercial UAVs for Indoor Search and Rescue Missions. In Proceedings of the 2021 7th International Conference on Automation, Robotics and Applications (ICARA), Prague, Czech Republic, 4–6 February 2021; pp. 106–113. [CrossRef]
99. Liang, Y.; Xu, W.; Liang, W.; Peng, J.; Jia, X.; Zhou, Y.; Duan, L. Nonredundant Information Collection in Rescue Applications via an Energy-Constrained UAV. *IEEE Internet Things J.* **2019**, *6*, 2945–2958. [CrossRef]
100. Wang, Y.; Su, Z.; Xu, Q.; Li, R.; Luan, T.H. Lifesaving with RescueChain: Energy-Efficient and Partition-Tolerant Blockchain Based Secure Information Sharing for UAV-Aided Disaster Rescue. In Proceedings of the IEEE INFOCOM 2021—IEEE Conference on Computer Communications, Virtual, 10–13 May 2021; pp. 1–10. [CrossRef]
101. Yeong, S.P.; King, L.M.; Dol, S.S. A Review on Marine Search and Rescue Operations Using Unmanned Aerial Vehicles. *Int. J. Mar. Environ. Sci.* **2015**, *9*, 396–399.
102. Tuan, H.D.; Nasir, A.A.; Savkin, A.V.; Poor, H.V.; Dutkiewicz, E. MPC-Based UAV Navigation for Simultaneous Solar-Energy Harvesting and Two-Way Communications. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 3459–3474. [CrossRef]
103. Lee, J.S.; Yu, K.H. Optimal Path Planning of Solar-Powered UAV Using Gravitational Potential Energy. *IEEE Trans. Aerosp. Electron. Syst.* **2017**, *53*, 1442–1451. [CrossRef]
104. Oubbati, O.S.; Lakas, A.; Lorenz, P.; Atiquzzaman, M.; Jamalipour, A. Leveraging Communicating UAVs for Emergency Vehicle Guidance in Urban Areas. *IEEE Trans. Emerg. Top. Comput.* **2021**, *9*, 1070–1082. [CrossRef]
105. Verykokou, S.; Doulamis, A.; Athanasiou, G.; Ioannidis, C.; Amditis, A. UAV-based 3D modelling of disaster scenes for Urban Search and Rescue. In Proceedings of the 2016 IEEE International Conference on Imaging Systems and Techniques (IST), Chania, Greece, 4–6 October 2016; pp. 106–111. [CrossRef]
106. Adamopoulos, E.; Rinaudo, F. UAS-Based Archaeological Remote Sensing: Review, Meta-Analysis and State-of-the-Art. *Drones* **2020**, *4*, 46. [CrossRef]
107. Guyot, A.; Hubert-Moy, L.; Lorho, T. Detecting Neolithic Burial Mounds from LiDAR-Derived Elevation Data Using a Multi-Scale Approach and Machine Learning Techniques. *Remote Sens.* **2018**, *10*, 225. [CrossRef]
108. Linford, N. The application of geophysical methods to archaeological prospection. *Rep. Prog. Phys.* **2006**, *69*, 2205–2257. [CrossRef]
109. Ludeno, G.; Catapano, I.; Renga, A.; Vetrella, A.R.; Fasano, G.; Soldovieri, F. Assessment of a micro-UAV system for microwave tomography radar imaging. *Remote Sens. Environ.* **2018**, *212*, 90–102. [CrossRef]

110. Verhoeven, G.J. Near-Infrared Aerial Crop Mark Archaeology: From its Historical Use to Current Digital Implementations. *J. Archaeol. Method Theory* **2012**, *19*, 132–160. [CrossRef]
111. Stal, C.; Covataru, C.; Müller, J.; Parnic, V.; Ignat, T.; Hofmann, R.; Lazar, C. Supporting Long-Term Archaeological Research in Southern Romania Chalcolithic Sites Using Multi-Platform UAV Mapping. *Drones* **2022**, *6*, 277. [CrossRef]
112. Balsi, M.; Esposito, S.; Fallavollita, P.; Melis, M.G.; Milanese, M. Preliminary Archeological Site Survey by UAV-Borne Lidar: A Case Study. *Remote Sens.* **2021**, *13*, 332. [CrossRef]
113. Laugier, E.J.; Casana, J. Integrating Satellite, UAV, and Ground-Based Remote Sensing in Archaeology: An Exploration of Pre-Modern Land Use in Northeastern Iraq. *Remote Sens.* **2021**, *13*, 5119. [CrossRef]
114. Fiz, J.I.; Martín, P.M.; Cuesta, R.; Subías, E.; Codina, D.; Cartes, A. Examples and Results of Aerial Photogrammetry in Archeology with UAV: Geometric Documentation, High Resolution Multispectral Analysis, Models and 3D Printing. *Drones* **2022**, *6*, 59. [CrossRef]
115. Frodella, W.; Elashvili, M.; Spizzichino, D.; Gigli, G.; Adikashvili, L.; Vacheishvili, N.; Kirkitadze, G.; Nadaraia, A.; Margottini, C.; Casagli, N. Combining InfraRed Thermography and UAV Digital Photogrammetry for the Protection and Conservation of Rupestrian Cultural Heritage Sites in Georgia: A Methodological Application. *Remote Sens.* **2020**, *12*, 892. [CrossRef]
116. Tavukçuoğlu, A.; Düzgüneş, A.; Caner-Saltık, E.; Demirci, Ş. Use of IR thermography for the assessment of surface-water drainage problems in a historical building, Ağzıkarahan (Aksaray), Turkey. *NDT E Int.* **2005**, *38*, 402–410. [CrossRef]
117. Avdelidis, N.; Moropoulou, A.; Theoulakis, P. Detection of water deposits and movement in porous materials by infrared imaging. *Infrared Phys. Technol.* **2003**, *44*, 183–190. [CrossRef]
