AeroVerse-Review: Comprehensive survey on aerial embodied vision-and-language navigation

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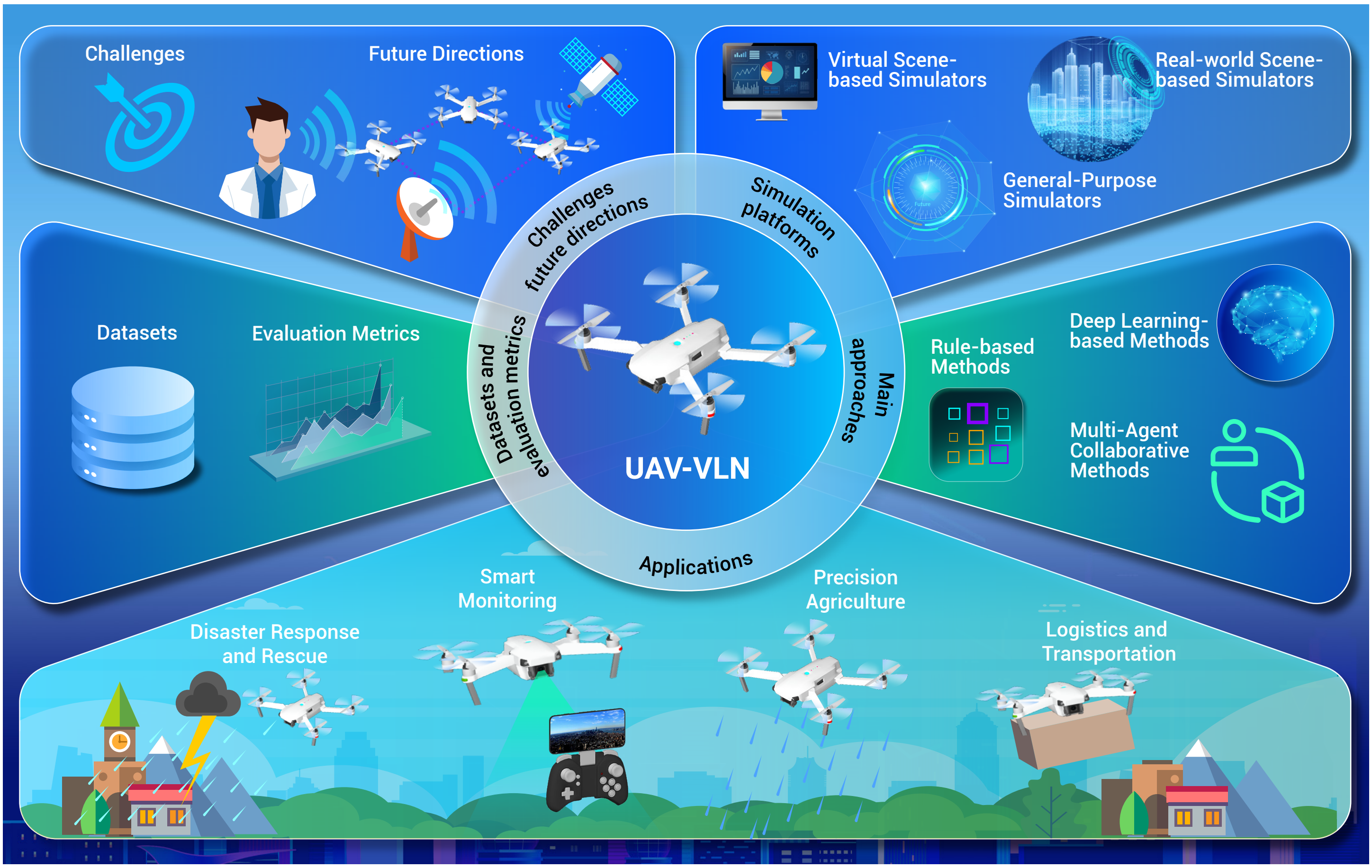
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Comprehensive review of unmanned aerial vehicle based vision-and-language navigation (UAV-VLN).
- Provide a summary of methodological evolution, from single-UAV navigation to multi-agent collaboration.
- Outline promising future directions, such as embodied world models and space-air-ground unmanned systems.

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With the rapid advancement of unmanned aerial vehicle (UAV) technology, embedding intelligence into aerial platforms has become an increasingly important research direction. UAV-based vision-and-language navigation (UAV-VLN), as a representative paradigm of aerospace embodied intelligence, requires UAVs to understand natural language instructions and integrate multimodal perception to autonomously plan and execute navigation tasks in three-dimensional environments. This survey provides a comprehensive review of UAV-VLN research, covering simulation platforms, task definitions, core methodologies, datasets and evaluation metrics, application scenarios, as well as key challenges and future directions. We first present the design principles and capabilities of mainstream simulators, followed by a structured summary of methodological progress, including rule-based approaches, deep learning-driven models, and multi-agent collaborative strategies. We then discuss critical technical challenges in UAV-VLN, such as dynamic feasibility and control in 3D space, perception and generalization in complex environments, linguistic ambiguity and cross-modal semantic grounding, long-term spatiotemporal reasoning, and deployment under resource constraints. Based on these challenges, we outline promising future directions, including standardized benchmark development, Sim-to-Real and cross-domain transfer, pretrained large model integration, embodied world model, collaborative and interactive UAV-VLN, and embodied navigation of space-air-ground unmanned systems. This survey aims to provide a structured reference for future research and to guide the practical deployment of UAV-VLN systems.

INTRODUCTION

Aerospace embodied intelligence aims to embed intelligence into aerospace platforms such as unmanned aerial vehicles (UAVs),[1] near-space airships, satellites, and planetary rovers, forming aerospace agents with autonomous perception, navigation, planning, and action capabilities.[2-8] With the rapid development of UAV technology, the demand for UAV applications in inspection, emergency response, logistics, and environmental monitoring has steadily increased.[9-12] An important challenge in aerospace embodied intelligence is enabling UAVs to understand human intentions and autonomously perform complex navigation tasks based on natural language instructions.[13-15] Vision-and-Language Navigation (VLN)[14,16-19] is a representative paradigm, requiring the integration of visual perception and language understanding to navigate unseen environments.

Compared with ground-based VLN, UAV-VLN involves higher degrees of freedom and more complex environmental constraints. UAVs can observe scenes from multiple angles and altitudes, capturing richer spatial and semantic information.[20,21] The navigation space is three-dimensional, involving pitch, yaw, and roll control as well as path optimization, which significantly increases the degrees of freedom compared with ground platforms.[22] Natural language instructions are often ambiguous, for example, "*fly over the small grove and land next to the red-roofed building*" requiring strong language understanding, multi-scale visual perception, and spatial reasoning capabilities. Perception data may also come from heterogeneous sources, such as RGB images, depth maps, semantic maps, remote sensing imagery, and GPS/IMU signals, which pose significant challenges for multi-modal information fusion. Tasks in UAV-VLN further extend beyond single-shot navigation to multi-hop planning, exploratory flight, and long-term memory-based planning.[23-27]

Thanks to advances in simulation platforms and data construction, UAV-VLN has gradually formed a structured research framework, spanning high-fidelity simulators, navigation algorithms, and evaluation metrics linked to downstream applications. Simulation platforms range from general-purpose environments such as Isaac Sim and AirSim[28] to UAV-VLN-specific tools, including CityNav,[29] AerialVLN,[30] and OpenFly.[31] Methodologically, UAV-VLN has evolved from early rule-based systems to learning-based approaches, including reinforcement learning,[32] imitation learning,[33] self-supervised learning,[34] multi-modal fusion,[35] and large model-driven frameworks,[36] with some methods further incorporating long-term memory to support complex navigation tasks.[37-39] In recent years, collaborative paradigms have gained attention, including multi-UAV systems[40-43] and satellite–UAV cooperative frameworks,[44-46] where coordination strategies and shared perception improve robustness and efficiency. Evaluation metrics have also moved beyond simple success rates to incorporate trajectory accuracy, efficiency, and path quality, offering more comprehensive assessments of navigation performance.

Despite these advances, UAV-VLN still faces challenges in generalization to complex environments, real-world deployment, ambiguous instruction understanding, and cross-modal long-term reasoning. Therefore, this survey provides a structured overview of UAV-VLN research, offering the first unified aerial-centric synthesis that links simulators, datasets, methods (rule-, learning-, and multi-agent), evaluation metrics, and applications, and further highlights key challenges and promising research directions. The main contributions of this survey are as follows:

• We review mainstream simulation platforms with their design principles and limitations, and provide a structured summary of methodological evolution, from rule-based pipelines to deep learning-driven models and from single-UAV navigation to multi-agent collaboration. We also discuss representative datasets and evaluation metrics, highlighting how different approaches vary in modeling perspectives, navigation strategies, and task adaptability.

• We identify key technical challenges in UAV-VLN, such as complex motion dynamics in 3D space, generalization in open environments, cross-modal spatiotemporal reasoning and lightweight deployment. Based on these challenges, we outline promising future directions, such as Sim-to-Real transfer, leveraging pretrained large models, embodied world models for UAVs, collaborative and interactive UAV-VLN, and embodied navigation of space-air-ground unmanned systems, with the aim of providing insights for future research and real-world applications.

The remainder of this paper is organized as follows. Section II introduces the preliminaries of UAV-VLN, including task definition and its relation to ground-based VLN and UAV navigation. Section III reviews UAV simulation platforms and categorizes them by construction approach. Section IV provides a systematic review of core UAV-VLN methods, including rule-based, deep learning-based, and multi-agent collaborative approaches. Section V presents representative applications and their navigation requirements. Section VI summarizes existing datasets and evaluation metrics. Section VII discusses the key challenges in UAV-VLN and highlights promising future research directions.

PRELIMINARIE

This section introduces the development of VLN and UAV navigation researches, as well as the basic definitions and characteristics of UAV-NAV tasks, providing background support for the subsequent review of the methodology.

Vision-and-language navigation (VLN)

Vision-and-Language Navigation (VLN) has emerged as an important research direction in recent years.[47-49] Its core objective is to enable an agent to autonomously plan and execute navigation paths in visual environments based on natural language instructions.[39,50-52] VLN was first defined on the Room-to-Room (R2R) dataset,[47] where the agent receives a language instruction (e.g., "*Walk through the hallway from the lobby, enter the kitchen, and stop by the table*") and first-person visual observations, and must perform step-wise actions to reach the target. Unlike traditional path planning, VLN integrates natural language understanding, visual perception, and action decision-making within a unified framework, posing challenges in semantic alignment, multimodal reasoning, and temporal control.[53-58]

Subsequent studies have extended VLN to handle more diverse and complex tasks. For example, the Room-for-Room (R4R) dataset introduces multi-hop long-horizon navigation, increasing the complexity of instruction-environment associations.[39] In outdoor urban environments, Chen et al. proposed the Touchdown dataset, requiring agents to navigate in Google Street View-level city scenes,[49] significantly increasing environmental complexity and language diversity. Such tasks not only emphasize local perception but also require long-term memory and cross-region reasoning.[59-61]

Overall, VLN research has gradually evolved from indoor to outdoor environments, from static to dynamic scenarios, and from small-scale datasets to large-scale pretraining. These developments provide a theoretical and methodological foundation for language-guided navigation in UAV scenarios.

