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Review

A Comprehensive Review of UAV-UGV Collaboration: Advancements and Challenges

Isuru Munasinghe [1], Asanka Perera [2] and Ravinesh C. Deo [3,*]

[1] Department of Electronic and Telecommunication Engineering, University of Moratuwa, Moratuwa 10400, Sri Lanka; isuru.munasinghe1998@gmail.com
[2] School of Engineering, University of Southern Queensland, Springfield, QLD 4300, Australia; asanka.perera@unisq.edu.au
[3] School of Mathematics, Physics and Computing, University of Southern Queensland, Springfield, QLD 4300, Australia
* Correspondence: ravinesh.deo@unisq.edu.au

Abstract: Unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) have rapidly evolved, becoming integral to various applications such as environmental monitoring, disaster response, and precision agriculture. This paper provides a comprehensive review of the advancements and the challenges in UAV-UGV collaboration and its potential applications. These systems offer enhanced situational awareness and operational efficiency, enabling complex tasks that are beyond the capabilities of individual systems by leveraging the complementary strengths of UAVs and UGVs. Key areas explored in this review include multi-UAV and multi-UGV systems, collaborative aerial and ground operations, and the communication and coordination mechanisms that support these collaborative efforts. Furthermore, this paper discusses potential limitations, challenges and future research directions, and considers issues such as computational constraints, communication network instability, and environmental adaptability. The review also provides a detailed analysis of how these issues impact the effectiveness of UAV-UGV collaboration.

Keywords: unmanned aerial vehicle; unmanned ground vehicle; heterogeneous robots; multi-robot collaboration

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1. Introduction

Unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) have seen rapid advancements in recent years, leading to their widespread use in various applications such as surveillance, environmental monitoring, disaster response, and precision agriculture [1–3]. The ability to combine the strengths of UAVs and UGVs into collaborative systems has extended new possibilities for complex tasks that require aerial and ground perspectives. Each type of vehicle has its own unique strength with UAVs offering aerial perspectives and rapid deployment and UGVs providing detailed ground level interaction and manipulation. The integration of these two systems into collaborative frameworks has opened new possibilities for complex missions that demand both aerial and terrestrial capabilities.

The collaboration between UAVs and UGVs represents a significant advancement in the field of robotics. This collaboration allows for the combination of aerial mobility with ground-based endurance and interaction, enabling more efficient and effective execution of tasks that neither system could achieve alone [4,5]. For instance, in search and rescue missions, UAVs can rapidly identify points of interest from the air, while UGVs, equipped with specialized tools, can navigate to those locations on the ground to perform rescue operations. This synergistic approach not only enhances operational outcomes but also provides greater flexibility in adapting to dynamic environments [6,7].

The rapid advancements in UAV-UGV systems have led to their increased deployment in various applications, each presenting its own set of challenges and practical requirements. The research community has responded by developing sophisticated algorithms and coordination mechanisms that enable these systems to work together seamlessly. Such developments have been crucial in addressing the complexities associated with the real-time operation of multiple autonomous vehicles in dynamic and often unpredictable environments [8].

Despite the significant progress, UAV-UGV collaboration still faces challenges, particularly in terms of optimizing communication, coordination, and operational efficiency in complex scenarios [9]. The limitations related to computational constraints, communication network instability, and environmental adaptability remain significant obstacles that must be overcome to fully realize the potential of these systems. These challenges underscore the need for ongoing research and innovation to enhance the robustness and reliability of UAV-UGV collaborative frameworks.

The main contributions of this review are as follows:

1. To provide a comprehensive analysis of advancements in UAV-UGV collaboration, highlighting their improved operational efficiency in different fields.
2. To evaluate the coordination mechanisms and communication technologies that enable seamless integration of UAV-UGV systems, contributing to the optimization of real-time collaborative operations.
3. To identify and analyze the key challenges limiting the full potential of UAV-UGV systems, providing insights into areas requiring further research and development for improved performance.

The rest of the article is organized as follows: The paper begins with an exploration of multi-UAV and multi-UGV systems, detailing their evolution and applications as presented in Section 2. Section 3 examines the mechanisms of collaboration between UAVs and UGVs, focusing on the roles these systems play in both aerial and ground operations. The discussion continues with an analysis of the communication technologies that support seamless data exchange and coordination in Section 4.1. The collaborative tasks and applications of UAVs and UGVs are discussed in Section 5. Finally, the paper addresses the significant limitations and challenges that persist in the field, offering insights into the areas where further research is needed in Section 6. Section 8 concludes the paper.

2. Multi-UAV and Multi-UGV Systems

The development and deployment of UAVs and UGVs have fundamentally transformed various industries, enabling operations in environments that are challenging, dangerous, or inaccessible to the humans [10,11]. Initially, single UAVs and UGVs were at the forefront of this transformation. Single UAVs have also been widely utilized in various fields, including military surveillance, environmental monitoring, and infrastructure inspection, due to their versatility. These UAVs offer advantages like high mobility, the ability to access difficult terrains, and the capability to provide real-time data from an aerial perspective [12–14]. Nevertheless, these UAVs have their own limitations. For example, small fixed wing UAVs, although offering fast velocity, a wide field-of-view, and excellent communication capabilities, are limited by their low load capacity and reduced observation accuracy. In contrast, small rotary wing UAVs excel in the vertical takeoff and landing and are particularly effective for reconnaissance missions. However, they also face constraints, notably a limited load capacity [15]. Despite these challenges, their applications have expanded to include disaster response, where they can quickly survey the affected areas, providing essential information for rescue operations, and environmental monitoring. The versatility and efficiency of single UAVs have made them essential for tasks that require fast and precise aerial assessments. Among these are UAVs used in disaster response to quickly access areas that are otherwise unreachable due to debris, collapsed infrastructure, or hazardous conditions. In addition to this, they can also provide real-time aerial imagery and thermal sensing, which is crucial for identifying survivors, assessing the damage, and planning effective rescue and relief operations.

On the ground, single UGVs have played a pivotal role in tasks that necessitate direct interaction with the environment. These vehicles range from small, agile robots employed for explosive ordnance disposal and reconnaissance in military contexts to larger, more robust robots such as Boston Dynamics' Spot, which is engineered for industrial inspections and remote operations in hazardous environments [16]. UGVs offer significant advantages, including high load capacity and precise observation of ground targets, making them well-suited for detailed and labor-intensive tasks. However, they face certain limitations, including a narrow field-of-view, low velocity, and weak communication capabilities [15]. A notable example of UGV utility is in agriculture, where autonomous tractors are utilized to perform precision farming operations such as sowing, weeding, and harvesting with minimal human intervention [17]. With UGVs, the requirement for human labor in challenging or dangerous situations can be reduced significantly due to their ability to perform repetitive, hazardous, or labor-intensive tasks with high precision. In industries such as agriculture, where accuracy and consistency are paramount, as well as in disaster recovery scenarios, where human presence may be too risky, these vehicles can be extremely valuable.

While single UAVs and UGVs provide significant benefits in their respective domains, their limitations in coverage, payload capacity, and operational endurance have driven the development of multi-UAV and multi-UGV systems. Multi-UAV systems leverage the aerial mobility and extensive coverage provided by multiple drones to address a broader range of applications. For instance, in disaster response operations, deploying multiple UAVs can rapidly survey large areas, providing real-time imagery and data that can be used to assess damage and coordinate rescue efforts. Similarly, in environmental monitoring, multiple UAVs can cover extensive areas more efficiently than a single drone, collecting data on wildlife, vegetation, or pollution levels with greater speed and accuracy. These systems are particularly beneficial in dynamic environments where timely information is critical, as they can operate simultaneously to gather comprehensive data over large or complex terrains.

On the other hand, multi-UGV systems excel in performing tasks that require coordinated physical interaction with the environment. These systems are ideal for applications such as precision agriculture, where multiple ground robots can work in tandem to monitor crops, apply fertilizers, or perform weeding. In logistics and supply chain management, multi-UGVs can automate the movement of goods within warehouses or across manufacturing facilities, improving efficiency and reducing the reliance on human labor [18,19]. The coordination of multiple UGVs in a single operation allows for the division of labor and parallel processing, which can greatly enhance the speed and effectiveness of the tasks performed [20].

Integrating multi-UAV and multi-UGV systems offers significant advantages in complex and unpredictable environments but managing computational constraints in such systems remains a critical challenge. High volumes of sensor data, communication overhead, and real-time decision making require efficient strategies to avoid bottlenecks. Distributed computing provides an effective solution by distributing computational tasks across multiple UAVs, UGVs, and external computing nodes. This allows functions like real-time mapping, object detection, and path planning to be processed concurrently, reducing delays and ensuring smoother system operations. As demonstrated in [21], the improved mission allocation model optimizes reconnaissance rewards by efficiently distributing UAV resources. Incorporating time window constraints and target importance leads to higher task completion rates and improved mission success compared to traditional genetic algorithms.

Energy efficiency, especially on low power devices, is also a crucial aspect of multi-UAV systems. In [22], the proposed hierarchical clustering based approach significantly reduces communication overhead, thereby extending the system's operational lifetime. This balance between communication and computational energy consumption minimizes data transmission distances and volumes, improving energy efficiency. The system's ability to enhance energy efficiency in resource constrained environments demonstrates its effectiveness. The computational demands of multi-UAV and multi-UGV systems are further supported by advancements in hardware and communication technologies. The use of GPUs, FPGAs, and real-time operating systems enhances processing speeds for tasks like simultaneous localization and mapping (SLAM) and object recognition [23–25]. High speed communication networks, such as 5G, ensure fast and reliable data transfer between units, reducing latency and enabling effective coordination across the entire system.

UAV enabled Mobile-Edge Computing (MEC) systems further enhance the computation efficiency and operational performance of multi-UAV systems in time sensitive applications. Optimizing UAV trajectory and resource allocation improves task completion rates and ensures that IoT devices finish their computational tasks within required time constraints, as noted in [26]. The proposed algorithm, which converges to a Karush Kuhn Tucker (KKT) solution, provides significant performance gains over baseline schemes, improving the system's efficiency and accuracy in managing time critical tasks. Additionally, the Distributed Allocation with Time Windows (DATW) method in [27], increases task success rates by up to 18% compared to traditional methods like Consensus-Based Bundle Algorithm. This method effectively manages complex time window constraints and minimizes task conflicts, resulting in higher accuracy and success rates in mission critical operations.

The collaboration between UAVs and UGVs further enhances the capabilities of these individually operated systems, offering a coordinated and powerful solution to address the limitations of single platform deployments [15]. While multi-UAVs excel in aerial monitoring and rapid data acquisition, multi-UGVs are effective in ground-based tasks that require physical manipulation or interaction. When integrated together, these systems have a strong potential to tackle complex missions that require both aerial and ground perspectives. For example, in search and rescue operations, UAVs can quickly identify points of interest from the air, while UGVs, equipped with specialized tools, can navigate to those locations on the ground to assist with rescue efforts or perform tasks. This collaborative approach maximizes the strengths of both platforms, providing a more comprehensive and effective solution than either system could achieve alone. The integration of UAVs and UGVs in a coordinated operation not only leaded to improved mission outcomes but also can enhance the resilience and adaptability of the systems in complex, unpredictable and practical environments.

3. Aerial and Ground Collaborative Systems

The collaboration between UAVs and UGVs represents a pivotal advancement in the field of robotics, allowing for a more sophisticated and integrated approach to undertake complex operations [28]. The integration of these systems leverages the unique strengths of each platform, enabling them to perform tasks that are beyond the capabilities of either system alone. UAVs, with their rapid aerial mobility and wide area data collection abilities, provide a broad situational overview, which is essential in scenarios requiring quick assessments over large areas. On the other hand, UGVs excel in detailed ground-level analysis and can carry out intricate tasks in difficult or hazardous terrains. This combination allows for the efficient execution of missions that demand both a wide perspective and precise ground-level interventions, making UAV-UGV collaboration particularly valuable in dynamic and complex environments [29].