118. Toprak, A.S.; Polat, N.; Uysal, M. 3D modeling of lion tombstones with UAV photogrammetry: A case study in ancient Phrygia (Turkey). *Archaeol. Anthropol. Sci.* **2019**, *11*, 1973–1976. [CrossRef]
119. Guo, Q.; Liu, H.; Hassan, F.M.; Bhatt, M.W.; Buttar, A.M. Application of UAV tilt photogrammetry in 3D modeling of ancient buildings. *Int. J. Syst. Assur. Eng. Manag.* **2022**, *13*, 424–436. [CrossRef]
120. Turner, I.L.; Harley, M.D.; Drummond, C.D. UAVs for coastal surveying. *Coast. Eng.* **2016**, *114*, 19–24. [CrossRef]
121. Zanutta, A.; Lambertini, A.; Vittuari, L. UAV Photogrammetry and Ground Surveys as a Mapping Tool for Quickly Monitoring Shoreline and Beach Changes. *J. Mar. Sci. Eng.* **2020**, *8*, 52. [CrossRef]
122. Giordan, D.; Notti, D.; Villa, A.; Zucca, F.; Calò, F.; Pepe, A.; Dutto, F.; Pari, P.; Baldo, M.; Allasia, P. Low cost, multiscale and multi-sensor application for flooded area mapping. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 1493–1516. [CrossRef]
123. Mancini, F.; Dubbini, M.; Gattelli, M.; Stecchi, F.; Fabbri, S.; Gabbianelli, G. Using Unmanned Aerial Vehicles (UAV) for High-Resolution Reconstruction of Topography: The Structure from Motion Approach on Coastal Environments. *Remote Sens.* **2013**, *5*, 6880–6898. [CrossRef]
124. Lin, Y.C.; Cheng, Y.T.; Zhou, T.; Ravi, R.; Hasheminasab, S.; Flatt, J.; Troy, C.; Habib, A. Evaluation of UAV LiDAR for Mapping Coastal Environments. *Remote Sens.* **2019**, *11*, 2893. [CrossRef]
125. Rangel-Buitrago, N.G.; Anfuso, G.; Williams, A.T. Coastal erosion along the Caribbean coast of Colombia: Magnitudes, causes and management. *Ocean Coast. Manag.* **2015**, *114*, 129–144. [CrossRef]
126. Elaksher, A.F. Fusion of hyperspectral images and lidar-based dems for coastal mapping. *Opt. Lasers Eng.* **2008**, *46*, 493–498. [CrossRef]
127. Tamura, T.; Oliver, T.S.N.; Cunningham, A.C.; Woodroffe, C.D. Recurrence of Extreme Coastal Erosion in SE Australia Beyond Historical Timescales Inferred From Beach Ridge Morphostratigraphy. *Geophys. Res. Lett.* **2019**, *46*, 4705–4714. [CrossRef]
128. Xu, G.; Shen, W.; Wang, X. Applications of Wireless Sensor Networks in Marine Environment Monitoring: A Survey. *Sensors* **2014**, *14*, 16932–16954. [CrossRef]
129. Yuan, S.; Li, Y.; Bao, F.; Xu, H.; Yang, Y.; Yan, Q.; Zhong, S.; Yin, H.; Xu, J.; Huang, Z.; et al. Marine environmental monitoring with unmanned vehicle platforms: Present applications and future prospects. *Sci. Total Environ.* **2023**, *858*, 159741. [CrossRef]
130. Kuntze, H.B.; Frey, C.W.; Tchouchenkov, I.; Staehle, B.; Rome, E.; Pfeiffer, K.; Wenzel, A.; Wöllenstein, J. SENEKA—sensor network with mobile robots for disaster management. In Proceedings of the 2012 IEEE Conference on Technologies for Homeland Security (HST), Waltham, MA, USA, 13–15 November 2012; pp. 406–410. [CrossRef]
131. Erdelj, M.; Natalizio, E. UAV-assisted disaster management: Applications and open issues. In Proceedings of the 2016 International Conference on Computing, Networking and Communications (ICNC), Kauai, HI, USA, 15–18 February 2016; pp. 1–5. [CrossRef]
132. Trasviña-Moreno, C.; Blasco, R.; Marco, Á.; Casas, R.; Trasviña-Castro, A. Unmanned Aerial Vehicle Based Wireless Sensor Network for Marine-Coastal Environment Monitoring. *Sensors* **2017**, *17*, 460. [CrossRef]
133. Barnett, A.; Fitzpatrick, R.; Bradley, M.; Miller, I.; Sheaves, M.; Chin, A.; Smith, B.; Diedrich, A.; Yick, J.L.; Lubitz, N.; et al. Scientific response to a cluster of shark bites. *People Nat.* **2022**, *4*, 963–982. [CrossRef]
134. Huveneers, C.; Blount, C.; Bradshaw, C.J.; Butcher, P.A.; Lincoln Smith, M.P.; Macbeth, W.G.; McPhee, D.P.; Moltschaniwskyj, N.; Peddemors, V.M.; Green, M. Shifts in the incidence of shark bites and efficacy of beach-focussed mitigation in Australia. *Mar. Pollut. Bull.* **2024**, *198*, 115855. [CrossRef] [PubMed]
135. Dudley, S.F.J. A comparison of the shark control programs of New South Wales and Queensland (Australia) and KwaZulu-Natal (South Africa). *Ocean Coast. Manag.* **1997**, *34*, 1–27. [CrossRef]

136. Sharma, N.; Scully-Power, P.; Blumenstein, M. Shark Detection from Aerial Imagery Using Region-Based CNN, a Study. In Proceedings of the AI 2018: Advances in Artificial Intelligence, Wellington, New Zealand, 11–14 December 2018; Mitrovic, T., Xue, B., Li, X., Eds.; Springer: Cham, Switzerland, 2018; pp. 224–236.