UAV navigation

UAV navigation has long been a core topic in robotics and automation, aiming to enable autonomous flight and task execution in complex and uncertain environments.[41,62–64] Compared with ground robots, UAVs are characterized by high degrees of freedom in three-dimensional flight, limited energy resources, and stringent requirements for real-time performance and robustness.

Traditional UAV navigation methods mainly rely on localization and planning techniques.[65-69] For localization, Visual-Inertial Odometry (VIO) and Simultaneous Localization and Mapping (SLAM) are commonly used solutions. For instance, ORB-SLAM2[70] has become a benchmark in UAV visual localization. For path planning, graph search algorithms (e.g., A*[71]), sampling-based methods (e.g., RRT[66,67]), and optimization-based approaches (e.g., MPC[72,73]) are widely applied. Kamel compared linear and nonlinear MPC for UAV trajectory tracking, providing theoretical insights for complex trajectory control.[69]

With the advancement of deep learning and reinforcement learning,[74-78] end-to-end learning and RL-based methods have been introduced to enhance autonomous perception and decision-making.[79,80] These approaches reduce reliance on traditional mapping and planning, making them more suitable for complex real-world environments. Recently, UAV navigation research has also explored multi-UAV collaboration and cross-domain perception.[41,81-84] For example, the AirSwarm framework[41] investigates the feasibility of multi-agent cooperative navigation with low-cost commercial UAVs. Meanwhile, multi-modal navigation combining satellite remote sensing and UAV data has become an emerging trend. Overall, UAV navigation is evolving from traditional model-based methods toward data-driven and multi-modal fusion approaches, laying a solid foundation for UAV-NAV tasks.[85-89]

UAV-VLN task definition

At the intersection of VLN and UAV autonomy, the UAV-based VLN task has been introduced. As shown in Figure 1, the aim of UAV-VLN is to enable UAVs to navigate aerial environments safely and efficiently by following natural language instructions. While UAV-VLN can be regarded as an extension of VLN to aerial agents, it is gradually forming into a research direction with its own characteristics. Formally, the UAV-VLN task can be defined as learning a policy "$\pi : (I_t, L) \rightarrow a_t$, where I_t denotes the multimodal observation (e.g., RGB images, depth maps, or GPS data) at time step t , and L represents a natural language instruction describing the navigation goal or route. The policy "π outputs an action $a_t \in \mathcal{A}$ from the action space $\mathcal{A}$ (e.g., *move forward*, *turn left/right*, *ascend*, *descend*, or *hover*). The objective is to generate an action sequence $\{a_1, a_2, \ldots, a_T\}$ that drives the UAV from its starting position to the target location specified by L, while minimizing trajectory deviation and avoiding collisions. Success is typically evaluated using standard UAV-VLN metrics such as Navigation Error (NE), Success Rate (SR), and Success weighted by Path Length (SPL), which jointly measure navigation accuracy and task completion. Compared with conventional VLN, UAV-VLN presents several distinctive aspects:

• UAVs operate in full 3D space with six degrees of freedom (6-DoF), where navigation must account for path.

• UAV-VLN often involves outdoor and large-scale unstructured environments (e.g., farmland, disaster areas, forests), where diverse terrains, multi-view observations, and varying altitudes introduce domain shifts and sim-to-real gaps, posing challenges for robust perception and generalization.[94,95]

• UAV platforms are restricted by onboard computation, payload, and energy budgets, necessitating lightweight and efficient models that support real-time multi-modal fusion and deployment.[96-98]

SIMULATION PLATFORMS

The UAV-VLN task requires agents to autonomously perform multimodal instruction-driven path planning and execution in realistic or near-realistic environments. Due to the high development cost, safety risks, and lack of controllability in real-world deployment, constructing high-fidelity and reproducible training simulators has become a key enabler for advancing this field. Such simulators typically virtualize UAV motion characteristics, sensor configurations, and environment interaction mechanisms, thereby providing a stable platform for algorithm training, testing, and evaluation. We categorize mainstream UAV simulators into three groups based on their construction methodology: general-purpose simulators, real-world scene reconstruction simulators, and virtual environment-based simulators.

General-purpose simulators

General-purpose simulators usually adopt a modular architecture, integrating high-precision physics engines (for 3D motion and dynamics simulation),

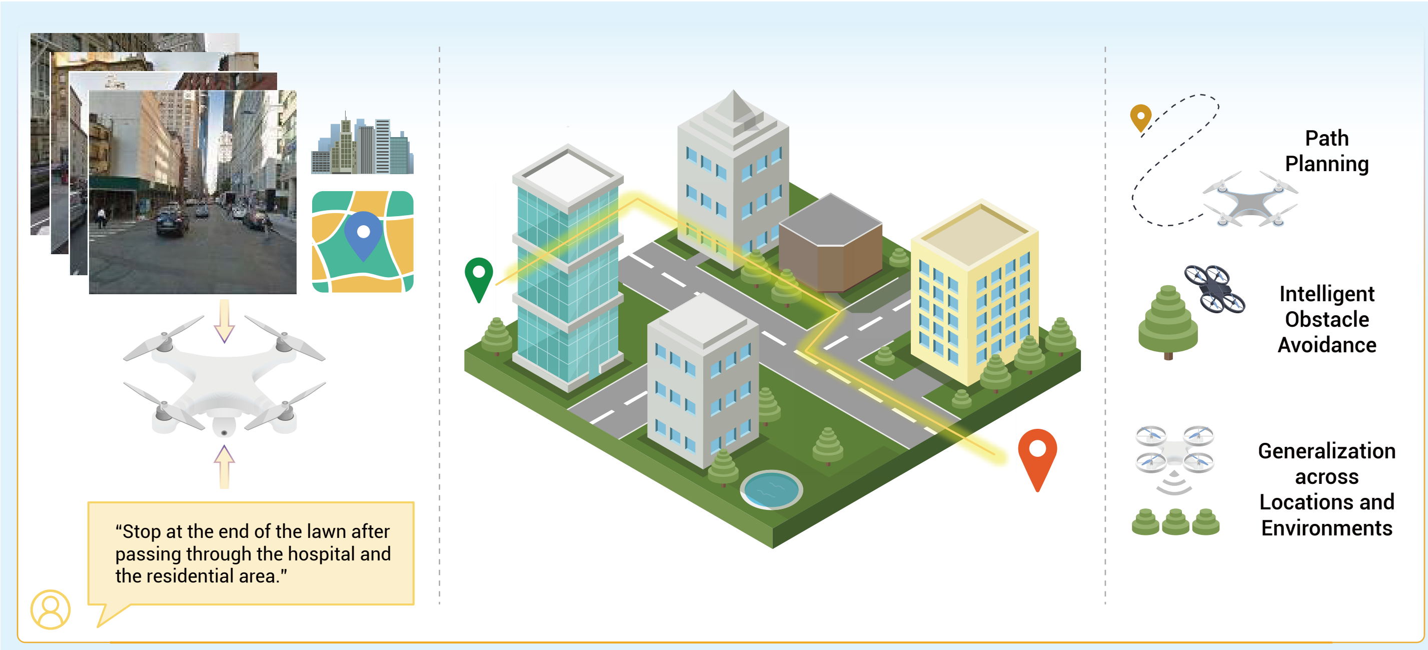

Figure 1. Schematic diagram of UAV-VLN tasks The UAV agent receives natural language instructions and environmental perception inputs, such as RGB images, depth maps, and semantic maps, to achieve autonomous planning and navigation, while possessing intelligent obstacle avoidance and environmental generalization capabilities.

3D environment rendering modules (supporting dynamic scenes and lighting simulation), multimodal sensor modeling (e.g., cameras, LiDAR, IMU), and interaction frameworks (supporting real-time control and event triggering). Together, these modules construct realistic environments for training and evaluation.

Isaac Sim,[99] built on the NVIDIA Omniverse platform and the PhysX engine, supports high-fidelity physical simulation, GPU-accelerated rendering, and parallel computation. It provides various sensor models (e.g., RGB, depth camera, Li-DAR, IMU) and is compatible with mainstream deep learning frameworks, making it suitable for large-scale synthetic data generation and agent training. Unreal Engine (UE)[100] offers photorealistic rendering and blueprint-based programmability. AirSim,[28] developed by Microsoft on top of UE, supports comprehensive physical and visual modeling with API access, and has been widely used for vision-based navigation, obstacle avoidance, and path planning research. Gazebo[101] is a widely adopted open-source robotics simulator, integrating physics engines such as ODE and Bullet. With seamless ROS integration, abundant robot models, and indoor/outdoor environments, it is suitable for SLAM, multi-agent coordination, and path control tasks. Google Earth[102] focuses on geospatial visualization based on satellite and street-view data. Although it lacks physical simulation capabilities, it is valuable for urban scene understanding and path planning visualization. GTA-V,[103] though originally a commercial game engine, has been widely adopted due to its high-fidelity city modeling, realistic traffic flow, and human–vehicle interactions, serving as a large-scale synthetic visual data source and a pretraining platform for navigation algorithms. CoppeliaSim[104] and Webots[105] provide multi-physics engine support and modular modeling interfaces, with APIs for Python, ROS, and other middleware, making them suitable for multi-robot control, path planning, and reinforcement learning experiments. MORSE,[106] based on Blender, emphasizes lightweight design and middleware compatibility (e.g., ROS, MOOS), and is particularly suitable for semantic-level interactions and multisensor modeling. USARSim,[107] also built on UE, targets urban disaster rescue scenarios, offering high-fidelity physical, visual, and environmental modeling, and is well-suited for research on search-and-rescue tasks and multisensor fusion.

Table 1 compares the main features and application scenarios of these 11 simulators. Most platforms support physics engines (e.g., PhysX, Bullet, ODE), standard sensor modeling (e.g., camera, LiDAR, IMU, GPS), and programmatic interface integration. Open-source platforms such as Gazebo, MORSE, and PyBullet place more emphasis on physical realism and ROS compatibility, albeit with limited rendering fidelity.[108] By contrast, Isaac Sim, UE+AirSim, and Unity[109] provide high-quality rendering, making them ideal for machine learning and visual perception research, though at the cost of higher configuration complexity. GTA-V, with its open-world urban environments and rich visual details, has emerged as an excellent tool for synthetic training. Apart from Google Earth, which mainly serves geospatial visualization purposes, all other simulators support real-time dynamic simulation and interactive control, thereby offering multi-level evaluation and model training environments for UAV-VLN tasks.