Search and rescue: One of the most significant advantages of UAV-UGV collaboration is the ability to carry out complex missions with increased level of efficiency and effectiveness [30]. In disaster response scenarios, for example, the UAVs can rapidly assess the extent of damage from above, identifying critical areas that need immediate attention. This aerial data can then guide UGVs on the ground, which are deployed to navigate through the debris or hazardous environments to perform crucial tasks such as search and rescue, delivering essential supplies, or conducting detailed structural inspections.

The combination of aerial surveillance with ground-level intervention not only accelerates response times but also enhances the overall quality and impact of the mission, ultimately leading to more lives saved and better resource management during critical situations. In addition, recent advancements in wireless communication technologies, such as 5G, have significantly improved the real-time data exchange between UAVs and UGVs. The integration of sophisticated AI algorithms allows for autonomous decision-making and adaptive mission planning. Enhanced sensor technologies, including LiDAR and thermal imaging, further enable these vehicles to operate efficiently in challenging environments.

Environmental monitoring: The environmental monitoring and resource management sectors also stand to gain significantly from UAV-UGV collaboration. In environmental monitoring, UAVs can cover large areas quickly, capturing data on environmental changes or potential threats such as wildfires or floods. UGVs can then be used to access specific areas of interest to perform detailed analysis or interventions, such as soil sampling or deploying firefighting equipment. This dual approach allows for a more comprehensive understanding of environmental conditions, as it combines the broad overview provided by UAVs with the detailed insights gained from UGVs. This integrated capability is particularly valuable for managing natural resources and responding to environmental crises, as it enables more informed decision-making and more effective action.

Precision agriculture: In the field of agriculture, UAV-UGV collaboration is driving significant advancements in precision agriculture, a practice that involves the use of technology to optimize crop management [1]. UAVs are used to monitor large agricultural fields from the air, identifying areas where crops may be stressed due to factors such as pests, disease, or inadequate water. This aerial data is then used to guide UGVs, which are deployed to perform targeted interventions such as applying fertilizers, pesticides, or irrigation. By integrating aerial monitoring with ground-level actions, this approach not only improves the efficiency and effectiveness of agricultural practices but also reduces the environmental impact by minimizing the use of chemicals and water. As a result, farmers can achieve higher yields while conserving resources, contributing to more sustainable agricultural practices. Aside from these environmental benefits, UAV-UGV technology can significantly reduce farmers' operating costs. In this way, farmers are able to save money and reduce the need for fertilizers, pesticides, and water by precisely targeting the areas that need special attention. Furthermore, automated systems handle tasks that would otherwise require extensive manual labor, which reduces labor costs.

Infrastructure inspection: Infrastructure inspection and maintenance are other areas where UAV-UGV collaboration is proving to be highly effective. The use of UAVs can provide a comprehensive aerial overview of large structures such as bridges, dams, and power lines, indicating potential issues that may not be visible from the ground [31]. Detailed inspections or repairs can then be performed with UGVs at specific locations, ensuring that any problems are addressed promptly and efficiently. Through this combined approach, infrastructure inspections become more thorough and accurate, reducing the risk of overlooking critical issues and improving safety. In addition, by automating parts of the inspection process, UAV-UGV collaboration can reduce the time and costs associated with maintaining infrastructure, making it a useful tool for public and private sector stakeholders.

Formation control: Formation control is a critical aspect of UAV-UGV collaboration, particularly in military and defense applications. Coordinated formation allows for the optimal spatial distribution of UAVs and UGVs, ensuring that each platform can perform its role effectively while supporting the other [15]. This capability is especially important in combat scenarios, where the ability to quickly adjust formations in response to changing conditions can be the difference between mission success and failure. Recent advancements in control algorithms and coordination strategies have made it possible for UAVs and UGVs to maintain optimal formations even in highly dynamic environments [32]. By enabling these platforms to work together more effectively, formation control enhances the overall operational effectiveness of UAV-UGV teams, making them more capable of handling complex and rapidly evolving missions.

Surveillance and reconnaissance: UAV-UGV collaboration also offers significant benefits in the field of surveillance and reconnaissance [33]. For identifying and tracking potential threats, UAVs can provide real-time aerial surveillance over large areas, providing a high-level perspective. In addition, UGVs can provide ground-level insight, allowing for detailed identification and monitoring of targets that may be obscured from the air. As a result of this combination of aerial and ground perspectives, surveillance operations become more accurate, reliable, and efficient, reducing security threats and enhancing detection, monitoring, and response. By integrating UAVs and UGVs into surveillance and reconnaissance operations, not only can situational awareness be improved, but also the range and scope of these operations can be expanded, making them more effective in civilian and military settings.

With UAV-UGV collaboration continuing to evolve, it is expected to become an increasingly vital component across a broad range of industries. As communication technologies, control algorithms, and autonomy advance, these collaborative systems will be able to operate more effectively and efficiently in a variety of environments [34]. UAV-UGV collaboration offers innovative solutions to some of the most challenging problems in modern robotics by addressing existing limitations and exploring new applications. In fields such as disaster response, environmental monitoring, agriculture, infrastructure maintenance, and defense, the integration of UAVs and UGVs has the potential to transform how we tackle complex tasks, enabling more efficient, effective, and sustainable solutions to a variety of problems.

Effective UAV-UGV collaboration is driven by the implementation of advanced technologies such as 3D mapping, localization, trajectory planning, object tracking, and autonomous navigation [29,35,36]. 3D mapping allows UAVs to create detailed maps of complex environments, which can then be used to guide UGVs through challenging terrains. With this capability, UGVs can navigate autonomously in areas with weak GPS signals by using the detailed spatial information provided by UAVs. In addition, localization algorithms are crucial to accurately determining the location of both UAVs and UGVs in real-time, allowing them to coordinate their movements. Sensor fusion, in which data from multiple sensors such as cameras, LIDARs, and ultrasonic sensors are combined, further enhances these techniques. By combining data from multiple sensors, UGVs can gain a more comprehensive understanding of the environment, allowing them to make better decisions about how to navigate. Sensor fusion also helps to reduce uncertainty and errors in localization, allowing for more accurate coordination between UAVs and UGVs.

4. Communication and Coordination in UAV-UGV Collaborative Systems

Establishing effective communication and coordination methods is essential for the success of UAV-UGV collaborative systems [37]. In complex and dynamic environments, these two elements are crucial to ensuring that multiple robotic units operate harmoniously and efficiently. Communication systems enable the exchange of critical data and commands between UAVs and UGVs, facilitating real-time information sharing and decision-making. The coordination mechanisms ensure that these units work seamlessly together to achieve common objectives, whether they are engaged in disaster relief operations, military operations, or industrial applications. In this section, we now examine the various communication technologies and coordination strategies utilized in UAV-UGV systems, emphasizing their impact on operational efficiency and effectiveness.

4.1. Communication Technologies

Considering their rapid advancements, both UAVs and UGVs are revolutionizing various sectors through their collaborative capabilities. However, effective collaboration between UAVs and UGVs relies heavily on advanced communication technologies that facilitate seamless data exchange and coordinated task execution. In Figure 1, we illustrate a comprehensive communication framework for cooperative UAV and UGV systems, particularly showcasing how these technologies integrate to optimize performance. This introduction delves into the critical role of communication technologies in UAV-UGV collaboration, highlighting advancements and challenges in this rapidly evolving field.

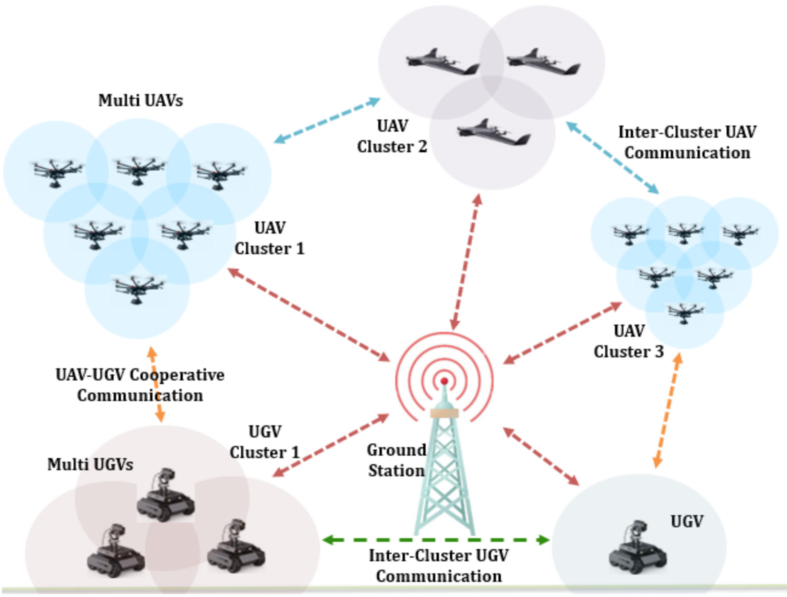

Figure 1. Communication Framework for Cooperative Multi-UAV and Multi-UGV Systems.

Relay systems: The system described in [38] demonstrates a sophisticated communication setup where a UAV integrates a relay pod to extend the control range of UGVs from the typical 1–2 km to up to 26 km. This relay pod allows for continuous and reliable tele-operated control over extended distances, significantly enhancing situational awareness in military urban operations. The UAV's communication relay effectively bridges the gap between the central control station and the UGVs, ensuring seamless data transfer and operational coordination. Meanwhile, ref. [39] describes a UAV designed to carry and communicate with a smaller UGV, or Rover, using nRF24L01 transceivers over the SPI protocol, integrated by a research team at Aydın Adnan Menderes University, Aydın, Turkey. The UAV serves as a communication relay, linking the central control station with the Rover, which operates independently after deployment. The system is designed to be lightweight (for portability and computational efficiency) and power efficient (for durability of its operations), enhancing the overall operational range and effectiveness of the UAV-UGV team.

Directional and Non-directional Wi-Fi, Satellite link and Beacons: The proposed wireless communication system in [40] connects Unmanned Surface Vehicles (USVs), UAVs, and Autonomous Underwater Vehicles (AUVs) to create a collaborative offshore network, utilizing multiple communication technologies as shown in Figure 2. The primary link between the Ground Control (GC) station and USV is established via a directional Wi-Fi connection. To ensure continuous connectivity in non-Line-of-Sight (LOS) scenarios, a UAV acts as a relay using directional Wi-Fi links between the USV, GC, and UAV. The UAV and AUV communicate through a non-directional Wi-Fi link, while both the USV and UAV are also equipped with satellite links for extended-range communication. Additionally, a beacon system is used for precise UAV landing. While the communication framework discussed here is primarily designed for USVs, UAVs, and AUVs, its underlying principles can be effectively adapted for UAV-UGV collaboration. In environments, where challenges, such as complex terrains and non-LOS communication issues arise, the integration of directional and non-directional Wi-Fi, satellite links, and beacon systems provides a robust and reliable solution. As such, this framework holds significant potential for improving communication and coordination in UAV-UGV collaborative operations, particularly in similarly challenging and complex environments.