137. Li, X.; Huang, H.; Savkin, A.V. A Novel Method for Protecting Swimmers and Surfers From Shark Attacks Using Communicating Autonomous Drones. *IEEE Internet Things J.* **2020**, *7*, 9884–9894. [CrossRef]
138. James, M.R.; Carr, B.; D'Arcy, F.; Diefenbach, A.; Dietterich, H.; Fornaciai, A.; Lev, E.; Liu, E.; Pieri, D.; Rodgers, M.; et al. Volcanological applications of unoccupied aircraft systems (UAS): Developments, strategies, and future challenges. *Volcanica* **2020**, *3*, 67–114. [CrossRef]
139. Bonali, F.L.; Tibaldi, A.; Marchese, F.; Fallati, L.; Russo, E.; Corselli, C.; Savini, A. UAV-based surveying in volcano-tectonics: An example from the Iceland rift. *J. Struct. Geol.* **2019**, *121*, 46–64. [CrossRef]
140. Chio, S.H.; Lin, C.H. Preliminary Study of UAS Equipped with Thermal Camera for Volcanic Geothermal Monitoring in Taiwan. *Sensors* **2017**, *17*, 1649. [CrossRef] [PubMed]
141. Wakeford, Z.E.; Chmielewska, M.; Hole, M.J.; Howell, J.A.; Jerram, D.A. Combining thermal imaging with photogrammetry of an active volcano using UAV: An example from Stromboli, Italy. *Photogramm. Rec.* **2019**, *34*, 445–466. [CrossRef]
142. Gailler, L.; Labazuy, P.; Régis, E.; Bontemps, M.; Souriot, T.; Bacques, G.; Carton, B. Validation of a New UAV Magnetic Prospecting Tool for Volcano Monitoring and Geohazard Assessment. *Remote Sens.* **2021**, *13*, 894. [CrossRef]
143. Rokhmana, C.A.; Andaru, R. Utilizing UAV-based mapping in post disaster volcano eruption. In Proceedings of the 2016 6th International Annual Engineering Seminar (InAES), Yogyakarta, Indonesia, 1–3 August 2016; pp. 202–205. [CrossRef]
144. Linchant, J.; Lisein, J.; Semeki, J.; Lejeune, P.; Vermeulen, C. Are unmanned aircraft systems (UAS s) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Rev.* **2015**, *45*, 239–252. [CrossRef]
145. Chrétien, L.P.; Théau, J.; Ménard, P. Visible and thermal infrared remote sensing for the detection of white-tailed deer using an unmanned aerial system. *Wildl. Soc. Bull.* **2016**, *40*, 181–191. [CrossRef]
146. Wich, S.; Dellatore, D.; Houghton, M.; Ardi, R.; Koh, L.P. A preliminary assessment of using conservation drones for Sumatran orang-utan (Pongo abelii) distribution and density. *J. Unmanned Veh. Syst.* **2015**, *4*, 45–52. [CrossRef]
147. Sweeney, K.L.; Helker, V.T.; Perryman, W.L.; LeRoi, D.J.; Fritz, L.W.; Gelatt, T.S.; Angliss, R.P. Flying beneath the clouds at the edge of the world: Using a hexacopter to supplement abundance surveys of Steller sea lions (Eumetopias jubatus) in Alaska. *J. Unmanned Veh. Syst.* **2015**, *4*, 70–81. [CrossRef]
148. Sykora-Bodie, S.T.; Bezy, V.; Johnston, D.W.; Newton, E.; Lohmann, K.J. Quantifying nearshore sea turtle densities: Applications of unmanned aerial systems for population assessments. *Sci. Rep.* **2017**, *7*, 17690. [CrossRef] [PubMed]
149. Kiszka, J.J.; Mourier, J.; Gastrich, K.; Heithaus, M.R. Using unmanned aerial vehicles (UAVs) to investigate shark and ray densities in a shallow coral lagoon. *Mar. Ecol. Prog. Ser.* **2016**, *560*, 237–242. [CrossRef]
150. Torres, L.G.; Nieukirk, S.L.; Lemos, L.; Chandler, T.E. Drone up! Quantifying whale behavior from a new perspective improves observational capacity. *Front. Mar. Sci.* **2018**, *5*, 319. [CrossRef]
151. Evans, I.; Jones, T.H.; Pang, K.; Evans, M.N.; Saimin, S.; Goossens, B. Use of drone technology as a tool for behavioral research: A case study of crocodilian nesting. *Herpetol. Conserv. Biol.* **2015**, *10*, 90–98.
152. Groves, P.A.; Alcorn, B.; Wiest, M.M.; Maselko, J.M.; Connor, W.P. Testing unmanned aircraft systems for salmon spawning surveys. *Facets* **2016**, *1*, 187–204. [CrossRef]
153. Hu, S.; Yuan, X.; Ni, W.; Wang, X.; Jamalipour, A. Visual Camouflage and Online Trajectory Planning for Unmanned Aerial Vehicle-Based Disguised Video Surveillance: Recent Advances and a Case Study. *IEEE Veh. Technol. Mag.* **2023**, *18*, 48–57. [CrossRef]
154. Huang, H.; Savkin, A.V.; Huang, C. *Autonomous Navigation and Deployment of UAVs for Communication, Surveillance and Delivery*; John Wiley & Sons: Hoboken, NJ , USA, 2022.