Real-world scene-based simulators

Compared to entirely synthetic environments, simulators based on real-world scenes bridge the gap between simulation and reality by integrating high-resolution satellite imagery, street-view data, or 3D models generated through photogrammetry. These simulators provide a more realistic interactive environment, thus improving the feasibility and robustness of deploying systems in real-world scenarios

AVDN[110] is a 2D continuous scene simulator developed by the University of California, Santa Cruz. It uses high-resolution satellite images from the xView dataset as visual input and allows drones to move freely to any given coordinates. This platform provides an interactive interface that supports human control and behavior collection, making it suitable for exploring navigation strategies from a top-down perspective.

CityNav[29] constructs a 3D environment using the Sensat-Urban urban point cloud data, covering an area of 8.7 square kilometers across Cambridge and Birmingham. It utilizes the WebGL-based Potree tool for visualization and supports six-degree-of-freedom flight control, making it ideal for structural perception-based path planning research.

Embodied City,[111] released by Tsinghua University, reconstructs the Guomao district of Beijing using Unreal Engine 5, simulating urban elements such as buildings, streets, vehicles, and pedestrians. The platform employs AirSim for perception modeling and path movement, emphasizing the integration of urban details and dynamic interactions.

AeroSimulator,[1] a core component of the AeroVerse platform developed by the Aerospace Information Research Institute of the Chinese Academy of Sciences, uses the UrbanScene3D dataset[112] to reconstruct urban scenes in cities like Shanghai and Shenzhen. It supports various flight states (e.g., speed, acceleration) and environmental variables (e.g., lighting, weather), enhancing generalization and adaptability in complex scenarios.

OpenFly,[31] developed by the Shanghai AI Laboratory, integrates multiple rendering engines (Unreal Engine 4/5, GTA-V, Google Earth) and 3D GS

Table 1. Comparison of general-purpose UAV simulators.

Simulator	High-fidelity Physics	Photorealistic Rendering	Parallel Computation	Multisensor Support	Real-time Dynamics	Physical Interaction	Open-source	Physics Engine	Research Domains
Isaac Sim	√	√	√	√	√	√	×	PhysX	Attitude control, navigation
PyBullet	×	×	√	√	√	√	√	Bullet	Navigation, swarm/formation control
Unity	×	√	√	√	√	√	×	PhysX	Reinforcement learning, visual perception, attitude control
UE + AirSim	√	√	√	√	√	√	√	PhysX	Attitude control, path planning, vision-based navigation, Sim2Real
Gazebo	×	×	√	√	√	√	√	ODE, Bullet, Simbody, DART	Obstacle avoidance, path planning, multi-agent collaboration
Google Earth	×	×	×	×	×	×	×	N/A	Geolocation, street-view navigation
GTA-V	√	√	×	√	√	√	×	Euphoria	Object detection, vision-based navigation
CoppeliaSim	×	×	×	√	√	√	×	ODE, Bullet, Vortex	Manipulation control, mobile platforms
Webots	×	√	×	√	√	√	√	ODE	Mobile robot navigation, SLAM
MORSE	×	×	×	√	√	√	√	Bullet	Robot perception algorithms, sensor fusion
USARSim	×	×	×	√	√	√	√	PhysX	Disaster response search-and-rescue, multi-robot formation control

reconstruction techniques. It constructs 18 real-world scenes spanning 11 cities and covering over 150 square kilometers, including business districts, campuses, and historical buildings. With a unified perception and action control interface, OpenFly is well-suited for navigation modeling and evaluation in large-scale, diverse environments.

The aforementioned simulators each have their distinct advantages. AVDN uses satellite imagery for global navigation modeling, making it suitable for tasks that require alignment of instructions with geographic images. However, due to its top-down view, it is limited in perceiving vertical structures. CityNav provides high-precision 3D point cloud environments, but lacks dynamic elements, making it less suitable for simulating real-time changes such as crowds or traffic flow. Embodied City emphasizes detailed urban modeling and dynamic interaction, making it suitable for multi-modal, multi-entity environments.

AeroSimulator offers higher freedom in flight physics modeling and environmental disturbance, ideal for simulating complex maneuvers. OpenFly stands out for its large-scale, multi-source real-world urban reconstruction, focusing on cross-city and cross-style generalization, making it one of the most comprehensive benchmark platforms available.

In summary, simulators based on real-world scenes offer significant advantages in enhancing environmental fidelity, perceptual challenges, and interaction complexity. They are progressively becoming a crucial infrastructure for research in UAV-VLN.

Virtual scene-based simulators

In UAV navigation research, obtaining large-scale and realistic diverse training data is often constrained by high costs, low controllability, and difficulty in scene reproduction. Simulators based on virtual environments create digital scenes through existing digital resources or procedural generation, allowing researchers to quickly and cost-effectively synthesize large amounts of experimental data. They also enable the flexible construction of diverse task scenarios with specific features, facilitating efficient algorithm development and testing.

Aerial VLN[30] is an early virtual simulation platform for aerial VLN proposed by Northwestern Polytechnical University. Built on the UE4 engine and AirSim, it includes 25 city-level virtual scenes (e.g., blocks, subways, factories) and over 870 object categories. The platform allows drones to capture RGB and depth images from a first-person perspective and perform eight types of actions, including forward movement, turning, vertical/horizontal movement, achieving 4-degree-of-freedom motion control.

OpenUAV[113] is a multi-scenario outdoor navigation platform developed by Beihang University. It integrates UE and CARLA, introducing 22 urban, rural, and natural scenes, and supports scene editing and dynamic environmental changes (e.g., lighting, vegetation sway). The drone on this platform features 6-degree-of-freedom control, supports multimodal sensor configurations (RGB, depth, IMU, LiDAR, GPS), and can be controlled manually or in position-based mode, making it suitable for complex flight strategy research.

UnrealZoo[114] is an open-world embodied intelligence simulator based on Unreal Engine and UnrealCV. It contains 100 immersive virtual scenes and 77 embodied agents across seven categories. The platform supports tasks such as visual navigation and target tracking, and provides both discrete and continuous control modes, making it suitable for multi-agent path planning and interaction behavior modeling.

The Embodied Crowd Counting Simulator[115] is specifically designed for simulating and analyzing large-scale crowds. UnrealZoo excels in constructing complex open worlds, where various types of agents can simultaneously interact and navigate. GRUtopia[116] focuses on training robots in highly interactive scenarios to help them adapt better to real-world conditions. MetaUrban[117] is focused on simulating ground robots in complex urban traffic scenarios (e.g., dense crowds of pedestrians). These virtual simulators collectively drive the algorithm validation and capability enhancement of UAVs and other embodied agents in diverse and complex virtual environments.

Overall, Figure 2 and Figure 3 provide a comprehensive comparison of real-world and virtual scene-based simulators in terms of environment type, platform, scene editing capabilities, dynamic assets, number of scenes, scene scale, main sensors, and action degrees of freedom, which can serve as a reference for selecting appropriate simulators for UAV-VLN research.

MAIN APPROACHES

We categorize UAV-VLN approaches into three main paradigms: rule-based methods, deep learning-based methods, and multi-agent collaborative methods. Rule-based methods explicitly combine language parsing, visual recognition, and mapping modules, relying on manually designed strategies to accomplish navigation. Deep learning-based methods leverage neural networks to jointly model visual and linguistic features, and optimize navigation

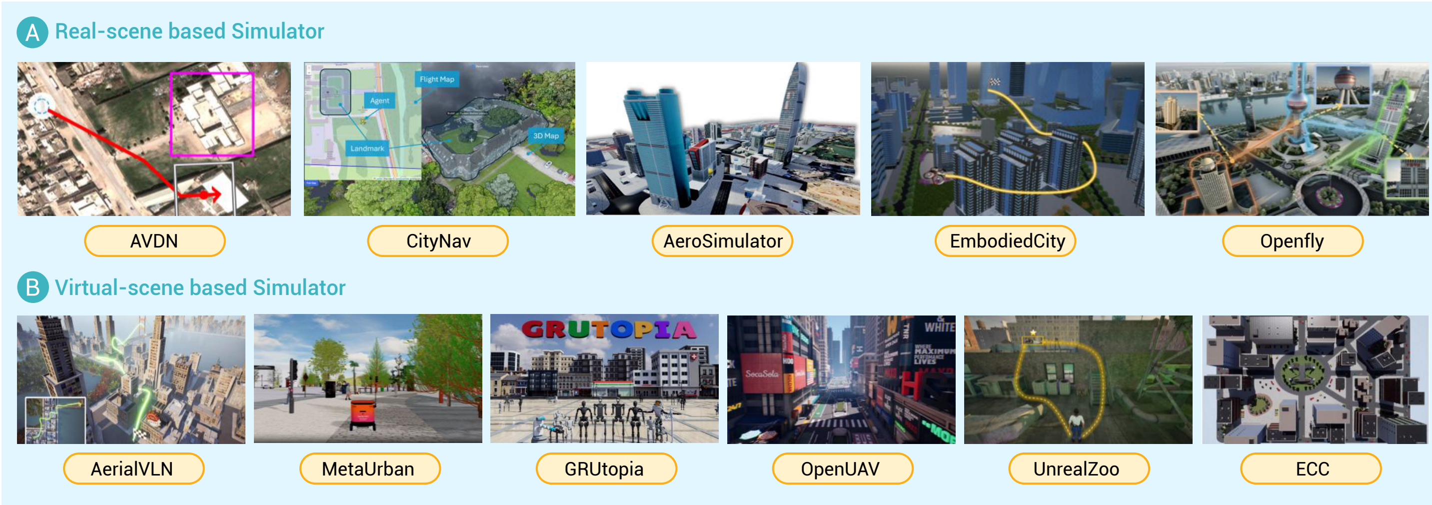

Figure 2. Typical scenarios of simulators based on real scene reconstruction and virtual scene construction.

Table 2. Comparison of simulators based on real and virtual environments.