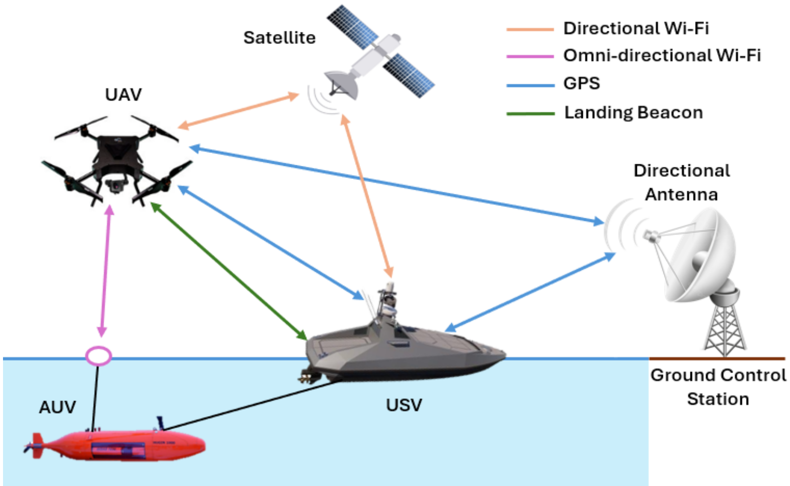

Figure 2. Communication system for UAV-USV-AUV Collaboration, Integrating Directional and Omni-directional Wi-Fi, GPS, and Landing Beacons for Maritime Coordination.

Xbee modules: The solution presented by Arbanas et al. [41] explores a UAV-UGV cooperative system where the UAV performs aerial manipulation tasks, and the UGV provides support and transportation. The communication between these systems is managed through a low level control and sensor collecting board using XBee modules. The reference values for angular and linear speed are transmitted to the UGV via ZigBee, facilitating efficient and reliable data exchange. The system also supports ad-hoc networks for adaptable communication in diverse mission scenarios.

Radar, QoS, and 5G technologies: The integration of radar aided localization and QoS-aware communication in UAV-UGV systems is discussed in [42,43]. As part of these studies, UAVs are used to assist UGVs in environments with damaged communication infrastructure, such as post-disaster scenarios. To improve performance and data delivery in high mobility operations, millimeter-wave (mmWave) communication and joint radar-aided downlink transmission are used. Despite limited infrastructure, the solutions proposed address the challenge of maintaining effective communication. In [44], a cooperative UAV-UGV system is introduced where the UAV acts as a flying sensor and tether attachment device. As a result of this setup, extensive aerial scanning and mapping can be conducted, while the UGV is able to climb steep terrain with the aid of the tether. The system includes an autonomous framework for collaborative navigation and tether attachment, with communication managed through a serial link that transmits telemetry data at 100 Hz. The paper [45] reviews radio frequency (RF) based localization approaches, emphasizing the communication technologies involved. As a significant advancement in the field of UAV and UGV localization, the ubiquitous 5G NR (New Radio) cellular network is highlighted. In addition, it discusses the potential of 5G NR to address current localization challenges and its integration with existing robotic systems. To ensure seamless integration into current localization systems, utilizing 5G's unexplored capabilities will be crucial for future research, highlighting the transformative impact of advanced communication technologies on UAV and UGV localization.

Game theory: The paper [46] presents a game theoretical approach for managing bandwidth in UAV-UGV disaster relief networks, where traditional communication methods are disrupted. The Stackelberg game model is used to allocate bandwidth, with UGVs determining their capacities and UAVs choosing access based on these capacities. This method optimizes communication in emergency scenarios. It is concieved that this method can optimize the communication in emergency scenarios. In particular, the Stackelberg game model can benefit this scenario by providing a structured hierarchy where UGVs act as the 3 leaders and UAVs as the followers, ensuring efficient and prioritized bandwidth allocation. When implemented practically, this can lead to optimal resource utilization and minimization of the latency in critical communication scenarios. Additionally, it can also allow for scalable and adaptable strategies in dynamic disaster environments, which is usually a practical need of UAV-UGV disaster relief networks.

Fuzzy Logic Control: Recent research demonstrates how fuzzy logic-based systems enhance control, coordination, and communication in heterogeneous UAV-UGV systems, particularly in challenging environments with uncertainties. In [47], a fuzzy switching observer was implemented to estimate unavailable states during Denial of Service (DoS) attacks, allowing the system to maintain stable tracking and coordination despite external disturbances. Communication between UAVs and UGVs remained smooth even during the attacks, ensuring uninterrupted collaboration. In a similar study [48], a Feedback Multilayer Fuzzy Neural Network (FMFNN) was employed within a formation control strategy, allowing UAVs and UGVs to follow planned trajectories and maintain formation, despite model uncertainties. The system minimized the communication frequency while maintaining data accuracy, contributing to reliable coordination. These studies highlight the importance of fuzzy logic in enhancing UAV-UGV collaboration, ensuring stable trajectory tracking, formation control, and continuous communication, even under challenging conditions.

4.2. Coordination Mechanisms

The UAV-UGV coordination system involves the collaboration of UAVs and UGVs to achieve a common goal by leveraging their unique capabilities. UAVs can move quickly, provide comprehensive and detailed views of the environment, and are less affected by communication and GPS signal issues. Conversely, UGVs can carry heavier payloads, endure longer missions, and operate close to the environment, allowing them to deploy sensors, communicate devices, and perceive details that UAVs might miss. Despite their individual limitations, the complementary strengths of UAVs and UGVs make the UAV-UGV coordination system a powerful tool for completing complex tasks.

Arena et al. [49] demonstrate the importance of cellular neural networks (CNNs) with constant templates in enabling self organizing behaviors, like wavefronts and spiral patterns, essential for modeling complex, adaptive systems. CNNs consist of interconnected cells that interact with their neighbors to fulfill common goals. Traditionally, CNNs use centralized, synchronous learning methods, yet a decentralized asynchronous learning (DAL) framework allows each cell to learn in a spatially and temporally distributed environment [50]. This decentralized approach is particularly valuable for UAV-UGV coordination, as it supports autonomous, adaptive decision making in dynamic environments. CNN based DAL frameworks enhance system resilience and scalability by allowing UAVs and UGVs to manage their roles independently. Implementing such frameworks in UAV-UGV networks could lead to improved operational efficiency in complex applications, advancing research in autonomous coordination.

The distributed real-time control architecture for UAV-UGV systems offers a resilient framework for managing coordinated real-time operations between aerial and ground vehicles. This architecture eliminates dependency on central ground based controllers by enabling autonomous decision making within each UAV and UGV, which is critical in environments like space exploration and defense where continuous communication may be unreliable or absent [51,52]. Each vehicle processes data independently and executes essential tasks, such as crowd detection, tracking, and motion planning, directly onboard [53]. This decentralized approach not only enhances scalability but also reduces data transmission loads, supporting highly responsive and efficient performance across large, complex operational areas. The architecture's adaptability and independence make it ideal for dynamic, remote applications that demand robust and agile systems. The cross dimensional distributed control strategy for heterogeneous UAV-UGV systems tackles the challenge of tracking time varying output formation (TVOF) by addressing nonzero leader inputs, parameter uncertainties, and external disturbances [54]. This approach uses adaptive observers to estimate leader information and coordinate TVOF across aerial and ground vehicles. Importantly, it operates without the need for precise disturbance limits or full network information, making it robust and flexible for practical implementation.

The paper [55] explores a distributed adaptive cooperative control approach for human-in-the-loop (HiTL) UAV-UGV systems, designed to facilitate real-time, decentralized decision making across multiple agents. Each UAV and UGV can independently process human inputs and adjust their trajectory based on locally available information, thereby reducing reliance on a centralized control unit. This distribution enables each agent to respond autonomously to human motion signals while maintaining coordinated behavior with others in the network. The system addresses signal discontinuities in conventional HiTL methods by integrating adaptive observers across the UAV-UGV network, ensuring smooth transitions and synchronized control. This kind of distributed real-time control architecture for UAV-UGV systems can be greatly enhanced by integrating a data driven learning approach, similar to the H_∞ control method used in adaptive cruise control systems, to manage complex, dynamic environments with greater accuracy [56]. This approach allows each UAV and UGV to independently estimate unknown system dynamics by taking advantage of real-time input-output data, enabling an uninterrupted adjustment to changing conditions without relying on pre-modeled dynamics. Each vehicle's control settings might be constantly adjusted through data driven learning, enabling real-time response to changes in mission requirements, parameter uncertainties, and disturbances. Since the neural networks in this data driven approach have no approximation errors and refine the control directly based on actual operating data, the accuracy is further improved [57]. Hence, such integration supports the distributed architecture's autonomy, providing each unit with advanced responsiveness and real-time adaptability.

The functional roles of UGVs and UAVs in a coordination system depend on their capabilities. The main challenge in UAV-UGV collaboration is how to best utilize their complementary strengths to complete tasks that are difficult for other coordination types. According to Ding et al. [3], there are four primary functional roles in a UAV-UGV coordination system, from a control system perspective (Figure 3). They are:

- **Sensors**: Detect environmental changes or events and relay this information to other components or vehicles.
- **Actuators**: Execute specific actions or tasks.
- **Decision Makers**: Make critical decisions, such as task planning and motion planning, for other components or vehicles.
- **Auxiliary Facilitators**: Provide essential services such as energy, communication, and computation, supporting the sensors, actuators, and decision makers.

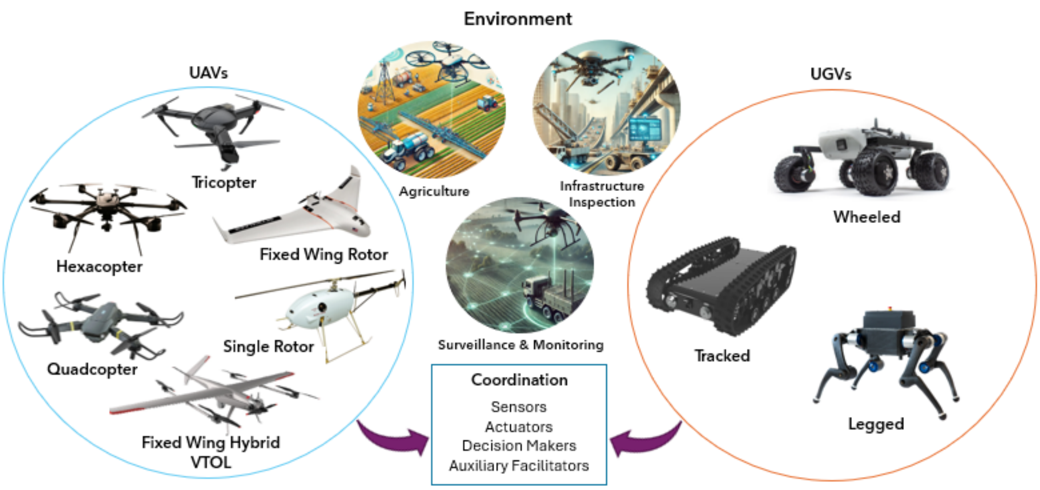

Figure 3. UAV-UGV coordination system showcasing different types of UAVs and UGVs.

The existing UAV-UGV coordination systems generally focus on designing one or more of these functional roles according to the application's needs. UAVs and UGVs can assume one or more of the aforementioned roles within a system to achieve specific tasks. In the following sections, we discuss various coordination systems and their applications.

4.2.1. UAVs Serving as Sensors and UGVs as Actuators or Decision Makers

In this collaborative air-ground system, the UAV operates as a sensor, responsible for collecting, transmitting, detecting, and tracking data. Concurrently, the UGV utilizes the information provided by the UAV to plan its route and offers real-time updates on the roadway conditions, allowing for timely adjustments. UAVs are known for their high mobility and extensive field of view, which enables rapid data acquisition. As a result, the information sent to the UGV greatly improves the overall efficiency of the task [58].