155. Barr, J.R.; Green, M.C.; DeMaso, S.J.; Hardy, T.B. Drone surveys do not increase colony-wide flight behaviour at waterbird nesting sites, but sensitivity varies among species. *Sci. Rep.* **2020**, *10*, 3781. [CrossRef]
156. Chabot, D.; Bird, D.M. Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in? *J. Unmanned Veh. Syst.* **2015**, *3*, 137–155. [CrossRef]
157. Li, X.; Huang, H.; Savkin, A.V. Autonomous Navigation of an Aerial Drone to Observe a Group of Wild Animals with Reduced Visual Disturbance. *IEEE Syst. J.* **2022**, *16*, 3339–3348. [CrossRef]
158. Hodgson, J.C.; Koh, L.P. Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Curr. Biol.* **2016**, *26*, R404–R405. [CrossRef]
159. Barnas, A.; Newman, R.; Felege, C.J.; Corcoran, M.P.; Hervey, S.D.; Stechmann, T.J.; Rockwell, R.F.; Ellis-Felege, S.N. Evaluating behavioral responses of nesting lesser snow geese to unmanned aircraft surveys. *Ecol. Evol.* **2018**, *8*, 1328–1338. [CrossRef] [PubMed]
160. Mulero-Pázmány, M.; Jenni-Eiermann, S.; Strebel, N.; Sattler, T.; Negro, J.J.; Tablado, Z. Unmanned aircraft systems as a new source of disturbance for wildlife: A systematic review. *PLoS ONE* **2017**, *12*, e0178448. [CrossRef] [PubMed]
161. Savkin, A.V.; Huang, H. Bioinspired Bearing Only Motion Camouflage UAV Guidance for Covert Video Surveillance of a Moving Target. *IEEE Syst. J.* **2021**, *15*, 5379–5382. [CrossRef]
162. Arafat, M.Y.; Moh, S. Bio-Inspired Approaches for Energy-Efficient Localization and Clustering in UAV Networks for Monitoring Wildfires in Remote Areas. *IEEE Access* **2021**, *9*, 18649–18669. [CrossRef]

163. Hu, S.; Ni, W.; Wang, X.; Jamalipour, A. Disguised Tailing and Video Surveillance with Solar-Powered Fixed-Wing Unmanned Aerial Vehicle. *IEEE Trans. Veh. Technol.* **2022**, *71*, 5507–5518. [CrossRef]
164. Wu, Q.; Zeng, Y.; Zhang, R. Joint Trajectory and Communication Design for Multi-UAV Enabled Wireless Networks. *arXiv* **2018**, arXiv:1705.02723.
165. Park, S.; Choi, Y. Applications of Unmanned Aerial Vehicles in Mining from Exploration to Reclamation: A Review. *Minerals* **2020**, *10*, 663. [CrossRef]
166. Lee, S.; Choi, Y. Reviews of unmanned aerial vehicle (drone) technology trends and its applications in the mining industry. *Geosystem Eng.* **2016**, *19*, 197–204. [CrossRef]
167. Ren, H.; Zhao, Y.; Xiao, W.; Hu, Z. A review of UAV monitoring in mining areas: Current status and future perspectives. *Int. J. Coal Sci. Technol.* **2019**, *6*, 320–333. [CrossRef]
168. Li, H.; Savkin, A.V.; Vucetic, B. Autonomous Area Exploration and Mapping in Underground Mine Environments by Unmanned Aerial Vehicles. *Robotica* **2020**, *38*, 442–456. [CrossRef]
169. Freire, G.; Cota, R. Capture of images in inaccessible areas in an underground mine using an unmanned aerial vehicle. In Proceedings of the UMT 2017: Proceedings of the First International Conference on Underground Mining Technology, Australian Centre for Geomechanics, Sudbury, ON, Canada, 11–13 October 2017.
170. Turner, R.M.; MacLaughlin, M.M.; Iverson, S.R. Identifying and mapping potentially adverse discontinuities in underground excavations using thermal and multispectral UAV imagery. *Eng. Geol.* **2020**, *266*, 105470. [CrossRef]
171. Wang, Q.; Wu, L.; Chen, S.; Shu, D.; Xu, Z.; Li, F.; Wang, R. Accuracy evaluation of 3d geometry from low-attitude uav collections a case at zijin mine. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2014**, *40*, 297–300. [CrossRef]
172. Lee, S.; Choi, Y. On-site demonstration of topographic surveying techniques at open-pit mines using a fixed-wing unmanned aerial vehicle (drone). *Tunn. Undergr. Space* **2015**, *25*, 527–533. [CrossRef]
173. Lee, S.; Choi, Y. Topographic survey at small-scale open-pit mines using a popular rotary-wing unmanned aerial vehicle (drone). *Tunn. Undergr. Space* **2015**, *25*, 462–469. [CrossRef]
174. Rossi, P.; Mancini, F.; Dubbini, M.; Mazzone, F.; Capra, A. Combining nadir and oblique UAV imagery to reconstruct quarry topography: Methodology and feasibility analysis. *Eur. J. Remote Sens.* **2017**, *50*, 211–221. [CrossRef]
175. Hasan, A.; Kramar, V.; Hermansen, J.; Schultz, U.P. Development of Resilient Drones for Harsh Arctic Environment: Challenges, Opportunities, and Enabling Technologies. In Proceedings of the 2022 International Conference on Unmanned Aircraft Systems (ICUAS), Dubrovnik, Croatia, 21–24 June 2022; pp. 1227–1236. [CrossRef]
176. Urban, K. A New (Cold) Front in Polar Intelligence? Trends and Implications of Technology-Enabled Monitoring in the Arctic. *J. Sci. Policy Gov.* **2021**, *19*. [CrossRef]
177. Goetzendorf-Grabowski, T.; Rodzewicz, M. Design of UAV for photogrammetric mission in Antarctic area. *Proc. Inst. Mech. Eng Part G J. Aerosp. Eng.* **2017**, *231*, 1660–1675. [CrossRef]
178. Florinsky, I.; Bliakharskii, D. Detection of crevasses by geomorphometric treatment of data from unmanned aerial surveys. *Remote Sens. Lett.* **2019**, *10*, 323–332. [CrossRef]