Simulator	Environment	Base Platform	Scene Editing	Dynamic Assets	Number of Scenes	Scene Size (km²)	Main Sensors	Action DOF
CityNav	Real	Potree	×	×	2	8.7	RGB-D, Pose	4
AVDN	Real	Satellite Images	×	×	1	N/A	RGB, Pose	4
Embodied City	Real	UE 5	√	√	1	6.72	RGB-D, Pose, Semantic Segmentation	4
AeroSimulator	Real	UE 4	√	×	4	N/A	LiDAR, Semantic Segmentation, RGB-D, Pose	6
OpenFly	Real and Virtual	UE 4, UE 5, GTA-V, Google Earth, 3D GS	√	×	18	150	LiDAR, Semantic, RGB-D, Pose	4
Aerial VLN	Virtual	UE 4	×	×	25	N/A	RGB-D, Pose	4
Open UAV	Virtual	UE 4	√	√	22	N/A	LiDAR, RGB-D, Pose, IMU, GPS	6
UnrealZoo	Virtual	Unreal Engine 4/5	√	√	100	16 (Largest)	Color, RGB-D, Gray, Pose, Mask	3
Embodied Crowd Counting	Virtual	Unreal Engine 4	√	√	60	40 (Average per scene)	RGB-D, Semantic, LiDAR	6
GRUtopia	Virtual	Isaac Sim	√	√	100k	N/A	RGB-D, Pose	Various
Metaurban	Virtual	PyBullet	√	√	12.9k	20 (Average per scene)	RGB-D, Semantic, LiDAR	Various

policies through supervised learning. Multi-agent collaborative methods target multi-objective and dynamic environments, employing agent cooperation mechanisms to achieve task decomposition and parallel navigation. Figure 3 provides a taxonomy of UAV-VLN methods, visually summarizing the paradigms and their representative techniques.

Rule-based methods

Rule-based methods rely on manually designed features, mathematical models, and logical reasoning rather than learning-based approaches. They are intuitive and highly interpretable but have limited generalization capability, making them more suitable for well-defined tasks or environments. Typically, rule-based methods decompose UAV navigation into three sub-problems: localization, environmental perception, and planning.

Localization. The goal of localization is to determine the relative position of the UAV and the target, which serves as the input for subsequent route or action planning (Figure 4). Depending on the sensing modality, existing approaches can be divided into those relying on onboard sensors (e.g., cameras, LiDAR) and those using external sources such as GPS or UWB.

Early works in the 2000s adopted GPS for outdoor UAV localization. For example, Hui et al.[125] integrated GPS with electronic maps to achieve dynamic UAV navigation and visualization. Williamson et al.[126] fused GPS with INS sensors to achieve formation flight localization accuracy within 10 cm for F18 aircraft. However, GNSS signals are unstable and prone to blockage, ionospheric activity, or deliberate jamming, which significantly limits their usability in complex environments.[127,128]

With sensor miniaturization and increasing onboard computation, many works have adopted cameras or LiDAR for UAV localization. For instance, Mohta et al.[121] extended the MSCKF visual odometry framework[119] into a dual-sided version for UAV localization, enabling agile indoor and outdoor flight. Mohta et al.[129] leveraged the SVO framework[130] for localization in cluttered warehouse environments. Ren et al.[122] applied Fast-LIO2[123] to achieve UAV navigation in forest environments. Nevertheless, vision and LiDAR odometry only provide relative localization and suffer from drift over long distances, restricting their scalability.

To overcome this, hybrid solutions combine relative odometry with global positioning (e.g., GNSS or prior map matching) to eliminate drift. Cao et al.[124] tightly fused raw GNSS, vision, and IMU data in an optimization-based manner, enabling robust localization even with limited satellite visibility in large-scale indoor-outdoor mixed environments. Wang et al.[131] exploited geomagnetic field matching to compensate for INS drift. Overall, multi-sensor fusion has become mainstream for UAV localization, though significant challenges remain in ensuring robustness in highly complex environments.

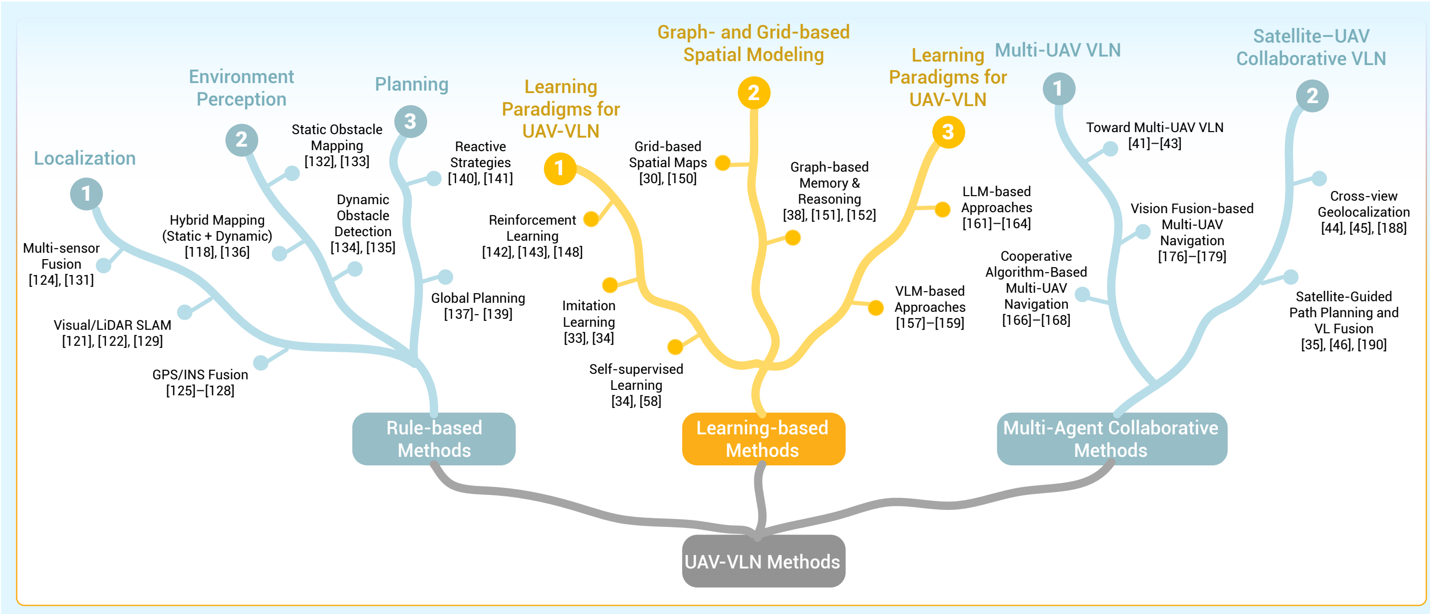

Figure 3. A taxonomy of UAV-VLN methods, covering rule-based, learning-based, multi-agent collaborative paradigms.

Environmental perception. Environmental perception aims to capture information about static and dynamic obstacles to ensure safe UAV flight. Static obstacles are often represented via occupancy grids, 3D voxels, ESDF maps, or point cloud maps. For instance, Mohta et al.[129] used 2D grids for global maps and 3D voxels for local maps; Fang et al.[132] modeled environments using pre-built voxel maps; Oleynikova et al.[133] incrementally constructed ESDF maps. These methods perform well in static environments but struggle to reflect dynamic changes in real time.

Dynamic obstacle detection typically relies on visual or LiDAR data, with results represented by ellipses or bounding boxes. For example, Oleynikova et al.[134] detected obstacles from disparity maps and modeled them with 2D ellipses. Lin et al.[135] extended this to 3D bounding boxes with continuous estimation of position, size, and uncertainty, improving adaptability in complex dynamic scenes. Yet, purely geometric representations may be insufficient in highly cluttered environments.

To simultaneously handle static and dynamic information, hybrid mapping approaches have been proposed. For instance, Xu et al.[118] and Wang et al.[136] adopted two-layer structures: static layers modeled with occupancy voxels and dynamic layers represented by ellipsoids, with point cloud occlusion used to detect moving objects.

Planning. Once the UAV's position, target, and obstacles are obtained, the system must plan a safe trajectory or action sequence. Planning methods can be broadly divided into two categories.

The first category is global planning methods, which generate consistent, globally optimal paths, similar to bird migration, but typically require complete maps and high computational resources. For instance, Mohta et al.[129] applied A* on a hybrid 2D/3D map and optimized safe trajectories via Safe Flight Corridors. Oleynikova et al.[133], building on,[120] combined RRT global search with minimum-snap smoothing. Zhou et al.[137] initialized paths with A*, then optimized collision-free trajectories using B-splines in ESDF maps. However, ESDF construction is time-consuming; hence, Zhou et al.[138] proposed an optimization-based method without ESDF for improved efficiency. Most of these methods assume static environments. To handle dynamics, Xu et al.[118] first generated a minimum-snap trajectory in the static layer, then avoided dynamic obstacles using chance-constrained MPC. Xu et al.[139] further combined occupancy grids and dynamic ellipsoids to build two-layer maps, generating B-spline trajectories that jointly account for static and dynamic obstacles.

The second category is reactive motion strategies, which resemble insect reflexes, relying on minimal prior information with low computational demand but at the cost of path quality. For example, Liu et al.[140] integrated Lyapunov methods with artificial potential fields for dynamic obstacle avoidance. Jenie et al.[141] extended the 3D velocity obstacle approach with buffered velocity sets to improve robustness. These methods respond quickly but fail to generate globally consistent and efficient paths.

In summary, global planning methods demand globally consistent continuous maps (e.g., ESDF) to support trajectory optimization and gradient computation, while reactive strategies emphasize local perception and rely on lightweight maps such as occupancy grids to enable fast responses. Thus, map modeling and path planning must be co-designed to balance accuracy and efficiency for improved performance and adaptability.

Deep learning-based methods

With the breakthroughs of deep learning in computer vision and natural language processing, its powerful feature representation and cross-modal modeling capabilities have gradually become the backbone of UAV-VLN research. Unlike traditional approaches that rely on handcrafted rules or shallow models, deep learning enables UAVs to leverage large-scale data and end-to-end training to significantly enhance perception, reasoning, and decision-making in complex environments. This subsection reviews UAV-VLN methods from three perspectives: learning paradigms, graph and grid-based spatial modeling and large model-based methods.

Learning paradigms for UAV-NLN. The choice of learning paradigm directly affects a navigation model's perceptual ability, decision-making efficiency, and generalization performance. For example, reinforcement learning (RL) optimizes policies through continuous interaction with environments, enabling UAVs to gradually learn how to follow natural language instructions and visual observations in long-horizon tasks. Self-supervised learning (SSL) exploits massive unlabeled data via pretraining mechanisms such as contrastive learning and masked modeling to acquire cross-modal representations, alleviating the challenges of data scarcity and high annotation cost. Imitation learning (IL), by contrast, emphasizes learning from expert demonstrations, which is particularly useful in avoiding unsafe behaviors and facilitating fast adaptation to novel environments. Recent studies combining these paradigms with UAV-VLN have demonstrated promising results in both simulation and real-world UAV experiments, laying the foundation for intelligent navigation in dynamic and complex missions.