The study of [59] has used UAVs to generate a 2D map and photogrammetry to create a detailed 3D map of the area, aiding UGVs in effective route planning. In [60], a system was implemented where UAVs utilize stereo vision and parallax to produce a depth map, which helps UGVs make informed decisions with accurate spatial information. The research work in [61] presents a pursuit-evasion system where the UAV, a quadrotor, acts as an aerial sensor, continuously capturing terrain data and the evader's location within a complex 3D polygonal environment. The UGV, a Mecanum vehicle, processes this information using an improved boundary value problem (BVP) to execute optimal path planning and control strategies, particularly in scenarios where the evader's location is partially or fully unknown. This framework, integrating real-time UAV sensing and UGV decision making, enables efficient coordination and rapid adaptation to evolving environmental and pursuit conditions, as shown in Figure 4.

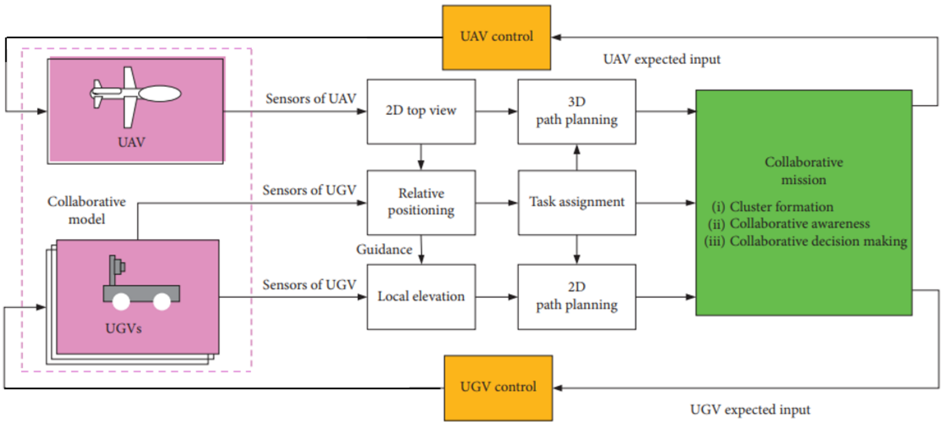

Figure 4. Cooperative path planning and communication architecture for UAV-UGV Pursuit-Evasion in 3D Polygonal Environments [61].

In the paper [62], an elevation map based localization system was developed to allow UGVs to determine their position using terrain data from UAVs, eliminating the need for GPS. The system described in [63] created an autonomous framework where UAVs provide UGVs with bird's eye views to assist in obstacle avoidance and path planning, thereby enhancing navigation and mission efficiency. A real-time collaborative system proposed in [30] employs UAVs to offer overhead views that guide and dynamically adjust the UGV's path, improving both accuracy and responsiveness. The abstraction model for UGV teams introduced in [64,65] enables UAVs to manage and coordinate the team without needing detailed knowledge of each vehicle, focusing on overall formation and positioning.

The study of [66] has explored how UAVs can coordinate multiple UGVs in urban environments, enhancing their deployment and operational effectiveness. A vision based control method in [67] uses UAVs with cameras to guide ground robots into desired formations, combining centralized control with distributed strategies. Another study [68] developed a vision based control approach that reduces resource requirements for UGVs and provides a flexible, robust architecture to handle various errors. In [69], a method was demonstrated where UAVs use camera observations to control UGVs along a specific trajectory, improving navigation precision. The paper [70] introduced a technique called supervised morphogenesis, where UAVs guide the self assembly of UGVs using aerial views to manage and adjust their formation. Hailong et al. [71] presented an autonomous exploration and mapping system that integrates UAVs and UGVs for GPS denied environments. In this system, the UGV performs rapid autonomous exploration and active 2.5-D SLAM to create a preliminary environment model. This model then guides a UAV in conducting detailed 3-D mapping to refine the navigation reference. In a similar study by Hu and Assaad [72] proposed a method to enable cognitive sharing between UAVs and UGVs by recognizing and identifying the same objects, enhancing coordination and efficiency.

4.2.2. UAVs Serving as Auxiliary Facilities and UGVs as Actuators

In UAV-UGV coordination systems, UAVs act as auxiliary facilities that enhance the operational capabilities of UGVs, especially in challenging environments. Additionally, UAVs can be used to transport UGVs to difficult terrain that would otherwise be inaccessible due to obstacles or steep slopes. Using this capability, UGVs are able to perform tasks in environments where ground mobility alone is not sufficient. In addition to being able to transport UGVs to these hard-to-reach areas, UAVs are also capable of executing critical missions requiring ground based operations, thereby extending the reach and flexibility of the robotic system.

Additionally, UAVs can provide essential support to UGVs by supplying power, fuel, or other resources necessary for their sustained operation. In remote or harsh environments where refueling or recharging stations are unavailable, UAVs can deliver these supplies directly to the UGVs, ensuring continuous operation without the need for frequent returns to base stations. This auxiliary role of UAVs not only extends the operational duration of UGVs but also enhances their performance by mitigating the limitations imposed by energy constraints. By serving as both transporters and resupply units, UAVs significantly contribute to the overall effectiveness and efficiency of UGVs in executing complex tasks.

In Miki et al. [44], the authors describe a system where a UAV can help a UGV to climb steep inclines by attaching a tether to an anchor point at the top of a cliff. This tether then allows the UGV to ascend by winding it, overcoming obstacles that would otherwise be impassable. In this setup, the UAV acts as both a sensor and an auxiliary facility, providing aerial scanning and mapping while directly supporting the UGV's climbing efforts. Similarly, Heven Drones, in partnership with Roboteam, introduced an integrated land and air robotic solution at Israel's ISDEF exhibition. This system combines Heven Drones' aerial technology with Roboteam's ground robots, creating a unified UAV-UGV platform. The UAV's ability to lift the UGV to complex terrains underscores its role in overcoming obstacles and enabling operation in otherwise inaccessible areas, with the system controlled through a single interface that supports both flying and driving modes [73].

4.2.3. UAVs Serving as Sensors and UGVs as Auxiliary Facilities

UAVs, with their aerial mobility and ability to access inaccessible locations, serve as versatile sensors, providing high resolution data collection and real-time monitoring. However, their limited battery life and payload capacity constrain their operational range and duration. To address these limitations, UGVs can be deployed as auxiliary facilities, offering ground support to UAVs. UGVs can extend the operational range of UAVs by acting as mobile charging stations, transportation units, and launch platforms, enabling UAVs to cover larger areas and conduct prolonged missions. This symbiotic relationship between UAVs and UGVs has the potential to revolutionize applications in precision agriculture, infrastructure inspection, and environmental monitoring, where efficient and comprehensive data collection is critical.

The study [1] presents a symbiotic UAV-UGV system designed for precision agriculture, where UAVs act as sensors and UGVs serve as auxiliary facilities. The research introduces two new informative path planning problems designed to optimize the use of aerial and ground robots for agricultural tasks. The first problem, the Sampling Traveling Salesperson Problem with Neighborhoods (SAMPLINGTSPN), addresses scenarios where UGVs are used to conduct time consuming soil measurements. The objective is to select optimal sampling locations within overlapping areas (disks) and plan a tour that minimizes the combined travel and measurement time. The second problem involves maximizing the number of aerial measurements by a UAV with limited energy. The study proposes a symbiotic system where the UAV lands on the UGV, allowing the UGV to transport the UAV between deployment locations. This cooperation effectively extends the UAV's operational range and efficiency. Roperoe et al. [74] introduced TERRA (cooperaTive ExploRation Routing Algorithm), a path planning algorithm for cooperative UGV-UAV exploration, tailored to scenarios like planetary surface exploration. In this system, the UAV's limited energy capacity is mitigated by the UGV acting as a moving charging station, enabling the UAV to efficiently reach all target points. The approach combines classic combinatorial techniques with modern evolutionary strategies to optimize travel distance.

Liu et al. [75] explore a novel high voltage powerline inspection system, where the UGV functions as a mobile platform, launching and recycling the UAV, which flies over powerlines for inspection within its limited endurance. The coordination between the UGV and UAV enables efficient inspection of large powerline networks, introducing a new Two-Layer Point-Arc Routing Problem (2L-PA-RP) with algorithms designed to optimize the inspection process and improve routing efficiency. The system described in [76] introduced a novel approach to vehicle assisted multi-drone surveillance, addressing the limitations of UAVs' battery capacities by leveraging vehicle drone cooperation. This cooperation combines the extended driving range of vehicles with the high mobility of UAVs, enabling efficient surveillance over wide areas. The research proposes a new problem, the vehicle assisted multi-drone routing and scheduling problem, and introduces the Vehicle assisted multi-UAV Routing and scheduling algorithm to solve it.

4.2.4. UAVs Serving as Actuators and UGVs as Auxiliary Facilities

In this cooperative system, UGVs can play a crucial auxiliary role by supporting UAV operations. UGVs can transport UAVs to locations near surveillance targets or maintenance sites, extending the UAVs' operational range and conserving their battery life. Additionally, UGVs can serve as reference stations for the Global Navigation Satellite System (GNSS), helping to reduce navigation uncertainties for UAVs [58]. For rapid and economical services over congested areas, such as search and rescue (SAR) missions or delivery services, UGV assistance is invaluable. The vertical takeoff and landing capabilities of multi-rotor UAVs enable them to dock with UGVs, which act as mobile charging stations and support platforms. This ability to autonomously land and recharge extends the UAVs' operational duration and efficiency. By working together, UAVs and UGVs enhance each other's capabilities, making their collaboration essential for a wide range of applications.

The results presented in [77] introduces a hybrid camera array based system for the autonomous landing of a UAV on a moving UGV in GPS denied environments. The system employs a combination of fisheye and stereo cameras to provide accurate location and depth imaging of the UGV. A motion compensation based state estimation algorithm determines the UGV's movement, allowing the UAV to align its motion accordingly. A nonlinear controller ensures precise landing of the UAV on the moving UGV. As discussed in [78], a vision based control system for the autonomous landing of a quadrotor UAV on a moving UGV is presented. This system operates without direct communication between the UAV and UGV. A fractional order fuzzy proportional integral derivative controller is designed to handle the quadrotor's nonlinear dynamics and wind induced disturbances. The control system includes a feedback linearization term to address model nonlinearities and a supervisory control algorithm to ensure fast, smooth, and precise landings.

The approach outlined in [79] introduces a vision based autonomous landing system for multirotor UAVs on a moving platform using Deep Reinforcement Learning. The Deep Deterministic Policy Gradients algorithm is employed to manage continuous state and action spaces, enabling the UAV to learn landing maneuvers through simulation and real world scenarios. The paper [80] presents a control method for the autonomous landing of a quadrotor UAV onto a skid steered UGV, focusing on time delays. The method details local controllers for feedback linearization and a joint decentralized controller for coordinating the landing. The impact of time delays on stability is analyzed using Retarded Functional Differential Equations, with delay margins assessed for various configurations. Simulation results demonstrate the effectiveness of this approach for outdoor autonomous coordinated landings.

4.2.5. UAVs and UGVs Functioning as Sensors

UAVs and UGVs function as mobile sensor platforms, each leveraging their unique capabilities to enhance data collection and monitoring. UAVs equipped with an array of sensors such as high resolution cameras, LiDAR, thermal imaging, and multispectral sensors, can quickly and efficiently cover large areas from the air. As they fly over these areas, they collect a vast amount of data, capturing detailed images and measurements that can be processed in real-time. This ability to gather data from an aerial perspective is particularly valuable in applications such as environmental monitoring, where UAVs can track changes in vegetation, water bodies, and wildlife habitats, or in disaster response, where they provide critical information about the extent of damage and aid in search and rescue operations.