179. Dąbski, M.; Zmarz, A.; Rodzewicz, M.; Korczak-Abshire, M.; Karsznia, I.; Lach, K.; Rachlewicz, G.; Chwedorzewska, K. Mapping glacier forelands based on UAV BVLOS operation in Antarctica. *Remote Sens.* **2020**, *12*, 630. [CrossRef]
180. Li, Y.; Qiao, G.; Popov, S.; Cui, X.; Florinsky, I.V.; Yuan, X.; Wang, L. Unmanned Aerial Vehicle Remote Sensing for Antarctic Research: A review of progress, current applications, and future use cases. *IEEE Geosci. Remote Sens. Mag.* **2023**, *11*, 73–93. [CrossRef]
181. Li, T.; Zhang, B.; Xiao, W.; Cheng, X.; Li, Z.; Zhao, J. UAV-Based Photogrammetry and LiDAR for the Characterization of Ice Morphology Evolution. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 4188–4199. [CrossRef]
182. Yuan, X.; Qiao, G.; Li, Y.; Li, H.; Xu, R. Modelling of glacier and ice sheet micro-topography based on unmanned aerial vehicle data, Antarctica. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2020**, *43*, 919–923. [CrossRef]
183. Dąbski, M.; Zmarz, A.; Pabjanek, P.; Korczak-Abshire, M.; Karsznia, I.; Chwedorzewska, K.J. UAV-based detection and spatial analyses of periglacial landforms on Demay Point (King George Island, South Shetland Islands, Antarctica). *Geomorphology* **2017**, *290*, 29–38. [CrossRef]
184. Osińska, M.; Bialik, R.J.; Wójcik-Długoborska, K.A. Interrelation of quality parameters of surface waters in five tidewater glacier coves of King George Island, Antarctica. *Sci. Total Environ.* **2021**, *771*, 144780. [CrossRef]
185. Rauhala, A.; Tuomela, A.; Davids, C.; Rossi, P. UAV Remote Sensing Surveillance of a Mine Tailings Impoundment in Sub-Arctic Conditions. *Remote Sens.* **2017**, *9*, 1318. [CrossRef]
186. Lucieer, A.; Robinson, S.; Turner, D.; Harwin, S.; Kelcey, J. Using a Micro-UAV for Ultra-High Resolution Multi-Sensor Observations of Antarctic Moss Beds 2012. Available online: https://isprs-archives.copernicus.org/articles/XXXIX-B1/429/2012/ (accessed on 7 May 2024).
187. Park, H.L.; Park, S.Y.; Hyun, C.U.; Hong, S.G.; Kim, H.c.; Lee, R. UAV based very-high-resolution imaging on Barton Peninsula Antarctica 2014. Available online: https://openpolar.no/Record/ftdatacite:10.12760%2F03-2014-27 (accessed on 7 May 2024).
188. Benassi, F.; Dall'Asta, E.; Diotri, F.; Forlani, G.; Morra di Cella, U.; Roncella, R.; Santise, M. Testing accuracy and repeatability of UAV blocks oriented with GNSS-supported aerial triangulation. *Remote Sens.* **2017**, *9*, 172. [CrossRef]

189. Florinsky, I.; Skrypitsyna, T.; Bliakharskii, D.; Ishalina, O.; Kiseleva, A. Towards the modeling of glacier microtopography using high-resolution data from unmanned aerial survey. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2020**, *43*, 1065–1071. [CrossRef]
190. Laborie, J.; Christiansen, F.; Beedholm, K.; Madsen, P.T.; Heerah, K. Behavioural impact assessment of unmanned aerial vehicles on Weddell seals (Leptonychotes weddellii). *J. Exp. Mar. Biol. Ecol.* **2021**, *536*, 151509. [CrossRef]
191. Fudala, K.; Bialik, R.J. Breeding colony dynamics of southern elephant seals at Patelnia Point, King George Island, Antarctica. *Remote Sens.* **2020**, *12*, 2964. [CrossRef]
192. Oosthuizen, W.C.; Krüger, L.; Jouanneau, W.; Lowther, A.D. Unmanned aerial vehicle (UAV) survey of the Antarctic shag (Leucocarbo bransfieldensis) breeding colony at Harmony Point, Nelson Island, South Shetland Islands. *Polar Biol.* **2020**, *43*, 187–191. [CrossRef]
193. Krause, D.J.; Hinke, J.T.; Goebel, M.E.; Perryman, W.L. Drones minimize Antarctic predator responses relative to ground survey methods: An appeal for context in policy advice. *Front. Mar. Sci.* **2021**, *8*, 152. [CrossRef]
194. Lewicki, T.; Liu, K. Multimodal Wildfire Surveillance with UAV. In Proceedings of the 2021 IEEE Global Communications Conference (GLOBECOM), IEEE, Madrid, Spain, 7–11 December 2021; pp. 1–6.
195. Shi, C.; Lai, G.; Yu, Y.; Bellone, M.; Lippiello, V. Real-Time Multi-Modal Active Vision for Object Detection on UAVs Equipped with Limited Field of View LiDAR and Camera. *IEEE Robot. Autom. Lett.* **2023**, *8*, 6571–6578. [CrossRef]
196. Jalil, B.; Leone, G.R.; Martinelli, M.; Moroni, D.; Pascali, M.A.; Berton, A. Fault detection in power equipment via an unmanned aerial system using multi modal data. *Sensors* **2019**, *19*, 3014. [CrossRef] [PubMed]
197. Khelifi, A.; Ciccone, G.; Altaweel, M.; Basmaji, T.; Ghazal, M. Autonomous service drones for multimodal detection and monitoring of archaeological sites. *Appl. Sci.* **2021**, *11*, 10424. [CrossRef]
198. Brooke, C.; Clutterbuck, B. Mapping heterogeneous buried archaeological features using multisensor data from unmanned aerial vehicles. *Remote Sens.* **2019**, *12*, 41. [CrossRef]
199. Slingsby, J.; Scott, B.E.; Kregting, L.; McIlvenny, J.; Wilson, J.; Williamson, B.J. A Review of Unmanned Aerial Vehicles Usage as an Environmental Survey Tool within Tidal Stream Environments. *J. Mar. Sci. Eng.* **2023**, *11*, 2298. [CrossRef]
200. Rey, N. Combining UAV-Imagery and Machine Learning for Wildlife Conservation. Technical Report. 2016. Available online: https://infoscience.epfl.ch/record/221527?ln=en&v=pdf (accessed on 7 May 2024).