For instance, Wang et al.[34] addressed poor generalization and low exploration efficiency in VLN by combining Reinforced Cross-Modal Matching (RCM) with Self-supervised Imitation Learning (SIL), thereby improving agent navigation in indoor environments. In UAV tracking scenarios with long trajectories, complex 3D scenes, and frequent occlusion, Wu et al.[32] proposed ORTrack, which integrates a spatial Cox-process masking strategy with adaptive knowledge distillation, achieving robust and real-time performance.

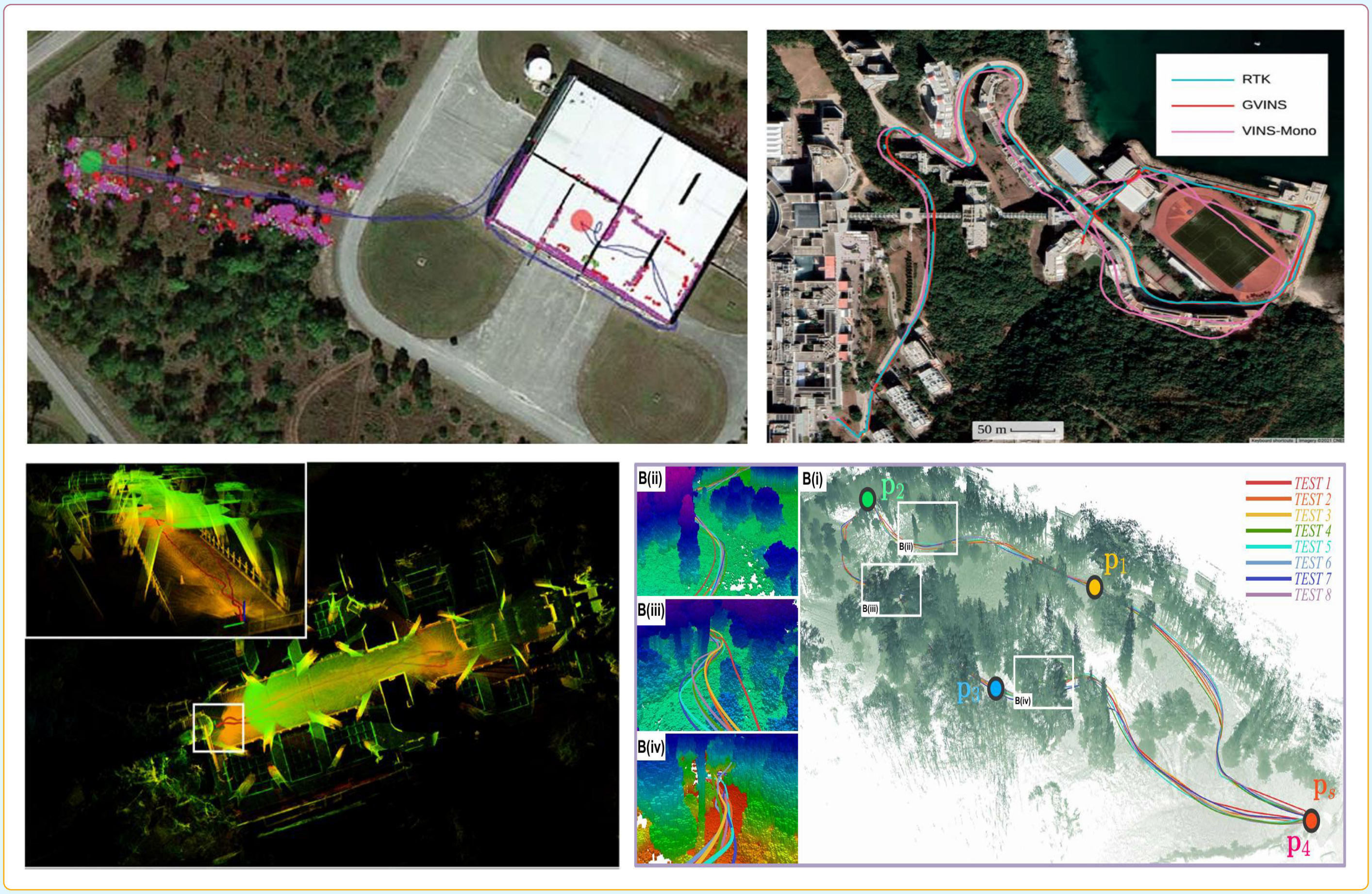

Figure 4. UAV localization: determining relative position for navigation and action planning through onboard sensors and external sources DPMPC[118] utilizes the temporal information to generate a reactive trajectory for avoidance. MSCKF[119] estimates the trajectory with blue line overlaid on a map of area. Another work locates the original goal point which is not visible from the start position over time.[120] Some work successfully locate destination point in complex outdoor environment.[121-124] (Reproduced with permission.[121] Copyright 2018, IEEE)(Reproduced with permission.[122] Copyright 2025, Science)(Reproduced with permission.[123] Copyright 2022, IEEE)(Reproduced with permission.[124] Copyright 2022, IEEE)

Emami et al.[142] combined diffusion models (DMs), reinforcement learning, and digital twins (DT) to address decision-making and modeling challenges in UAV communications. For VTOL-UAV landing on offshore charging platforms, Ali et al.[143] proposed a staged RL framework, applying model-based control during approach and PPO-based policy learning during landing to enhance disturbance robustness.

In multi-UAV collaborative scenarios, Zhu et al.[144] developed the ZD-RL method, which decomposes the Z-function to jointly optimize transmit power and UAV trajectories, maximizing localization accuracy. To counteract physical sensor attacks (e.g., GPS spoofing), Dash et al.[145] introduced ARMOR, a two-stage robust RL framework where a teacher encoder leverages privileged information to generate robust latent states, while a student encoder approximates them via LSTM using only historical sensor data. For simulation support, Tai et al.[146] presented PyFlyt, a Bullet-based UAV simulation platform with standardized tasks and support for sparse-reward RL training, improving portability and efficiency compared to existing tools.

Furthermore, He et al.[147] investigated communication and trajectory joint optimization for multi-UAV collaboration, proposing RL-TP for trajectory planning and C-TOP for convex optimization-based topology adaptation, thereby maximizing throughput under neighbor and power constraints. Xu et al.[148] proposed NavRL, a PPO-based framework for safe UAV navigation in dynamic environments, integrating velocity obstacle theory with linear programming to refine RL outputs for collision avoidance. Wang et al.[33] combined RL and IL in a synergistic framework, enabling UAVs to perform visual-based autonomous flight in complex river environments.

Graph and grid-based spatial modeling. In complex urban environments, UAVs face challenges such as long trajectories, multi-hop instructions, and frequent target switching, where immediate perception alone is insufficient for robust decision-making. To overcome these limitations, recent research has increasingly adopted graph- and grid-based spatial modeling to explicitly encode visual, geometric, and semantic information, while maintaining structured memory of the environment. By supporting dynamic updates and long-horizon reasoning, these models enable UAVs to perform more reliable planning, revisitation, and instruction following.

To address the demands of long trajectories and coupled 3D maneuvers, EventFly[37] reformulates navigation as a view-selection problem. It integrates six-view representations with top-down grid maps, consolidating navigation history into a unified spatial memory that significantly improves robustness in dynamic urban scenarios.

For large-scale spatial reasoning and multi-stage navigation strategies, GeoNav[149] introduces a multimodal framework that integrates a global cognitive map (SCM), a hierarchical scene graph (HSG), and multi-stage strategies (MNS) (Figure 5A). This design enables explicit geographic reasoning and landmark-based planning, improving both efficiency and accuracy in language-guided navigation.

Several works further highlight the utility of grid-based spatial modeling. For instance, AerialVLN[30] augments bird's-eye-view (BEV) grid maps with real-time updates, allowing UAVs to fuse semantic and geometric cues for fine-grained navigation. Similarly, Wu et al.[150] proposed a low-cost system that generates occupancy grid maps from 2D LiDAR, combining offline path planning with reinforcement learning–based obstacle avoidance for deployment in unknown environments.

Graph-based modeling approaches, on the other hand, emphasize relational reasoning and long-term memory. The Structured Scene Memory