On the other hand, UGVs complement UAVs by operating on the ground, where they navigate through difficult terrains and confined spaces. They can perform close up inspections and gather data from a ground perspective equipped with similar sensors, including cameras, LiDAR, and various environmental sensors. This is particularly useful in scenarios like infrastructure inspection, where UGVs can access and examine the condition of bridges, tunnels, and pipelines [72]. In addition, UGVs are used in hazardous environments, such as in chemical plants or disaster sites, where they can safely collect data without putting human operators at risk. The data collected by UGVs provides detailed, ground level insights that, when combined with the aerial data from UAVs, create a comprehensive view of the environment.

Shkurti et al. [81] describe a heterogeneous multi-robot system for environmental monitoring, specifically marine ecosystem inspection. The system includes a fixed wing aerial vehicle, an autonomous airboat, and an agile legged underwater robot. These robots operate hierarchically and interact with remote scientists to autonomously collect visual footage of underwater regions from multiple scales and mediums. Field trials demonstrated the system's effectiveness in multi-domain monitoring of coral reefs, enabling real-time interaction with marine biologists for comprehensive and efficient environmental assessments. The deployment and recovery of autonomous or remotely piloted platforms from research vessels significantly enhance the capabilities and reach of the research fleet. The paper [82] discusses the use of ship launched and ship recovered Boeing Insitu Scan Eagle UAVs to study the marine atmospheric boundary layer and ocean surface processes. During the October 2012 Equator Mix experiment and the July 2013 Trident Warrior experiment, these UAVs provided detailed atmospheric and oceanographic measurements, uncovering longitudinal atmospheric roll structures and surface signatures of internal waves. The UAV data, combined with ship based instruments, demonstrated the UAVs' ability to offer high resolution observations in remote ocean areas, thereby extending the research fleet's capabilities for oceanographic and atmospheric studies.

A heterogeneous team of aerial and ground robots for persistent monitoring of terrains has been explored in [83]. This robot team is tasked with surveillance and mapping along a predefined path. Both types of robots are equipped with cameras for terrain monitoring within their fields of view. A key feature of this study is the aerial robots' capability to occasionally land and recharge, optimizing their operational time. The primary goal is to minimize the total time required for monitoring by finding optimal paths for the robots, considering terrain constraints and fuel limitations. The study [84] introduces a switched cooperative control scheme where UAVs and UGVs work together to locate a moving target. The UGVs form a guarding formation using a navigation function, effectively acting as a perimeter. While UAVs follow a designated trajectory, they scan the enclosed area to provide aerial surveillance. The UAVs and UGVs operate as sensors by combining decentralized flocking algorithms with navigation functions, which allow them to avoid obstacles, reach specific positions, and maintain direction control. This cooperative effort enhances situational awareness and ensures effective target detection.

4.3. Advanced Learning Based Techniques for UAV-UGV Cooperative Optimization

Recent advancements in UAV-UGV collaboration demonstrate substantial progress in developing algorithms and frameworks that enhance cooperative capabilities within complex environments. These approaches enable more efficient task execution, resource allocation, and navigation, advancing UAV-UGV team effectiveness in practical applications, utilizing reinforcement learning, artificial intelligence, and neural networks. Innovations such as autonomous landing systems, advanced path planning, proficiency based coordination, and natural language based scene understanding contribute to overcoming specific challenges in UAV-UGV operations. These methods collectively strengthen UAV-UGV collaboration, establishing it as a scalable, intelligent solution adaptable across various sectors for complex missions.

The Imitation Augmented Deep Reinforcement Learning (IADRL) model proposed in [85] enables UAVs and UGVs to form a cooperative coalition to address limitations encountered when operating independently. The IADRL algorithm learns complementary behaviors of UAVs and UGVs from a demonstration dataset based on simple, non optimized strategies in basic scenarios. These observations allow the algorithm to create an optimized policy that directs the UAV-UGV coalition to work together efficiently, minimizing costs while achieving task objectives. Reinforcement learning techniques are employed to continuously enhance the cooperation strategy through environmental feedback. Moreover, IADRL supports multiple UAV-UGV coalitions, scaling effectively to handle complex tasks in dynamic environments. In [86], a hybrid approach is presented that combines clustering with multi agent reinforcement learning for UAV-UGV coalition path planning. This approach utilizes a modified mean shift clustering algorithm (MEANCRFT) to segment targets into circular zones based on density and range, substantially reducing time to reach these targets. By enabling simultaneous engagement with multiple targets, this method improves task efficiency. Vehicles are trained with two reinforcement learning algorithms, Multi-agent Deep Deterministic Policy Gradient (MADDPG) and Multi-agent Proximal Policy Optimization (MAPPO), achieving nearly double the efficiency of prior methods in terms of target navigation and task completion.

The development of a novel vision based deep reinforcement learning approach in [87] facilitates autonomous landing of a quadrotor UAV on a moving UGV without direct communication between the vehicles. Using an Automatic Curriculum Learning (ACL) framework alongside the Twin Delayed Deterministic Policy Gradient (TD3) algorithm, the UAV dynamically adapts its landing strategy to environmental changes, such as UGV motion and wind interference. This system incorporates a Landing Vision System (LVS) with ORB algorithms for real-time localization and pose estimation, complemented by a “Ghosting” method to consolidate UGV motion trajectories for enhanced tracking and prediction. This approach achieved a landing success rate of 91% with a distance error of 0.44 m, outperforming traditional TD3 methods. A new framework for Apprenticeship Bootstrapping using Inverse Reinforcement Learning (ABS-IRL-DQN) is introduced in [88] to facilitate learning of complex UAV-UGV coordination tasks through simpler sub task demonstrations. ABS-IRL-DQN enables a UAV to keep multiple UGVs within its field of view, achieving performance levels comparable to those of human operators. This method breaks down tasks into manageable sub tasks demonstrated by less skilled operators, allowing the model to build complex skills from basic actions. Each sub task has unique actions and states, creating partial reward signals that approximate the complete reward, enabling the agent to autonomously perform full coordination tasks.

Proficiency Constrained Multi-Agent Reinforcement Learning (Mix-RL), introduced in [6], optimizes UAV-UGV coordination in dynamic environments such as disaster response and precision agriculture. This model matches task assignments with the unique strengths of each robot, such as speed, perception range, and adaptability, to maximize efficiency. Demonstrated in a criminal vehicle tracking scenario, Mix-RL achieved an 89.6% success rate with proficiency awareness, significantly outperforming the 55.2% success rate without it. Training episodes with proficiency awareness also resulted in improved reward outcomes, illustrating Mix-RL's effectiveness in complex environments. The deep reinforcement learning (DRL) approach proposed in [89] enables a UAV swarm to serve as Mobile Base Stations (MBSs) for optimal communication coverage for ground users in partially observable areas. The Deep Recurrent Graph Network (DRGN) architecture facilitates inter-UAV communication and utilizes recurrent units to harness historical data, addressing challenges of partial observation. When combined with maximum entropy learning, this model, called the Soft Deep Recurrent Graph Network, is both scalable and cost effective, surpassing previous DRL and heuristic methods in transferability and robustness.

In [90], an Artificial Neural Network (ANN) based system has been developed for precise positioning and navigation in UAV-UGV collaboration, particularly focused on path planning in unstructured environments. By integrating inputs from GPS, the Robot Vision System (RVS), and the Quadcopter Vision System (QVS), this system ensures accurate localization and decision making. Using competitive learning, the network generates collision free paths by dynamically adjusting to obstacles, enhancing UAV-UGV team capabilities for complex navigation tasks. The paper [91] introduces a Multi-Agent Robotic System (MARS) to support UAV-UGV path planning and sensory data collection in complex indoor settings. MARS utilizes an enhanced Shunting Short Term Memory model for pathfinding and obstacle avoidance, with a mediating agent facilitating communication between UAVs and UGVs. Field tests demonstrate that MARS effectively gathers 2D and 3D environmental data, making it a valuable tool for UAV-UGV coordination. In [92], a natural language based scene understanding framework is proposed to enhance inter robot communication and coordination among heterogeneous multi-robot systems, such as UAVs and UGVs. This system leverages deep learning to identify semantic meanings from environmental data, creating semantic graphs that support coordinated action. Using JENA-TDB for data storage, the framework enables efficient retrieval of mission relevant information, with a Planning Domain Definition Language (PDDL) planner generating action sequences based on mission parameters to facilitate real-time multi-robot cooperation.

5. Collaborative Tasks and Applications

This section examines the collaborative use of UAVs and UGVs in several important applications. This integration enhances capabilities in various fields by leveraging their complementary strengths. We focus on three key areas: Surveillance and Monitoring, Agriculture, and Infrastructure Inspection. In Surveillance and Monitoring, the combined use of UAVs and UGVs provides comprehensive coverage and real-time data collection, which is vital for security and emergency response. In agriculture, this collaboration enables precision farming, improving crop management and monitoring. For Infrastructure Inspection, UAVs and UGVs work together to conduct thorough and efficient assessments of critical structures, ensuring timely maintenance and safety.

5.1. Surveillance and Monitoring

The convergence of UAVs and UGVs has transformed surveillance and monitoring systems by combining their unique strengths. This integration has expanded the possibilities for applications in various fields, including disaster response, environmental monitoring, border security, and infrastructure inspection [93]. In disaster situations, UAVs can quickly assess damage, find survivors, and set up communication networks, whereas UGVs can navigate through dangerous terrain to deliver supplies and perform rescue missions. For environmental monitoring, UAVs are used to gather high-resolution aerial data, while UGVs perform detailed ground-level measurements and collect samples. By integrating UAVs and UGVs, these combined efforts enhance both the efficiency and reliability of data collection, leading to improved outcomes in surveillance and monitoring tasks.

Zhao et al. [94] focus on enhancing post disaster rescue and management through an integrated ground-air-space (GAS) communication system, particularly when traditional networks are unavailable. This system enables the timely collection of critical data from points of interest in disaster affected areas by coordinating UGVs and UAVs. It considers a GAS vehicular crowdsensing (VCS) campaign, where UGVs periodically dispatch and recall UAVs at multiple stops within a work zone. The goal is to maximize the total amount of collected data and ensure geographic fairness, while simultaneously minimizing energy consumption utilizing hierarchical multi-agent deep reinforcement learning with diffusion models. Moreover, Ma et al. [95] present an approach for dynamic task allocation in UAV-UGV operations within complex urban environments, using an adaptive depth graph neural network (AD-GNN) combined with biomimetic algorithms. AD-GNN adjusts its depth based on scenario complexity, while biomimetic algorithms optimize task distribution by mimicking natural processes. This method significantly enhances UAV-UGV collaboration in tasks such as reconnaissance, combat, and disaster management by providing real-time adaptability to unpredictable conditions, achieving operational efficiencies above 85% in search and rescue operations and 90–95% in disaster management scenarios after optimization.

The system described in [96] focuses on enhancing surveillance and targeting through the integration of PackBot UGVs and Raven UAVs. This study introduces a novel Decentralized Data Fusion technique that effectively merges data from both UAV and UGV platforms, improving the ability to track moving targets in open environments. Stolfi et al. [97] proposed a new surveillance system to detect individuals escaping from restricted areas. This system uses a new swarming mobility model, CROMM-MS (Chaotic Rossler Mobility Model for Multi-Swarms), which controls the trajectories of a diverse team of unmanned vehicles, including aerial, ground, and marine units. A Competitive Coevolutionary Genetic Algorithm is proposed to optimize vehicle parameters and enhance the evasion ability of the targets, employing a predator prey strategy. This system represents an advanced approach where UAVs, UGVs, and UMVs work together to detect escapers early, utilizing an extended version of the CROMM model that accommodates heterogeneous multi swarms.