201. Xu, J.; Solmaz, G.; Rahmatizadeh, R.; Turgut, D.; Bölöni, L. Animal monitoring with unmanned aerial vehicle-aided wireless sensor networks. In Proceedings of the 2015 IEEE 40th Conference on Local Computer Networks (LCN). IEEE, Clearwater Beach, FL, USA, 26–29 October 2015; pp. 125–132.
202. Vera-Amaro, R.; Rivero-Ángeles, M.E.; Luviano-Juárez, A. Data collection schemes for animal monitoring using WSNs-assisted by UAVs: WSNs-oriented or UAV-oriented. *Sensors* **2020**, *20*, 262. [CrossRef]
203. Botrugno, M.C.; D'Errico, G.; De Paolis, L.T. Augmented reality and UAVs in archaeology: Development of a location-based AR application. In Proceedings of the Augmented Reality, Virtual Reality, and Computer Graphics: 4th International Conference, AVR 2017, Ugento, Italy, 12–15 June 2017; Proceedings, Part II 4. Springer: Berlin/Heidelberg, Germany, 2017; pp. 261–270.
204. Maboudi, M.; Homaei, M.; Song, S.; Malihi, S.; Saadatseresht, M.; Gerke, M. A Review on Viewpoints and Path Planning for UAV-Based 3D Reconstruction. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2023**, *16*, 5026–5048. [CrossRef]
205. Zingoni, A.; Diani, M.; Corsini, G.; Masini, A. Real-time 3D reconstruction from images taken from an UAV. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2015**, *40*, 313–319. [CrossRef]
206. Sargolzaei, A.; Abbaspour, A.; Crane, C.D. Control of Cooperative Unmanned Aerial Vehicles: Review of Applications, Challenges, and Algorithms. In *Optimization, Learning, and Control for Interdependent Complex Networks*; Amini, M.H., Ed.; Springer International Publishing: Cham, Switzerland, 2020; pp. 229–255. [CrossRef]
207. Mohsan, S.A.H.; Khan, M.A.; Alsharif, M.H.; Uthansakul, P.; Solyman, A.A. Intelligent reflecting surfaces assisted UAV communications for massive networks: Current trends, challenges, and research directions. *Sensors* **2022**, *22*, 5278. [CrossRef] [PubMed]
208. Wu, Q.; Zhang, R. Towards Smart and Reconfigurable Environment: Intelligent Reflecting Surface Aided Wireless Network. *IEEE Commun. Mag.* **2020**, *58*, 106–112. [CrossRef]
209. Aggarwal, S.; Kumar, N. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. *Comput. Commun.* **2020**, *149*, 270–299. [CrossRef]
210. Zuo, Z.; Liu, C.; Han, Q.L.; Song, J. Unmanned aerial vehicles: Control methods and future challenges. *IEEE/CAA J. Autom. Sin.* **2022**, *9*, 601–614. [CrossRef]
211. Wang, B.; Zhao, D.; Li, W.; Wang, Z.; Huang, Y.; You, Y.; Becker, S. Current technologies and challenges of applying fuel cell hybrid propulsion systems in unmanned aerial vehicles. *Prog. Aerosp. Sci.* **2020**, *116*, 100620. [CrossRef]
212. Chen, J.; Zhang, X.; Xin, B.; Fang, H. Coordination between unmanned aerial and ground vehicles: A taxonomy and optimization perspective. *IEEE Trans. Cybern.* **2015**, *46*, 959–972. [CrossRef] [PubMed]
213. Chai, R.; Guo, Y.; Zuo, Z.; Chen, K.; Shin, H.S.; Tsourdos, A. Cooperative motion planning and control for aerial-ground autonomous systems: Methods and applications. *Prog. Aerosp. Sci.* **2024**, *146*, 101005. [CrossRef]
214. Shen, Y.; Wei, C. Target tracking and enclosing via UAV/UGV cooperation using energy estimation pigeon-inspired optimization and switchable topology. *Aircr. Eng. Aerosp. Technol.* **2023**, *95*, 768–783. [CrossRef]

215. Dinelli, C.; Racette, J.; Escarcega, M.; Lotero, S.; Gordon, J.; Montoya, J.; Dunaway, C.; Androulakis, V.; Khaniani, H.; Shao, S.; et al. Configurations and applications of multi-agent hybrid drone/unmanned ground vehicle for underground environments: A review. *Drones* **2023**, *7*, 136. [CrossRef]
216. Zhang, Y.; Shan, H.; Chen, H.; Mi, D.; Shi, Z. Perceptive Mobile Networks for Unmanned Aerial Vehicle Surveillance: From the Perspective of Cooperative Sensing. *IEEE Veh. Technol. Mag.* **2024**, 2–11. [CrossRef]
217. Li, J.; Sun, T.; Huang, X.; Ma, L.; Lin, Q.; Chen, J.; Leung, V.C.M. A Memetic Path Planning Algorithm for Unmanned Air/Ground Vehicle Cooperative Detection Systems. *IEEE Trans. Autom. Sci. Eng.* **2022**, *19*, 2724–2737. [CrossRef]
218. Li, J.; Deng, G.; Luo, C.; Lin, Q.; Yan, Q.; Ming, Z. A Hybrid Path Planning Method in Unmanned Air/Ground Vehicle (UAV/UGV) Cooperative Systems. *IEEE Trans. Veh. Technol.* **2016**, *65*, 9585–9596. [CrossRef]
219. Wang, J.; Jiang, C.; Han, Z.; Ren, Y.; Maunder, R.G.; Hanzo, L. Taking Drones to the Next Level: Cooperative Distributed Unmanned-Aerial-Vehicular Networks for Small and Mini Drones. *IEEE Veh. Technol. Mag.* **2017**, *12*, 73–82. [CrossRef]