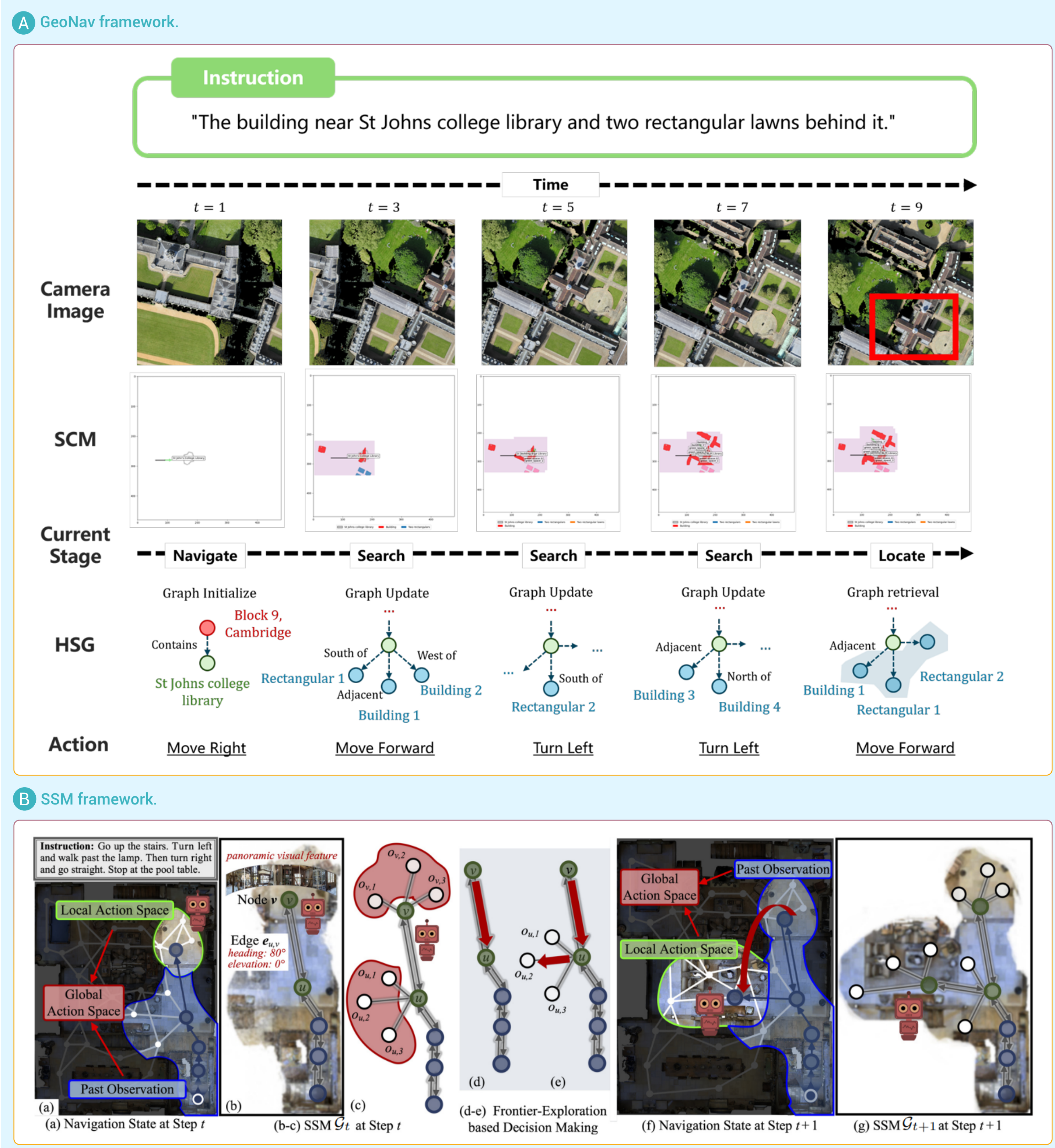

Figure 5. (A) The GeoNav framework[149] presents a qualitative example of its agent performing language-goal aerial navigation; the framework leverages natural language commands for task specification and demonstrates robust visual navigation capabilities on the CityNav benchmark. (Reproduced with permission.[149] Copyright 2025, arXiv) (B) The SSM framework[38] learns a graph-structured scene memory to capture historical observations and environmental layouts and integrates it with a global action space for robust navigation planning; its modeling of visual and geometric cues enables long-horizon reasoning and mitigates the limitations of local-action VLN agents. (Reproduced with permission.[38] Copyright 2021, IEEE)

(SSM)[38] encodes UAV observations as nodes and spatial relations as edges(Figure 5B), enabling revisitation and retrieval of past states. Building on this idea, CityNavAgent[151] applies a dynamic memory graph to urban-scale environments, while MCGPT[152] leverages memory topology graphs and demonstrations to diversify navigation strategies. Likewise, InstructNav[153] introduces multi-source value graphs to decompose complex instructions into manageable sub-tasks.

Overall, graph- and grid-based spatial modeling provides UAVs with structured, queryable, and updatable representations of their environment, bridging the gap between immediate perception and long-term decision-making in

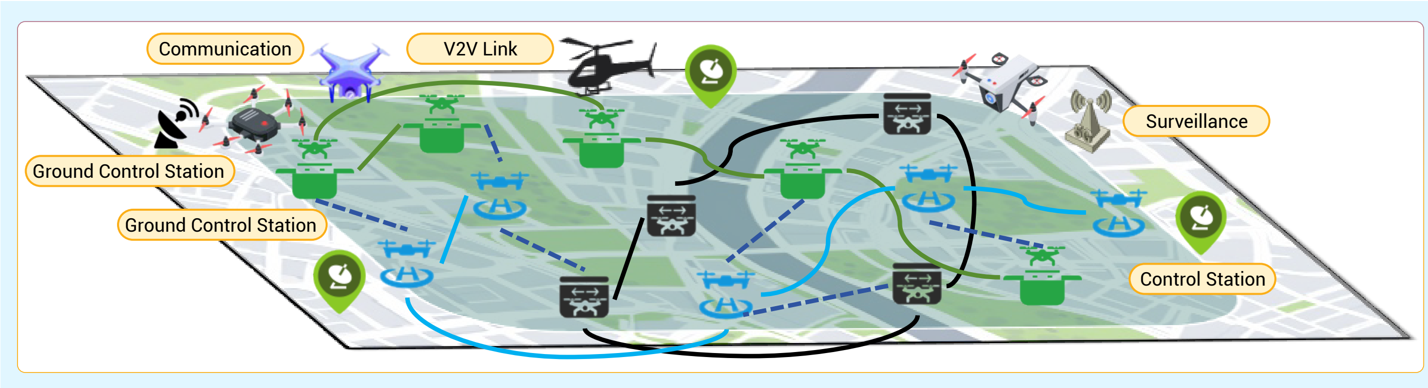

Figure 6. Multi-UAV cooperative navigation in urban low-altitude airspace Multiple UAV clusters coordinate routes between vertiports while maintaining communication–navigation–surveillance (CNS) links. Communication supports trajectory sharing and control handover; navigation combines satellite, ground beacons, and vision-based methods; surveillance feeds constraints from monitoring stations. The figure highlights concurrent multi-cluster operations under shared CNS services.

vision-and-language navigation.

Large model-based UAV-VLN. Recently, pretrained large models have become increasingly prominent in UAV-VLN, offering strong reasoning capabilities and extensive prior knowledge. By leveraging these models as agents for action prediction, UAVs can better handle complex spatial relations and semantic cues in outdoor environments.[154-156] Many approaches transform visual observations into textual descriptions or structured prompts, thereby enhancing generalization and data efficiency.

VLM-based approaches integrate visual and linguistic inputs to achieve end-to-end navigation. For example, Hong et al.[157] introduced a recurrent BERT model that maintains cross-modal states to address partially observable Markov decision problems, achieving state-of-the-art results on R2R and REVERIE. Zhang et al.[158] proposed a multimodal system for fine-grained delivery scenarios, combining lightweight large language models with vision-language models for request parsing, target detection, and action selection. Similarly, Fan et al.[110] developed the HAA-Transformer based on the AVDN dataset, enabling dialogue-guided navigation and human attention prediction. Cai et al.[159] combined supervised finetuning and group-relative policy optimization with a chain-of-thought reasoning mechanism, improving multimodal perception and structured decision-making. Liu et al.[2] proposed AeroVerse-NavAgent, a large Vision-Language Model-based approach for UAV navigation that integrates multi-scale environmental information including topological maps, panoramic observations, and fine-grained landmark recognition using GLIP.

LLM-based approaches primarily exploit large language models for instruction parsing, world modeling, and high-level reasoning. For instance, Wang et al.[34] uses an LLM to convert instructions into structured prompts, guiding vision-language models for zero-shot navigation. Wang et al.[160] proposed STMR, projecting landmarks onto top-down maps and encoding them as matrix-formatted textual prompts for LLM reasoning. Saxena et al.[161] and Li et al.[162] employ LLMs to interpret high-level semantic instructions, integrating them with visual context or model predictive control for trajectory optimization. MapGPT,[163] NavGPT,[36] and DiscussNav[164] convert environmental or semantic information into language prompts to guide navigation, while STMR[165] and NavCoT[156] leverage structured textual representations for precise spatial reasoning and world-model-based planning.

In summary, large model-based UAV-VLN leverages the reasoning power and knowledge integration capabilities of both LLMs and VLMs. VLMs enable end-to-end perception-action learning, while LLMs provide high-level reasoning, instruction parsing, and world modeling. Together, these approaches enhance generalization, support zero-shot navigation, and facilitate human-machine interaction in complex aerial environments.

Multi-agent collaborative methods

Although a single UAV has already demonstrated strong perception and decision-making capabilities in VLN, it still faces inherent limitations in scenarios requiring wide-area coverage, complex task decomposition, and high robustness. Single-agent systems are typically constrained by limited sensing range, computational resources, and task redundancy. To address these challenges, researchers have begun to explore multi-agent collaborative frameworks that integrate multi-source information and multi-agent decision-making. These frameworks aim to overcome the limitations of single UAVs while enhancing overall efficiency and reliability. This section introduces two representative categories: multi-UAV collaboration and satellite–UAV collaboration. Both paradigms highlight the advantages of multi-agent coordination at different levels and open up new research directions for UAV-VLN in urban management, disaster response, and intelligent logistics.

Multi-UAV VLN. Multi-UAV vision-and-language navigation (MU-VLN) integrates computer vision, natural language understanding, and multi-agent cooperative control, with the goal of guiding multiple UAVs to collaboratively accomplish complex navigation tasks via natural language instructions. Compared to single-UAV systems, MU-VLN not only faces the challenges of perception and reasoning but also requires addressing task decomposition, communication, and coordinated behavior planning (Figure 6). Early approaches often relied on distributed decision-making and real-time communication for collaborative navigation. Later, vision-based methods became increasingly popular in multi-UAV navigation due to their passive sensing, low cost, and adaptability to diverse environments. Moving forward, MU-VLN is expected to evolve toward higher autonomy, which multimodal fusion and language grounding jointly model scene semantics, spatial structure, and team-level strategies.

Cooperative algorithm-based multi-UAV navigation. Multi-UAV cooperative navigation techniques improve localization accuracy, path planning, and robustness by enabling UAVs to share positional, velocity, and attitude information in real time, compensating for individual blind spots. Early methods heavily relied on Global Navigation Satellite Systems (GNSS) and Inertial Navigation Systems (INS), such as the tightly coupled GNSS/INS framework in work,[40] which improved global localization. However, these approaches struggle in GNSS-denied environments such as urban canyons, under electromagnetic interference, or indoors. To overcome this, Pan et al.[166] proposed a geometry-based GPS-free cooperative localization method using relative configurations of three UAVs combined with Kalman filtering to reduce drift, while Horyna et al.[167] introduced an enhanced Multi-Robot State Estimation (MRSE) approach for fast onboard-only collaborative flight. Incorporating multimodal sensing, Zhang et al.[168] developed a cooperative integrated navigation method combining radar odometry and enhanced visual odometry, leveraging robust filtering to mitigate outliers in external information.

With the advancement of artificial intelligence, cooperative algorithms are increasingly integrated with learning-based approaches to optimize path planning and trajectory generation. For instance, Braik et al.[169] simulated the Coriolis effect in tornado physics to model swarm path planning; Zhou et al.[170] extended Conflict-Based Search (CBS) by incorporating flight constraints, spatial coordination, and rapid replanning under dynamic obstacles; and Tang et al.[171] proposed a multi-agent twin-delayed deep deterministic policy gradient with improved dynamic formation reward (MATD3-IDFRF), achieving robust formation stability and obstacle avoidance. Similarly, Zhou et al.[172] introduced a distributed model predictive control (DMPC) framework with a multi-strategy improved grey wolf optimization (MSIGWO) algorithm, while Chen et al.[173] designed a biologically inspired tribal competition algorithm for 3D multi-UAV path planning. Han et al.[174] improved the sparrow search algorithm with logarithmic spiral and adaptive step strategies (LASSA) for swarm trajectory optimization, and Wang et al.[175] developed a multi-objective dynamic prioritization model with unilateral collision-avoidance and congestion-weighted mapping.