In [98], a vehicular fog computing (VFC) system was introduced, where UGVs handle computation tasks offloaded from UAVs in natural disaster areas. UAVs are highly effective in these situations due to their rapid deployment and flexibility, but their performance is often constrained by limited energy and computational capacity. The VFC based system, using distributed computing, addresses these limitations by allowing UGVs to take over the computational tasks, conserving energy and processing power for the UAVs [99,100].The computation task offloading was formulated as a two sided matching problem, and a stable matching algorithm was used to assign each UAV the most suitable UGV to ensure efficient collaboration between UAVs and UGVs. This approach optimizes resource utilization and reduces average delay, ensuring smooth interaction between UAVs and UGVs. In [101], UAVs are recognized for their potential in surveillance tasks but are constrained by limited energy and computational power. While UAVs typically delegate tasks like image or video processing to mobile edge computing facilities at base stations, but this option is unavailable in rural areas [102]. To overcome this, the authors propose offloading tasks to UGVs that operate along fixed routes, such as highways. A secure communication strategy is developed to address the risk of eavesdropping and account for the movement of UGVs, which may exit the target area. Tasks cached on UAVs are modeled as a stochastic queue, and an iterative algorithm is introduced to optimize key factors like latency, power, and distance.

The study in [103] explores cooperative exploration for search and rescue operations in damaged buildings. It presents a system where a UGV navigates on the ground while a UAV provides an elevated perspective, enhancing situational awareness. A camera mounted on the UGV tracks a fiducial tag on the UAV, enabling the UAV to maintain a fixed position relative to the UGV. This setup allows the UAV to offer a bird's eye view to a remote operator, facilitating observation beyond the UGV's line of sight. The system described in [104] proposes a hierarchical control framework for a cooperative UAV-UGV platform focused on wildfire detection and suppression. This framework features a three-layered structure, with an airship acting as a mobile mission controller that coordinates UAVs and UGVs. It addresses task generation and allocation through integer linear programming, enabling dynamic waypoint assignment for UAVs based on wildfire spread models, resulting in improved mission efficiency, reduced resource usage, and autonomous decision-making in wildfire suppression. Khaleghi et al. [53] evaluates different control architectures for UAV and UGV teams in surveillance and crowd control. It compares centralized, hierarchical, distributed, and hybrid architectures, assessing their performance in crowd detection, tracking, and motion planning to determine the most effective approach for these tasks.

As described in [105], a multi agent framework is introduced for enhanced disaster surveillance. The framework utilizes the strengths of both vehicle types (UAVs' speed and coverage with UGVs' endurance and recharge capability) by utilizing UGVs as mobile recharging stations for UAVs. The study shows that this collaborative approach improves operational efficiency and route planning in disaster management scenarios, as demonstrated through a simulation covering 30 task points over a 4-h mission with different team configurations. The team with 4 UAVs and 2 UGVs performed best, reducing the operational cost by 63.73% compared to a single UAV-UGV team. However, increasing the number of agents beyond this does not proportionally improve performance due to higher energy costs. The study shows that a balance between UAV and UGV numbers is critical for the best performance and cost efficiency. Therefore, this framework not only improves route planning in disaster management but also provides valuable insights into the most suitable team configurations for continuous surveillance operations.

The research in [106] addresses the challenge of persistent surveillance in urban environments by integrating UAVs and UGVs. This study focuses on generating optimal circular paths for both UAVs and UGVs to ensure complete area coverage while minimizing travel time. The problem is formulated as a large scale 0–1 optimization problem and solved using a hybrid algorithm combining the Estimation of Distribution Algorithm (EDA) and Genetic Algorithm (GA). This approach enhances global and local search capabilities, while a sweep based method and an online local adjustment strategy are employed to refine path sequences and adapt to changing coverage requirements. The approach proposed in [4] introduces a path planning method for collaborative coverage monitoring in urban scenarios by integrating UGVs with UAVs. The model includes realistic elements such as restricted zones and building obstructions to simulate urban scenarios. A Three stage Alternating Optimization Algorithm is introduced, which involves prediction and rolling optimization to handle complex path planning tasks.

5.2. Agriculture

With the advancements in UAV technologies, numerous studies have explored their applications in agriculture, which holds the most significant potential for UAV utilization. The Association for Unmanned Vehicle Systems International (AUVSI) predicts that agricultural UAVs will dominate 80% of the commercial UAV market in the future [107]. Currently, agricultural UAVs are primarily utilized for pest control and monitoring various crops. In addition, the potential applications of agricultural UAVs extend to soil and field surveys, sowing, spraying, crop monitoring, irrigation management, growth evaluation, mapping, remote sensing, reconnaissance, and transportation [108].

Introducing UAVs into traditional agriculture has significantly reduced working hours and labor requirements while improving the efficiency of agricultural operations [109]. However, since UAVs rely on limited battery power, employing a multi-UAV system is more efficient than using a single UAV [110,111]. For instance, using a single UAV for tasks such as spraying or monitoring large farmlands is time consuming and energy intensive. In contrast, a multi-UAV system allows for simultaneous cooperative work (Figure 5), where individual UAVs perform specific tasks on assigned areas of the farmland, thereby expediting the completion of agricultural tasks on large farmlands. Therefore, multiple UAVs in agriculture enhances efficiency and speed for large scale tasks. They can collaborate or divide tasks, ensuring rapid completion with increased or equal accuracy due to overlapping mission areas. While a single UAV can achieve high accuracy with a well planned path but its performance is highly dependent on the path planning algorithm [112].

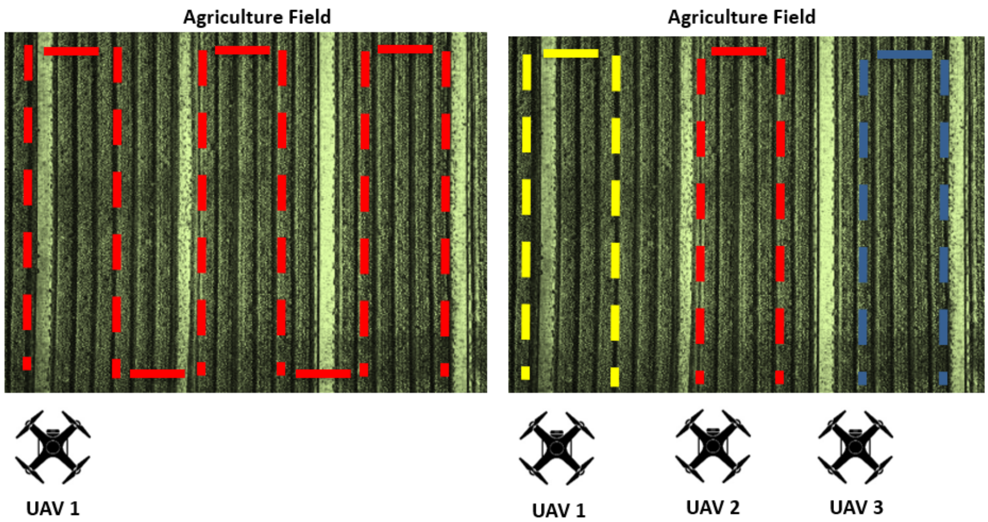

Figure 5. Task distribution of single UAV (**Left**) vs. Multi-UAV Systems (**Right**) in agricultural fields.

In agricultural operations involving multi-UAVs and multi-UGVs, it is crucial to create detailed maps of crop positions, shapes, and dimensions for effective obstacle avoidance and target localization. However, due to limited computational resources, varying velocities, and complex terrains, online SLAM procedures are often impractical. Autonomous mobile robots in agriculture still heavily depend on GNSS free localization systems, making robotic localization and mapping a challenging issue [113]. Despite numerous proposed solutions, significant improvements are still needed, which could lead to innovative approaches for autonomously localizing and operating outdoor robots in agriculture.

In study [114], a combined team of a UAV and a UGV was deployed in a strawberry field to address disease detection. The UAV scanned the entire crop field to identify areas of interest, and the UGV subsequently approached these marked locations to perform targeted analysis and collect samples. This approach enabled efficient disease detection by capitalizing on the aerial capabilities of the UAV to conduct wide area inspections, while the UGV managed ground level interventions. The RHEA project in [115], addressed pest control in cereal crops through coordinated operations involving two six-rotor drones and three tractors, as illustrated in Figure 6. The drones performed aerial inspection missions to identify weed and pest concentrations, and the tractors executed ground level treatments in response to drone data. A Mission Manager played a critical role by integrating data from both drones and trackers, optimizing robot trajectories and actions based factors such as cost and time. This setup showcased a well organized collaboration where the UAVs provided large scale coverage, and the UGVs handled specific intervention tasks, enhancing efficiency in pest control operations.

In another framework [116], a cooperative crop management system was implemented in lettuce fields, focusing on identifying and analyzing plant stresses due to water and nitrogen deficiencies, as illustrated in the Figure 7. The UAV conducted aerial scans, identifying specific locations of interest based on variations in vegetation. Both UAV and UGV platforms equipped with various sensors, while Multispectral and RGB images were collected using both multicopter and fixed wing UAVs to calculate the normalized differential vegetation index, learning classifiers aimed at predicting plant quality. Meanwhile, the UGV was responsible for ground level analysis, using tools such as a handheld spectrometer, chlorophyll meter, and leaf water potential meter for accurate ground truth data collection. This integrated UAV-UGV approach allowed for precise detection of crop stress factors and enabled timely interventions to optimize plant health.

Figure 6. The RHEA project for pest control in cereal crops: Deployment of two rotor drones and three tractors working collaboratively for aerial inspection and ground level treatments (**Left**). Additional RHEA tractors used in a related pest control initiative (**Right**) [115].

Figure 7. DJI 900 hexacopter manufactured by DJI, a leading technology company headquartered in Shenzhen, China, conducting an aerial survey over a lettuce field to capture multispectral data (**Left**). Husky UGV from Clearpath Robotics deployed at CPP's Spadra Farm for ground level support (**Right**) [116].

In the study [117,118], a UAV and a UGV generated individual point clouds of a field, representing its surface model and vegetation index. This methodology merged these datasets, producing a comprehensive map with detailed vegetation information, illustrating the value of UAV-UGV data fusion. The FREEDOM robot [119], is built for agricultural field exploration, providing valuable support to human operators in both routine and emergency scenarios. A distinctive feature of the FREEDOM robot lies in its ability to extend inspection missions by supplying power from the ground crawler to the aerial unit, thereby allowing the UAV to conduct prolonged field surveys. The crawler can also transport the UAV across challenging terrains, showcasing the adaptability of ground units in supporting aerial operations essential for monitoring crop health and assessing field conditions.

To meet the demands of future large scale, integrated industrialized agriculture, a UAV-UGV collaboration system is essential for improving operational efficiency. Despite their potential benefits, the technical capabilities required for effective UAV-UGV collaboration in real environments are not yet fully developed [120]. Current research on industrialized agriculture primarily offers broad comments and lacks detailed discussions on cutting edge technologies. Studies have shown that while UAVs excel in high dimensional broad vision and flexible motion for tasks such as monitoring, crop counting, and pesticide spraying [121], their limited load, size, and endurance make them unsuitable for long duration and large area tasks. Conversely, UGVs, which are used for harvesting, sowing, and mapping, have greater load capacity and endurance but lack the speed, flexibility, and field of view of UAVs [122,123]. Effective space ground cooperative systems can leverage the strengths of both UAVs and UGVs, with UAVs collecting environmental data and UGVs using this information for more efficient operations [124,125]. However, achieving this collaboration in real world scenarios requires overcoming key technical challenges such as energy management, control navigation, and operational efficiency. Table 1 provides an overview of the objectives and tasks identified in various studies on UAV-UGV collaboration in agriculture, highlighting the significant contributions and focus areas of each research work.