220. Wu, Y.; Low, K.H.; Lv, C. Cooperative path planning for heterogeneous unmanned vehicles in a search-and-track mission aiming at an underwater target. *IEEE Trans. Veh. Technol.* **2020**, *69*, 6782–6787. [CrossRef]
221. Wei, W.; Wang, J.; Fang, Z.; Chen, J.; Ren, Y.; Dong, Y. 3U: Joint Design of UAV-USV-UUV Networks for Cooperative Target Hunting. *IEEE Trans. Veh. Technol.* **2023**, *72*, 4085–4090. [CrossRef]
222. Pasini, D.; Jiang, C.; Jolly, M.P. UAV and UGV Autonomous Cooperation for Wildfire Hotspot Surveillance. In Proceedings of the 2022 IEEE MIT Undergraduate Research Technology Conference (URTC), Cambridge, MA, USA, 30 September–2 October 2022; pp. 1–5. [CrossRef]
223. Bushnaq, O.M.; Chaaban, A.; Al-Naffouri, T.Y. The Role of UAV-IoT Networks in Future Wildfire Detection. *IEEE Internet Things J.* **2021**, *8*, 16984–16999. [CrossRef]
224. Liu, D.; Zhu, X.; Bao, W.; Fei, B.; Wu, J. SMART: Vision-based method of cooperative surveillance and tracking by multiple UAVs in the urban environment. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 24941–24956. [CrossRef]
225. Butilă, E.V.; Boboc, R.G. Urban traffic monitoring and analysis using unmanned aerial vehicles (uavs): A systematic literature review. *Remote Sens.* **2022**, *14*, 620. [CrossRef]
226. Semsch, E.; Jakob, M.; Pavlicek, D.; Pechoucek, M. Autonomous UAV Surveillance in Complex Urban Environments. In Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology, Milan, Italy, 15–18 September 2009; Volume 2, pp. 82–85. [CrossRef]
227. Dai, R.; Fotedar, S.; Radmanesh, M.; Kumar, M. Quality-aware UAV coverage and path planning in geometrically complex environments. *Ad Hoc Netw.* **2018**, *73*, 95–105. [CrossRef]
228. Savkin, A.V.; Huang, H. Multi-UAV Navigation for Optimized Video Surveillance of Ground Vehicles on Uneven Terrains. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 10238–10242. [CrossRef]
229. Saha, D.; Pattanayak, D.; Mandal, P.S. Surveillance of Uneven Surface with Self-Organizing Unmanned Aerial Vehicles. *IEEE Trans. Mob. Comput.* **2022**, *21*, 1449–1462. [CrossRef]
230. Wei, J.; Li, S. A Method for Collision-free UAV Navigation around Moving Obstacles over an Uneven Terrain. In Proceedings of the 2023 IEEE International Conference on Robotics and Biomimetics (ROBIO), Samui, Thailand, 4–9 December 2023; pp. 1–6. [CrossRef]
231. Chodorek, A.; Chodorek, R.R.; Yastrebov, A. Weather sensing in an urban environment with the use of a uav and webrtc-based platform: A pilot study. *Sensors* **2021**, *21*, 7113. [CrossRef] [PubMed]
232. Thibbotuwawa, A.; Bocewicz, G.; Radzki, G.; Nielsen, P.; Banaszak, Z. UAV mission planning resistant to weather uncertainty. *Sensors* **2020**, *20*, 515. [CrossRef] [PubMed]
233. Thibbotuwawa, A.; Nielsen, P.; Bocewicz, G.; Banaszak, Z. UAVs Fleet Mission planning subject to weather fore-cast and energy consumption constraints. In *Automation 2019: Progress in Automation, Robotics and Measurement Techniques*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 104–114.
234. Hashesh, A.O.; Hashima, S.; Zaki, R.M.; Fouda, M.M.; Hatano, K.; Eldien, A.S.T. AI-Enabled UAV Communications: Challenges and Future Directions. *IEEE Access* **2022**, *10*, 92048–92066. [CrossRef]
235. Al-Turjman, F. (Ed.) *Unmanned Aerial Vehicles in Smart Cities*; Unmanned System Technologies; Springer International Publishing: Cham, Switzerland, 2020. [CrossRef]
236. Thakur, N.; Nagrath, P.; Jain, R.; Saini, D.; Sharma, N.; Hemanth, D.J. Artificial Intelligence Techniques in Smart Cities Surveillance Using UAVs: A Survey. In *Machine Intelligence and Data Analytics for Sustainable Future Smart Cities*; Ghosh, U., Maleh, Y., Alazab, M., Pathan, A.S.K., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 329–353. [CrossRef]
237. Yang, Z.; Chen, M.; Liu, X.; Liu, Y.; Chen, Y.; Cui, S.; Poor, H.V. AI-Driven UAV-NOMA-MEC in Next Generation Wireless Networks. *IEEE Wirel. Commun.* **2021**, *28*, 66–73. [CrossRef]
238. Eskandari, M.; Savkin, A.V. Deep-Reinforcement-Learning-Based Joint 3-D Navigation and Phase-Shift Control for Mobile Internet of Vehicles Assisted by RIS-Equipped UAVs. *IEEE Internet Things J.* **2023**, *10*, 18054–18066. [CrossRef]
239. Qiu, C.; Hu, Y.; Chen, Y.; Zeng, B. Deep deterministic policy gradient (DDPG)-based energy harvesting wireless communications. *IEEE Internet Things J.* **2019**, *6*, 8577–8588. [CrossRef]
240. Hou, Y.; Liu, L.; Wei, Q.; Xu, X.; Chen, C. A novel DDPG method with prioritized experience replay. In Proceedings of the 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE, Banff, AB, Canada, 5–8 October 2017; pp. 316–321.