Vision fusion-based multi-UAV navigation. With the rapid development of computer vision, vision-based cooperative navigation has become a mainstream research direction. As a passive sensor, vision offers low cost, small size, rich information, and strong localization autonomy, making it ideal for multi-UAV tasks. Leveraging shared visual inputs, UAV swarms can overcome failures due to occlusion or flight altitude limits, enabling wide-area positioning and navigation in complex environments.[176] Visual SLAM (Simultaneous Localization and Mapping) further enables UAVs to achieve GPS-independent localization and environment reconstruction, and its integration into multi-agent systems greatly improves efficiency in collaborative tasks. For example, Leishiman et al.[177] studied relative navigation using visual SLAM for formation flying and dynamic obstacle avoidance; Xu et al.[178] proposed D2SLAM, a decentralized, distributed system for collaborative SLAM in aerial swarms, robust to network delays and dynamic conditions; and Wang et al.[179] developed a real-time monocular SLAM system with a distributed architecture and innovative feature descriptors for efficient multi-UAV collaboration.

Reinforcement learning and deep learning have also been applied to visual-based multi-UAV navigation. Huang et al.[180] introduced a distributed obstacle avoidance strategy using deep reinforcement learning, combining depth maps and inertial data to enable autonomous navigation without communication. Mo et al.[181] proposed a Deep Reinforcement Adaptive Learning (DRAL) algorithm that imitates expert pilots to improve robustness in dynamic environments. Xu et al.[182] developed an independent-policy path planning algorithm (C51-Duel-IP) to allow UAVs to independently navigate dynamic environments with limited communication, and Wang et al.[183] employed an asymmetric actor–critic framework to exploit extra information during training, boosting navigation performance in partially observable environments.

Toward multi-UAV VLN. MU-VLN represents a natural extension of multi-UAV navigation into the multimodal domain, requiring not only traditional multi-agent coordination but also cross-modal alignment and language-driven decision-making. While most existing VLN models target single UAVs, extending them to multi-UAV systems requires aligning multi-view visual features, enabling each UAV to interpret natural language commands independently, and coordinating their path generation in real time. Key challenges include multimodal alignment, distributed decision-making, dynamic adaptation, and sim-to-real transfer.

Preliminary research has attempted to address these challenges. AirSwarm[41] demonstrated a low-cost, reproducible multi-UAV experimental platform using commercial off-the-shelf drones, visual SLAM, and hierarchical control, also exploring large language models (LLMs) and multi-agent decision frameworks for high-level task assignment and formation control. Zhang et al.[43] proposed an end-to-end approach integrating UAV physical modeling with deep learning, achieving robust real-world swarm navigation through differentiable physics training. Wu et al.[42] introduced a hierarchical two-UAV paradigm where a high-altitude UAV serves as a global "commander" while a low-altitude UAV acts as a "scout," collaboratively achieving efficient target search. Although evaluated primarily in simulation, these studies lower deployment barriers and enhance reproducibility for future real-world UAV-VLN research.

Given the lack of standardized benchmarks for aerial and multi-agent VLN, we preliminarily categorize representative MU-VLN tasks as follows: first, collaborative obstacle avoidance: UAV swarms adapt formations (e.g., "*maintain a triangular formation around the building*") while avoiding obstacles. Secondly, collaborative target localization: multiple UAVs follow language instructions (e.g., "*search the left area for a red vehicle*") to explore unknown environments and locate targets. Thirdly, collaborative data collection: UAVs collect images from multiple viewpoints to construct semantic 3D maps (e.g., "*mark all windows on the building*"). Finally, collaborative task allocation: UAVs dynamically distribute subtasks based on complex instructions (e.g., "*Drone-A inspect the roof, Drone-B scan the ground*"). Future MU-VLN research should emphasize optimizing inter-UAV information sharing, enhancing multimodal perception, and developing explainable formation decision-making strategies. Moreover, establishing open, realistic multi-UAV VLN benchmarks is crucial to enable fair comparison and systematic progress.

Satellite–UAV collaborative VLN. In environments where GNSS signals are limited (e.g., urban canyons, forest canopies, or complex indoor–outdoor hybrid scenes), UAVs that solely rely on satellite navigation are highly vulnerable to blockage, multipath effects, and interference, leading to a significant degradation in positioning accuracy.[184,185] Onboard visual localization can provide dense, infrastructure-free positional information while supporting multi-task perception such as mapping and object recognition.[186,187] Meanwhile, large-scale satellite imagery offers temporally stable geospatial priors, serving as global anchors for long-range flights without the need to maintain extensive 3D maps.[188,189] Natural language instructions compactly encode task intent (e.g., "*fly along the river and turn at the bridge*"), and when aligned with scene semantics, they directly define navigation goals and path constraints. Satellite–UAV collaborative vision-and-language navigation therefore aims to fuse satellite priors, onboard sensing, and language understanding to achieve high-precision, low-drift autonomous navigation in complex environments.

Cross-view geolocalization. This direction seeks to align UAV aerial images with geo-referenced satellite or aerial tiles to achieve global localization across scales. Mainstream approaches leverage contrastive learning and hierarchical retrieval,[188,189] extracting multi-scale semantic features from satellite and UAV views, and applying metric learning to reduce viewpoint discrepancies. Such methods can periodically reset VO drift during flight or provide pseudo-measurements when GNSS is weak. However, they are easily disturbed by visually similar regions (e.g., farmlands, forests) or heavy occlusions. Recent studies[44,45] enhance robustness by introducing multi-scale convolutions, attention mechanisms, and geographic constraints, and by integrating multi-modal sensing (e.g., depth, thermal imaging) to mitigate degradation caused by illumination and weather variations.

Satellite-guided path planning and vision–language fusion. Satellite imagery not only enables global localization but also supports large-scale task-oriented path planning. In VLN, some approaches directly feed high-resolution satellite images and natural language instructions into Transformer-based models to generate executable flight routes. For instance, the UAV-VLA framework generates end-to-end flight paths from satellite imagery and task descriptions,[190] while UAV-VLPA[46] further incorporates the traveling salesman problem (TSP) and A* search to achieve optimal multi-goal planning. UAV-CodeAgents[35] adopt a multi-agent ReAct framework, integrating satellite imagery, onboard vision, and parsed instructions, enabling pixel-level localization and task decomposition for collaborative flight. In engineering practice, such methods often require deploying parameter-efficient multimodal networks (e.g., lightweight RepVGG + Transformer) on UAV platforms, combined with model quantization, distillation, and small-window optimization, to ensure real-time performance on embedded computing hardware.[191,192]

APPLICATIONS

With advancements in sensors, batteries, UAV flight performance has significantly improved. Equipped with embodied intelligence and VLN capabilities, UAVs are increasingly able to autonomously perform tasks in complex environments. Thanks to their agility and independence from terrain constraints, UAVs have been widely applied in disaster response, remote monitoring, precision agriculture, and logistics transportation as shown in Figure 7.[193]

Disaster response and rescue

Emergency scenarios are often accompanied by challenges such as disrupted communication and blocked roads. UAVs, with their ability for rapid deployment and traversal in complex environments, have been utilized for target search, supply delivery, and temporary communication support.[194] Wolfe et al.[195] proposed a UAV-based approach for locating avalanche victims by detecting mobile phone signals. Bejiga et al.[196] developed a victim detection method by combining CNNs with SVMs. Martinez-Alpiste et al.[197]

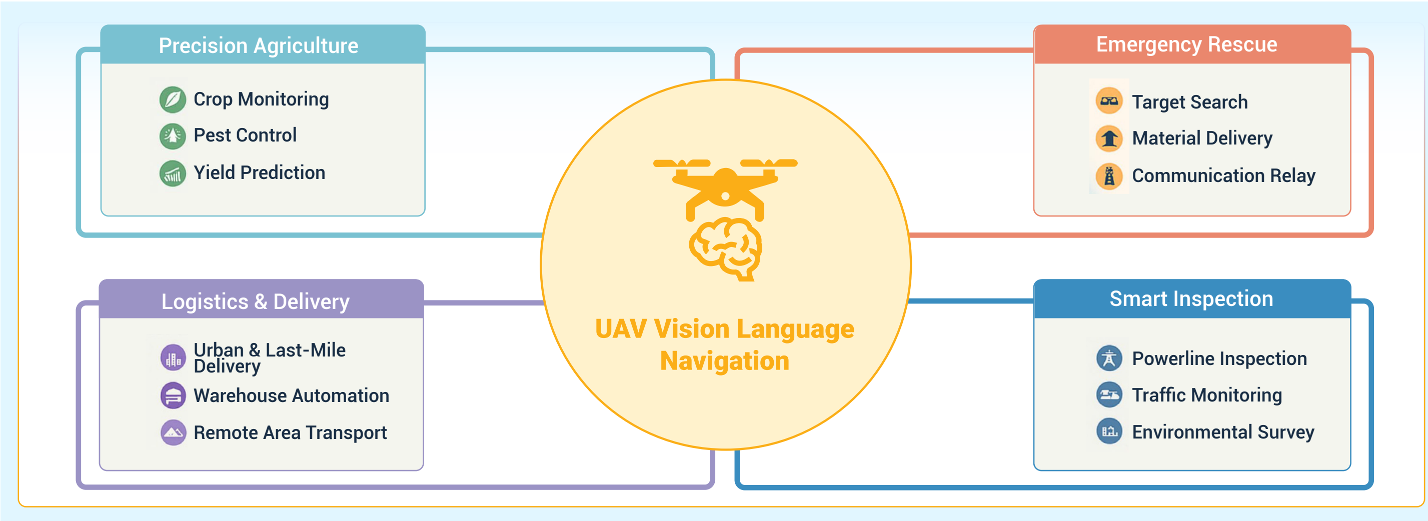

Figure 7. Embodied intelligence technologies centered on UAV-VLN are driving innovations across key industries Typical applications include emergency rescue, remote monitoring, precision agriculture, and logistics, highlighting the technology's potential in complex task scenarios.

designed a UAV–smartphone cooperative system in which smartphones performed real-time detection on UAV-transmitted images to determine target locations; this system has been applied in missing person search operations by the Scottish police. In addition, Zimroz et al.[198] constructed a UAV system for detecting distress calls in underground mines, while Jo et al.[199] developed heavy-lift UAVs with vertical takeoff and landing capabilities for cargo transport in rescue missions. For disaster area communication support, recent works leveraged multi-UAV reinforcement learning and large language models to optimize flight paths,[200,201] thereby establishing efficient aerial mobile base station networks. In these scenarios, natural language interaction can enable rescuers to issue high-level commands such as "search the east zone for survivors," allowing UAVs to interpret human intent directly and coordinate autonomously in uncertain environments.