Table 1. Summary of objectives and tasks in UAV-UGV collaborative research for agricultural applications.

Ref.	Objective	Task
[126]	Improve robot localization by integrating ground and aerial data	Compute detailed traversability maps by analyzing the filtered vegetation data, allowing the UGV to plan and follow optimal paths through complex and vegetated terrains, as illustrated in Figure 8.
[120]	Enhance UAV-UGV collaboration for future industrialized agriculture	Focus on dynamically assigning job roles between UAVs and UGVs, integrating and processing data from various sources, and enabling cooperative formation control strategies.
[120]	Optimize small and medium-sized UGV platforms for agricultural use	Emphasize safety in operations, reduce soil compaction, and improve positioning accuracy to enhance UGV performance in agricultural settings.
[113]	Improve multi-machine collaboration in precision agriculture	Facilitate collaboration among multiple UAVs, multiple UGVs, and combined UAV-UGV systems for enhanced precision agriculture practices.
[127]	Achieve efficient UAV-UGV coordination tasks in agriculture	Aim to complete agricultural tasks more efficiently and accurately by enabling real-time information exchange and coordination between UAVs and UGVs.
[128]	Implement multi-UAV collaboration for plant protection	Utilize multiple UAVs for tasks like remote sensing, mapping, spraying, and monitoring pests and weeds, to protect crops more effectively.
[129]	Utilize multi-UGV collaboration for large scale agricultural operations	Improve efficiency in large-scale farming by leveraging multiple UGVs and traditional agricultural vehicles to cover vast areas effectively.
[130]	Develop UAV-UGV systems for weed monitoring	Focus on automatic detection and spraying of weeds in large outdoor areas using UAV-UGV collaboration, enhancing weed control efforts.
[125]	Facilitate UAV-UGV collaboration for greenhouse environmental mapping	Use UAVs and UGVs to remotely sense and map key environmental variables within greenhouses, such as temperature, humidity, brightness, and CO_2 levels.

Table 1. *Cont.*

Ref.	Objective	Task
[131]	Combine UAV-UGV systems for rugged terrain adaptation	Develop UAV-UGV systems that can move across amphibious and rugged terrains, overcoming challenges related to vision and movement flexibility.
[132]	Innovate with embodied intelligent technology for UAV-UGV coordination	Integrate advanced features like autonomous coordination, perception, decision-making, interactive learning, and self-improvement capabilities into UAV-UGV systems.

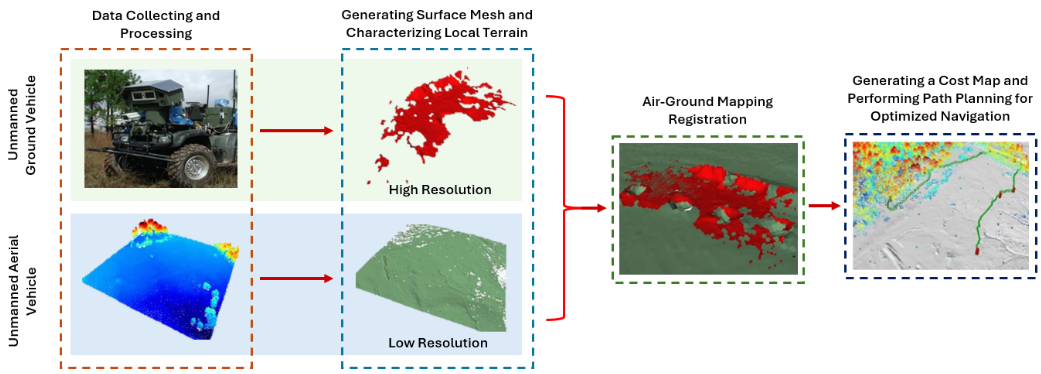

Figure 8. Terrain-Based localization for collaborative UAV-UGV mapping enables the generation of detailed traversability maps using filtered vegetation data, facilitating optimized UGV path planning in complex environments [58,126].

5.3. Infrastructure Inspection

Traditional quality inspections of buildings involve manual processes that are time consuming and prone to human error [133–135]. These methods typically include visual assessments, photography, and measuring tools compared with Building Information Modeling (BIM) models, often leading to inconsistencies and inefficiencies [136]. Regular inspection and monitoring of buildings and infrastructure are essential for maintaining safety and functionality in construction fields [137,138]. The built environment encompasses a range of infrastructure, including commercial and residential buildings, roads, bridges, tunnels, and pipelines.

The integration of UAVs and UGVs represents a significant advancement in the field of infrastructure inspection. Relevance can be drawn from the advancements in UAV technology, especially its applications in architecture, engineering, and construction have been expanded, leading to improvements in operations and safety [139]. The use of UAVs and UGVs together provides a highly effective solution for inspecting and monitoring infrastructure. UAVs offer an aerial perspective and mobility, while UGVs provide detailed ground level capabilities. This collaborative approach enhances the efficiency, accuracy, and safety of inspections, reducing human error and increasing operational effectiveness [140].

The paper [141] introduce a new theoretical framework for inspecting complex 3D infrastructures with multiple UAVs. This framework ensures complete coverage of the infrastructure by dividing it into horizontal planes and assigning specific areas to each UAV. The images captured by the UAVs are then processed using Structure from Motion, stereo SLAM, and mesh reconstruction algorithms to create detailed 3D meshes for visual inspection. The study [142] proposed a multi Quadruped Robot system automates the data collection and analysis process, enhancing reliability and efficiency. In this system, a master robot gathers general data and identifies regions of interest, while a slave robot provides detailed inspections of these areas. It improves the detection of construction defects such as cracks and alignment errors. In fact, the paper [136] presents a vision based mobile robotic system that can autonomously navigate and be aware of their surroundings are becoming essential. The solution is proposed through a UAV-UGV collaboration system, where autonomous navigation is performed by the UGV, and an external viewpoint to observe inaccessible areas is provided by the UAV. This system improves navigation efficiency in cluttered, GPS denied environments by continuously estimating the UAV's position and using sensors for localization, mapping, and path planning.

Furthermore, studies in [143,144] propose using an UAV to work cooperatively with a UGV to enhance data collection and mapping. The UAV first captures 3D terrain data through images, which aids in planning paths and determining scanning locations for the UGV. Inspecting large and complex dams is time consuming and costly as it requires specialized equipments and poses significant safety risks to inspectors. UAVs offer a promising solution by serving as data acquisition platforms for photogrammetric 3D reconstruction and analysis. The paper [145] presents a case study at Brighton Dam in Maryland, where multiple UAVs were used to create high resolution 3D models of the dam. The models demonstrated sub-millimeter accuracy in detecting various defects and provided valuable insights into mission planning and imaging specifications, showcasing the effectiveness of UAVs in enhancing dam inspection processes. Another system uses multiple UAVs for autonomous and cooperative inspection of 3D structures [146]. Each UAV independently covers a section of the structure while avoiding collisions, relying solely on onboard computers and sensors. The collected visual data is then processed collaboratively to generate detailed 3D models.

Various studies present systems combining underwater robots with USV for inspecting underwater structures like bridge piers and dams [147–149]. With cameras, depth sensors, and IMUs for posture control, the remotely operated vehicle (ROV) conducts detailed underwater inspections using the USV's surface navigation. These systems operate with minimal personnel and integrate GPS and LRF for precise positioning. In comparison to human divers, the robots displayed a significant improvement in inspection efficiency and safety in field experiments. It should be noted however, that these robotic systems still face several potential challenges. One major limitation is the difficulty in maintaining stable communication between the underwater ROV and the surface USV, especially in deep or turbulent waters. Additionally, navigating complex underwater environments with obstacles and limited visibility can pose significant operational challenges for the robots.

6. Limitations and Challenges of Air-Ground Collaboration

Air-ground collaborative systems, which combine the strengths of UAVs and UGVs, offer significant advantages across various applications due to the complementary nature of these robots. However, this diversity also introduces complexities that can hinder smooth collaboration. Integrating these components requires careful attention to ensure they work together effectively and enhance overall mission efficiency.

One of the key challenges in these systems is the computational burden. UAVs and UGVs, often limited by size and weight, have restricted computational capacities. This becomes particularly critical in real-time operations, where data needs to be processed and decisions made instantly. Communication network instability can further disrupt the smooth interaction required for effective collaboration. Dynamic load balancing can distribute tasks evenly across UAVs and UGVs, preventing any single component from becoming overwhelmed even when network conditions fluctuate, contributing to network optimization and improving overall network stability [150,151]. Adaptive routing methods, such as Ad-hoc On Demand Distance Vector and Optimized Link State Routing, dynamically adjust communication pathways based on real-time network conditions, ensuring more stable and efficient data transfer [152,153]. Moreover, delay tolerant networking further enhances reliability by buffering data during periods of disconnection and transmitting it once connectivity is restored [154]. Placing computational resources closer to the UAVs and UGVs, known as multi-access edge computing, reduces latency and manages bandwidth, thereby supporting network optimization [155]. Additionally, fuzzy logic based network control adjusts parameters in response to real-time conditions, providing a flexible solution for handling environmental uncertainties.

Table 2 provides an overview of limitations in existing UAV-UGV systems, including issues related to communication range, data transmission rates, mapping accuracy, and UAV landing techniques.

Table 2. Summary of limitations in existing UAV-UGV systems.

Section	Ref.	Limitation
Communication	[41]	Reliance on XBee modules may limit communication range and data rate, potentially hindering scalability in larger or more complex missions. These limitations could impact real-time data transmission, leading to challenges with latency and reliability, particularly in high-speed or extended-area operations.
	[42]	The system's dependency on mmWave technology could face challenges due to lower sensitivity caused by the smaller antenna size. Additionally, mmWave signals are more susceptible to being blocked by physical barriers like walls, buildings, and trees.
	[44]	The serial link for telemetry data transmission at 100 Hz may not accommodate higher data rates required for complex applications. This limitation could impact the system's ability to process sophisticated sensor data or manage multiple operations simultaneously, potentially affecting effectiveness in scenarios needing rapid and detailed analysis.
	[45]	The potential limitations in 5G NR integration with existing systems, particularly in areas with limited infrastructure coverage, could lead to inconsistent connectivity. Moreover, integration with legacy systems may encounter compatibility issues, slowing the adoption of advanced 5G features.
Mapping	[156]	The system's effectiveness relies on the accurate overlap between aerial and ground maps. Insufficient overlap can impede the precise registration of data, resulting in less reliable position estimation and updating for the UGV.
	[157]	The effectiveness of this method depends on the accurate overlap between the dense 3D reconstructions from the Micro Aerial Vehicle (MAV) and the maps generated by the ground robot. Inadequate overlap can impair the alignment process, leading to less reliable localization and map augmentation.
	[158]	The method depends on the presence of distinct planar surfaces for accurate registration, which may be ineffective in environments with sparse or irregular features. Additionally, it relies on globally scaled point clouds, limiting its applicability in GPS denied or scale-challenged environments.
	[159]	The system's reliance on GPS for positioning and obstacle mapping limits its effectiveness in areas where GPS signals are unavailable or unreliable. This significantly restricts its use in urban canyons, dense forests, and indoor settings, where GPS signals are often compromised.
UAV Landing	[160]	The proposed approach relies heavily on deep learning and reinforcement learning, which may require extensive training data and computational resources. While the MCTD3 and ACOACH algorithms improve precision and training efficiency, they may struggle to generalize to highly dynamic or unpredictable UGV movements not encountered during training.