241. Xu, Y.H.; Yang, C.C.; Hua, M.; Zhou, W. Deep deterministic policy gradient (DDPG)-based resource allocation scheme for NOMA vehicular communications. *IEEE Access* **2020**, *8*, 18797–18807. [CrossRef]
242. Wang, X.; Gursoy, M.C.; Erpek, T.; Sagduyu, Y.E. Learning-Based UAV Path Planning for Data Collection with Integrated Collision Avoidance. *IEEE Internet Things J.* **2022**, *9*, 16663–16676. [CrossRef]
243. Sandamini, C.; Maduranga, M.W.P.; Tilwari, V.; Yahaya, J.; Qamar, F.; Nguyen, Q.N.; Ibrahim, S.R.A. A review of indoor positioning systems for UAV localization with machine learning algorithms. *Electronics* **2023**, *12*, 1533. [CrossRef]
244. Gohari, A.; Ahmad, A.B.; Rahim, R.B.A.; Supa'at, A.S.M.; Abd Razak, S.; Gismalla, M.S.M. Involvement of surveillance drones in smart cities: A systematic review. *IEEE Access* **2022**, *10*, 56611–56628. [CrossRef]
245. Srivastava, A.; Badal, T.; Saxena, P.; Vidyarthi, A.; Singh, R. UAV surveillance for violence detection and individual identification. *Autom. Softw. Eng.* **2022**, *29*, 28. [CrossRef]
246. Ding, Y.; Yang, Z.; Pham, Q.V.; Hu, Y.; Zhang, Z.; Shikh-Bahaei, M. Distributed machine learning for uav swarms: Computing, sensing, and semantics. *IEEE Internet Things J.* **2023**, *11*, 7447–7473. [CrossRef]
247. Wu, G.; Fan, M.; Shi, J.; Feng, Y. Reinforcement Learning Based Truck-and-Drone Coordinated Delivery. *IEEE Trans. Artif. Intell.* **2023**, *4*, 754–763. [CrossRef]
248. Kong, F.; Wang, Q.; Gao, S.; Yu, H. B-APFDQN: A UAV Path Planning Algorithm Based on Deep Q-Network and Artificial Potential Field. *IEEE Access* **2023**, *11*, 44051–44064. [CrossRef]
249. Petritoli, E.; Leccese, F. Unmanned autogyro for mars exploration: A preliminary study. *Drones* **2021**, *5*, 53. [CrossRef]
250. Sharma, M.; Gupta, A.; Gupta, S.K.; Alsamhi, S.H.; Shvetsov, A.V. Survey on unmanned aerial vehicle for Mars exploration: Deployment use case. *Drones* **2022**, *6*, 4. [CrossRef]
251. Galvez-Serna, J.; Vanegas, F.; Gonzalez, F.; Flannery, D. Towards a probabilistic based autonomous UAV mission planning for planetary exploration. In Proceedings of the 2021 IEEE Aerospace Conference (50100), IEEE, Big Sky, MT, USA, 6–13 March 2021; pp. 1–8.
252. Zhao, P.; Li, R.; Wu, P.; Liu, H.; Gao, X.; Deng, Z. Review of Key Technologies of Rotary-Wing Mars UAVs for Mars Exploration. *Inventions* **2023**, *8*, 151. [CrossRef]
253. Brommer, C.; Fornasier, A.; Scheiber, M.; Delaune, J.; Brockers, R.; Steinbrener, J.; Weiss, S. The INSANE dataset: Large number of sensors for challenging UAV flights in Mars analog, outdoor, and out-/indoor transition scenarios. *Int. J. Robot. Res.* **2024**, 02783649241227245. [CrossRef]
254. Crisp, J.A.; Adler, M.; Matijevic, J.R.; Squyres, S.W.; Arvidson, R.E.; Kass, D.M. Mars exploration rover mission. *J. Geophys. Res. Planets* **2003**, *108*. [CrossRef]
255. Sand, S.; Zhang, S.; Mühlegg, M.; Falconi, G.; Zhu, C.; Krüger, T.; Nowak, S. Swarm exploration and navigation on mars. In Proceedings of the 2013 International Conference on Localization and GNSS (ICL-GNSS). IEEE, Torino, Italy, 25–27 June 2013; pp. 1–6.
256. Marin, D.B.; Becciolini, V.; Santana, L.S.; Rossi, G.; Barbari, M. State of the Art and Future Perspectives of Atmospheric Chemical Sensing Using Unmanned Aerial Vehicles: A Bibliometric Analysis. *Sensors* **2023**, *23*, 8384. [CrossRef] [PubMed]
257. Jońca, J.; Pawnuk, M.; Bezyk, Y.; Arsen, A.; Sówka, I. Drone-Assisted Monitoring of Atmospheric Pollution—A Comprehensive Review. *Sustainability* **2022**, *14*, 11516. [CrossRef]
258. Shelekhov, A.; Afanasiev, A.; Shelekhova, E.; Kobzev, A.; Tel'minov, A.; Molchunov, A.; Poplevina, O. Low-altitude sensing of urban atmospheric turbulence with UAV. *Drones* **2022**, *6*, 61. [CrossRef]
259. Samad, A.; Alvarez Florez, D.; Chourdakis, I.; Vogt, U. Concept of using an unmanned aerial vehicle (UAV) for 3D investigation of air quality in the atmosphere—example of measurements near a roadside. *Atmosphere* **2022**, *13*, 663. [CrossRef]
260. Ropero, F.; Muñoz, P.; R-Moreno, M.D. A Strategical Path Planner for UGV-UAV Cooperation in Mars Terrains. In *Artificial Intelligence XXXV*; Bramer, M., Petridis, M., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2018; Volume 11311, pp. 106–118. [CrossRef]
261. Ismail, Z.H.; Sariff, N.; Hurtado, E.G. A survey and analysis of cooperative multi-agent robot systems: Challenges and directions. *Appl. Mob. Robot.* **2018**, *5*, 8–14.
262. Lakas, A.; Belkhouche, B.; Benkraouda, O.; Shuaib, A.; Alasmawi, H.J. A framework for a cooperative UAV-UGV system for path discovery and planning. In Proceedings of the 2018 International Conference on Innovations in Information Technology (IIT). IEEE, Al Ain, United Arab Emirates, 18–19 November 2018; pp. 42–46.