As the complexity of air-ground collaborative missions grows, there is also an increasing need for advanced embedded hardware that can manage the high computational demands. This challenge is tough for UAVs because they need to minimize weight and power consumption, which limits the types of hardware they can use. Developing efficient and resilient embedded systems capable of handling these demands is crucial for the success of air-ground collaboration. The Table 3 provides a detailed overview of the primary issues associated with UAV-UGV collaboration systems, highlighting areas that require focused attention.

Table 3. Challenges and limitations in UAV-UGV collaboration systems.

Key Areas of Concern	Challenges and Limitations
Complex Coordination	• Differences in dynamics, speed, and communication protocols between UAVs and UGVs complicate task coordination [105,161]. • Advanced algorithms are needed for efficient real-time decision-making.
Communication Latency and Bandwidth Constraints	• High dependency on low-latency communication to ensure timely data exchange [42]. • Bandwidth limitations can hinder the amount and quality of data shared between UAVs and UGVs. • Limited infrastructure in certain environments exacerbates communication challenges, impacting overall system coordination [162].
Energy and Resource Management	• UAVs have limited flight time due to energy constraints, restricting mission duration [31,163]. • Managing energy resources effectively is crucial, especially in environments with limited access to recharging or refueling [105]. • Poor resource management can lead to mission failure or reduced operational efficiency.
Environmental and Terrain Challenges	• UAVs may encounter difficulties operating in adverse weather conditions, affecting flight stability and data collection [164]. • UGVs face challenges in navigating rough or uneven terrain, which can slow down or halt progress. • Terrain-adaptive algorithms and environment-aware planning are essential for overcoming these obstacles and ensuring mission success.
Computational Burden	• UAVs and UGVs often have limited computational capacity due to size and weight constraints, making it difficult to handle real-time operations. • The need for real-time data processing and decision-making places a significant strain on these systems. • Failure to manage computational tasks effectively can lead to delays, errors, or system crashes.
Communication Network Instability	• Instability in communication networks can disrupt the flow of information between UAVs and UGVs, leading to coordination failures. • Unstable communication can result in missed opportunities, errors, or mission failure [162].
Embedded Hardware Limitations	• UAVs have restrictions due to the need to minimize weight and power consumption, limiting the types of hardware they can use [43]. • Balancing high performance with lightweight and power-efficient hardware can make system design and implementation more complex [165].

7. Discussion

Multi-robotic systems, including multi-UAVs and multi-UGVs, are transforming the operational landscape for tasks requiring high mobility and resilience across complex terrains. With current advancements in task allocation algorithms and energy efficient clustering, multi-UAV and multi-UGV systems are gaining significant operational capability. However, a key limitation remains in computational resources when handling real-time data from multiple agents, especially in remote areas. Exploring more advanced distributed computing methods and dynamic role switching among agents to adapt to unpredictable environments remains a crucial research direction. Future developments could integrate real-time environmental learning, enabling systems to respond autonomously to changes, such as shifting terrain or variable weather, maximizing mission efficiency.

The synergy between UAVs and UGVs enables an advanced framework for tackling diverse tasks, such as disaster response and infrastructure inspection. As a timely and rapidly advancing topic, UAV-UGV collaboration represents an open field for research, with ongoing developments that promise to address critical gaps in autonomous systems. By combining UAVs' wide range data acquisition with UGVs' detailed ground interventions, these systems address tasks neither could accomplish alone. However, limitations like dependency on stable communication links persist, especially in high interference areas. We have discussed more flexible control frameworks that allow UAVs and UGVs to adjust roles based on real-time situational analysis, enhancing resilience and adaptability. Looking to the future, there is potential to integrate advanced AI driven mission planning that autonomously tailors UAV-UGV interactions based on task demands, maximizing their versatility. Furthermore, research could explore autonomous swarm coordination, where multiple UAVs and UGVs work together in complex environments, and predictive maintenance, where UAVs inspect UGVs in the field for real-time diagnostics. Advancements in human-robot collaboration are also anticipated, wherein UAV-UGV systems interact with human responders in disaster relief, enabling more responsive and intelligent air-ground operations across increasingly complex scenarios.

Establishing robust communication and coordination is fundamental for effective UAV-UGV collaboration, especially in complex and dynamic environments. Advanced communication technologies, such as relay systems, 5G NR cellular networks, directional Wi-Fi, and satellite links, have greatly enhanced data exchange and coordination, allowing UAVs and UGVs to perform synchronized tasks even in challenging non-line-of-sight settings. These technologies are critical for applications in urban, military, and space exploration scenarios where reliable connectivity is often compromised. However, despite these advancements, maintaining stable communication in high interference or GPS denied areas remains a significant challenge. Future research in this rapidly evolving field could focus on decentralized and autonomous communication models, where UAVs and UGVs can operate independently under fluctuating connectivity, thereby extending their utility in high stakes situations. Techniques such as game theoretical bandwidth allocation and neural network driven adaptive communication offer promising directions for ensuring reliable, low latency data transfer in critical missions. This open research area holds substantial potential to establish more resilient, adaptable UAV-UGV systems capable of meeting the demands of increasingly complex, real-time collaborative operations.

In domains such as precision agriculture, surveillance, and infrastructure inspection, integrating aerial and terrestrial robotic systems has markedly enhanced data accuracy and operational effectiveness by utilizing each platform's specialized capabilities. In precision agriculture, aerial units conduct large scale remote sensing to detect biotic and abiotic stress factors in crops, while terrestrial units perform targeted interventions, such as precise soil sampling and agrochemical applications, thus optimizing resource distribution and minimizing environmental impact. In surveillance, aerial platforms provide high resolution, wide area monitoring, rapidly identifying potential security threats from above, while ground platforms enable close up inspections, object tracking, and physical interactions in complex or obstructed terrains. Similarly, in infrastructure maintenance, aerial systems enable efficient, comprehensive surveys of large structures like bridges or pipelines to identify potential vulnerabilities, while ground systems execute detailed diagnostics, repairs, and material assessments, often using high precision tools and sensors. A critical limitation, however, remains in the substantial energy demand for continuous and expansive operations, which affects mission endurance and reliability. Addressing this challenge will require further refinement in task specific resource allocation, allowing UAVs to prioritize high altitude, large scale assessments while UGV systems focus on localized, intensive interventions.

UAV-UGV collaborative systems and their technologies remain highly dynamic and open to research, with continuous developments needed to address challenges in computational capacity, connectivity, and energy efficiency. As these systems advance, they are set to play an increasingly important role across diverse applications, making this a critical and evolving area for future research.

8. Conclusions

In this paper, we provided a comprehensive review of UAV-UGV collaboration and particularly highlighted the advancements and challenges reported in high quality studies. In this review, it was found that integrating UAVs and UGVs into collaborative systems represents a significant leap forward in the field of robotics, with implications for a wide range of industries. Due to the capability of UAVs to provide high level aerial surveillance, combined with the detailed control capabilities of UGVs, it is possible to accomplish complex missions that neither system would be able to accomplish on its own. The collaboration enhances operational efficiency and expands the range of applications, making it possible to address challenges in fields such as disaster response, environmental monitoring, and infrastructure inspection. In spite of these advances, the field still faces significant challenges, particularly in the areas of communication technologies, coordination mechanisms, and computational resources. As these systems operate in unpredictable and dynamic environments, robust, adaptable solutions that can function reliably in real-time are required.

This review has also highlighted the significant progress made in the development of collaborative UAV-UGV systems, along with advancements in communication frameworks and coordination strategies that underpin these efforts. However, fully realizing the potential of UAV-UGV collaboration necessitates continued research focused on addressing technical limitations and ensuring that these systems can operate autonomously and efficiently in a wide range of complex environments. The ongoing evolution of these technologies presents a promising avenue for innovative solutions to some of the most critical challenges faced across various sectors. By systematically addressing existing limitations, particularly those related to communication, coordination, and computational efficiency, UAV-UGV systems can be further optimized to perform more sophisticated and demanding tasks with enhanced reliability and precision. This continued development will not only improve the operational capabilities of these systems but also broaden their applicability to emerging fields, solidifying UAV-UGV collaboration as a leading force in the advancement of robotics technology.

In closing, it should also be noted that AI can play a crucial role in enhancing UAV-UGV systems by enabling more sophisticated decision-making processes and adaptive behaviors, purely based on data-driven approaches [166–168]. AI algorithms can optimize path planning, obstacle avoidance, and real-time data processing, which are essential for autonomous operations. This is especially applicable to situational awareness, disaster response, or routine applications in agriculture and other practically deployable environments. Additionally, machine learning techniques can improve the systems' ability to learn from past experiences and adapt to new environments, further increasing their efficiency and reliability. It is therefore possible that in the foreseeable future, a combination of AI and machine learning methods with UAV-UGV systems can lead to major advancements in the capabilities of standalone systems to tackle adversarial problems we face today.

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Abbreviations

The following abbreviations are used in this manuscript:

5G NR	5G New Radio
2L-PA-RP	Two-Layer Point-Arc Routing Problem
ACOACH	Adaptive Critic Online Actor-Critic Heuristic
ACL	Automatic Curriculum Learning
AD-GNN	Adaptive Depth Graph Neural Network
AI	Artificial Intelligence
ANN	Artificial Neural Network
AUV	Autonomous Underwater Vehicle
AUVSI	The Association for Unmanned Vehicle Systems International
BIM	Building Information Modeling
BVP	Boundary Value Problem
CNN	Cellular Neural Networks
CROMM	Chaotic Rossler Mobility Model
CROMMMS	Chaotic Rossler Mobility Model for Multi-Swarms
DAL	Decentralized Asynchronous Learning
DATW	Distributed Allocation with Time Windows
DRGN	Deep Recurrent Graph Network
DRL	Deep Reinforcement Learning
EDA	Estimation of Distribution Algorithm
FMFNN	Feedback Multilayer Fuzzy Neural Network
FPID	Fractional Proportional-Integral-Derivative
GA	Genetic Algorithm
GAS	Ground-Air-Space
GC	Ground Control station
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HiTL	Human-in-The-Loop
IADRL	Imitation Augmented Deep Reinforcement Learning
IMU	Inertial Measurement Unit
KKT	Karush-Kuhn-Tucker
LOS	Line-of-Sight
LVS	Landing Vision System
MADDPG	Multi-agent Deep Deterministic Policy Gradient
MAPPO	Multi-agent Proximal Policy Optimization
MARS	Multi-Agent Robotic System
MAV	Micro Aerial Vehicle
MCTD3	Multi-Critic Twin Delayed Deep Deterministic Policy Gradient
MEC	Mobile-Edge Computing
MEANCRFT	Modified Mean-Shift Clustering Algorithm
Mix-RL	Proficiency Constrained Multi-Agent Reinforcement Learning
mmWave	Millimeter-Wave
PDDL	Planning Domain Definition Language
QoS	Quality of Service
RF	Radio Frequency
ROV	Remotely Operated Vehicle
ROS	Robot Operating System
SAMPLINGTSPN	Sampling Traveling Salesperson Problem with Neighborhoods

SAR	Search and Rescue
SLAM	Simultaneous Localization and Mapping
TD3	Twin Delayed Deterministic Policy Gradient
TVOF	Time Varying Output Formation
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
UMV	Unmanned Marine Vehicle
USV	Unmanned Surface Vehicle
VCS	Vehicular CrowdSensing
VFC	Vehicular Fog Computing

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