Smart monitoring

UAVs have demonstrated high efficiency in tasks such as security surveillance, intelligent transportation, power line inspection, geological surveying, and wildlife monitoring.[202-205] Applications include monitoring illegal activities in forests,[202] identifying potential hazards in urban traffic systems,[204] and detecting power line faults or vegetation interference using thermal cameras and radar sensors.[206,207] Iversen *et al.* further integrated soft robotic grippers with UAVs, enabling line-grasping operations and opening possibilities for automated maintenance.[208] Beyond infrastructure monitoring, UAVs have also been applied in geological exploration and wildlife behavior studies.[209,210] In monitoring tasks, language understanding allows operators to describe targets or areas of interest (e.g., "inspect the south power line" or "track the animal near the riverbank"), enabling UAVs to adapt sensing behaviors without manual waypoint setup.

Precision agriculture

UAV systems, with their unique advantages of low cost, operational precision, high flexibility, automation capabilities, and ease of use, have played an important role in tasks such as pest and disease monitoring, crop condition assessment, precision spraying, and yield prediction.[211] For example, deep learning models have been applied for segmentation and detection of grapevine diseases,[212] recognition of cashew anthracnose,[213] and analysis of winter wheat water absorption.[214] At the operational level, Shendryk et al.[215] designed a low-volume spraying system for precise pesticide application. Using LiDAR and multispectral cameras, UAVs can also capture crop phenotypic data to assist in biomass and nutrient status prediction, such as nitrogen content estimation in sugarcane for optimizing fertilization strategies.[216] In this domain, VLN could enable UAVs to follow intuitive instructions (e.g., "inspect the northern field for pest damage") for assisting agricultural monitoring and treatment, improving operational efficiency and reducing the need for expert control.

Logistics and transportation

In the logistics sector, UAVs are increasingly favored for their speed and independence from terrain constraints. Their applications mainly include cargo delivery to remote areas such as mountains and islands, urban "last-mile" delivery,[217] and short-range transport between different sections within supply chain warehouses. Li et al.[218] proposed a UAV–vehicle collaborative delivery system for mountainous regions, combining the flexibility of UAVs with the load capacity of vehicles to improve efficiency. Oy et al.[219] studied the current status and challenges of UAV-based logistics in urban environments. Awasthi et al.[220] highlighted that UAV-based cargo transportation can reduce carbon emissions and alleviate traffic congestion. Beyond large-scale delivery in mountainous or urban areas, UAVs have also been deployed for intra-warehouse cargo transfer. Rejeb et al.[221] discussed the potential and challenges of UAV applications in supply chain management (SCM) and logistics. For such scenarios, VLN integration (e.g., "deliver to Zone C" or "return to base") enhances UAV autonomy, enabling flexible coordination and reducing manual workload.

DATASETS AND EVALUATION METRICS

Datasets

Similar to other embodied intelligence tasks,[222-229] UAV-VLN research relies on simulation datasets that typically include visual observations, natural language instructions, and corresponding navigation trajectories. Several datasets have been proposed in recent years, which can be broadly categorized into top-view datasets and three-dimensional scene datasets. Several representative UAV-VLN datasets are summarized in Table 3.

Top-view datasets. Top-view datasets are primarily constructed from satellite imagery, offering higher realism and close alignment with real geospatial information. Built on a top-down satellite imagery environment (see Section III-B), AVDN provides 3k dialogue-driven navigation trajectories; visual observations are derived from the xView dataset. On top of this environment, the AVDN dataset was collected, consisting of 3,064 aerial navigation trajectories. Notably, AVDN incorporates human–machine interactive settings: crowd-sourced "commanders" issue language instructions to simulated "UAV experts", enabling multi-turn dialogue navigation. Additionally, human attention distribution data on aerial imagery during task execution were collected, providing valuable insights into how language instructions align with visual environments.

UAV-VLPA-nano-30[190] is another benchmark dataset designed for UAV-VLN, comprising 30 high-resolution satellite images that cover diverse environments including urban, suburban, rural, and natural landscapes (e.g., buildings, stadiums, water bodies, and transportation infrastructure). The images have a resolution of 1.5 meters per pixel, with each image covering approximately 760 square meters, and include precise geospatial metadata for path planning and location alignment. The dataset's task design evalu-

Table 3. UAV-VLN datasets.

Name	Year	Types	Description
AVDN	2022	Top-View	3k trajectories with human-human asynchronous dialogues
UAV-VLPA-nano-30	2025	Top-View	30 high-resolution satellite images covering diverse environments
HaL-13k	2025	Top-View	High-altitude bird's-eye views + low-altitude first-person views for multi-UAV collaboration
UAV-VLN	2025	Top-View	1,000 human tasks with sub-structures to study LLMs' high-level planning decomposition
OpenUAV	2025	Top-View	12k 6-DoF trajectories and assistant prompts for language-guided planning and control
AerialVLN	2022	3D	8.4k trajectories based on virtual game engine
CityNav	2024	3D	Urban reconstruction with high-precision point clouds and large-scale human navigation trajectories
AeroVerse(CyberAgent-Ego500k)	2024	3D	A virtual image-text-pose alignment dataset for pre-training aerospace world models
AeroVerse(AerialAgent-Ego10k)	2024	3D	A large-scale, real-world image-text pre-training dataset from a UAV's first-person perspective
AeroVerse(SkyAgent-Scene3k)	2024	3D	An instruction dataset for the fine-tuning of aerospace embodied scene awareness
AeroVerse(SkyAgent-Reason3k)	2024	3D	An instruction dataset for the fine-tuning of aerospace embodied spatial reasoning
AeroVerse(SkyAgent-Nav3k)	2024	3D	An instruction dataset for the fine-tuning of aerospace embodied navigational exploration
AeroVerse(SkyAgent-Plan3k)	2024	3D	An instruction dataset for the fine-tuning of aerospace embodied task planning
AeroVerse(SkyAgent-Act3k)	2024	3D	An instruction dataset for the fine-tuning of aerospace embodied motion decision
OpenFly	2025	3D	100k trajectories across diverse scenes with varied heights and trajectory lengths
VDUAV	2025	3D	Pairs satellite with UAV views for cross-modal alignment, a key VLN pre-training resource
RefDrone	2025	3D	8,536 images with 17,900 expressions for understanding small, multiple, or absent targets
UrbanVideo-Bench	2025	3D	1.5k aerial videos and 5.2k multiple-choice questions for multimodal memory and reasoning evaluation

ates UAV systems' ability to understand language instructions and generate corresponding flight paths: human operators manually create a flight path for each image within 35 minutes (e.g., flying over a target building marked with a purple bounding box), while recording quantitative measures such as path length. This benchmark places high demands on models' global vision–language understanding and is particularly suitable for testing navigation performance in complex geographical environments.

More recently, to address multi-UAV vision-and-language navigation tasks, Wu *et al.* proposed the HaL-13k dataset,[42] targeting high-altitude–low-altitude UAV collaborative navigation. HaL-13k consists of approximately 13,000 instruction–trajectory pairs, with each entry including natural language navigation commands, initial and target states, flight paths, and corresponding perceptual inputs. Unlike traditional single-UAV VLN datasets, HaL-13k is designed to enable two UAVs at different altitudes and perspectives to collaborate: the high-altitude UAV provides global bird's-eye perception and reasoning, while the low-altitude UAV executes fine-grained, ground-level navigation. Through unified scene annotations and task objectives, the dataset ensures semantic information sharing between UAVs, simulating a more realistic division of labor for multi-level collaborative tasks.

The *UAV-VLN* dataset[230] serves as a pioneering benchmark in the field, establishing a foundation for continuous point-to-point navigation tasks in top-down views. It provides a suite of diverse instructions paired with satellite image-based environments, challenging agents to reason about spatial relationships from an aerial perspective. The *OpenUAV* benchmark[231] extends this paradigm by focusing on generalization across unseen environments. It aggregates over 100 distinct real-world locations, each with multiple navigation tasks, specifically designed to test the robustness and zero-shot capabilities of VLN models in open-world settings.

3D datasets. Compared with conventional top-down environments, three-dimensional (3D) datasets provide richer spatial information, such as height variations, occlusion relationships, and multi-view observations, making them closer to real-world UAV flight scenarios. These datasets are typically constructed on virtual simulation engines (e.g., Unity3D, AirSim, and Unreal Engine)[232-234] and are generated through point cloud reconstruction, procedural modeling, or manual design to create complex environments that support high-degree-of-freedom navigation tasks guided by natural language. In recent years, researchers have continuously advanced dataset construction along the axes of scene diversity, task complexity, and data scale, thereby driving algorithmic progress in UAV Vision-and-Language Navigation (VLN).[30]

Early datasets such as *AerialVLN* [30] were primarily built upon virtual game engines, with limited realism and interactive capability. With the progress of 3D reconstruction and hybrid simulation techniques, a new generation of datasets has begun to integrate real urban point clouds (e.g., *CityNav* [29]) and multi-source modeling strategies (e.g., *OpenFly* [31]). A notable contribution in this area is *AeroVerse*,[1] which aims to establish a comprehensive benchmark suite that integrates simulation, pre-training, fine-tuning, and evaluation to support end-to-end aerospace embodied intelligence research. This suite explicitly defines five downstream tasks: scene awareness, spatial reasoning, navigational exploration, task planning, and motion decision. To this end, it includes two large-scale pre-training datasets (AerialAgent-Ego10k, a real-world image-text dataset, and CyberAgent-Ego500k, a virtual image-text-pose alignment dataset) and five corresponding instruction datasets for fine-tuning (SkyAgent-Scene3k, SkyAgent-Reason3k, SkyAgent-Nav3k, SkyAgent-Plan3k, and SkyAgent-Act3k). Similarly, *CityNav*[29] provides language-goal aerial navigation with large-scale human trajectories collected via a web-based simulator (see Section III-B for scene construction). *OpenFly* [31] offers a mixed-source toolchain that combines semantic understanding and automated collision-free trajectory generation to build large-scale trajectories while substantially reducing manual annotation costs (platform details in Section III-B). Benefiting from these advances, the dataset scale has expanded from around 8,400 trajectories in *AerialVLN* [30] to the hundred-thousand level in *OpenFly*,[31] while supporting six-degree-of-freedom (6-DoF) flight modeling.

Modern 3D datasets also design tasks that better align with real-world application requirements. *CityNav*[29] incorporates real-world geographic information (e.g., building structures, semantic labels) and high-level language

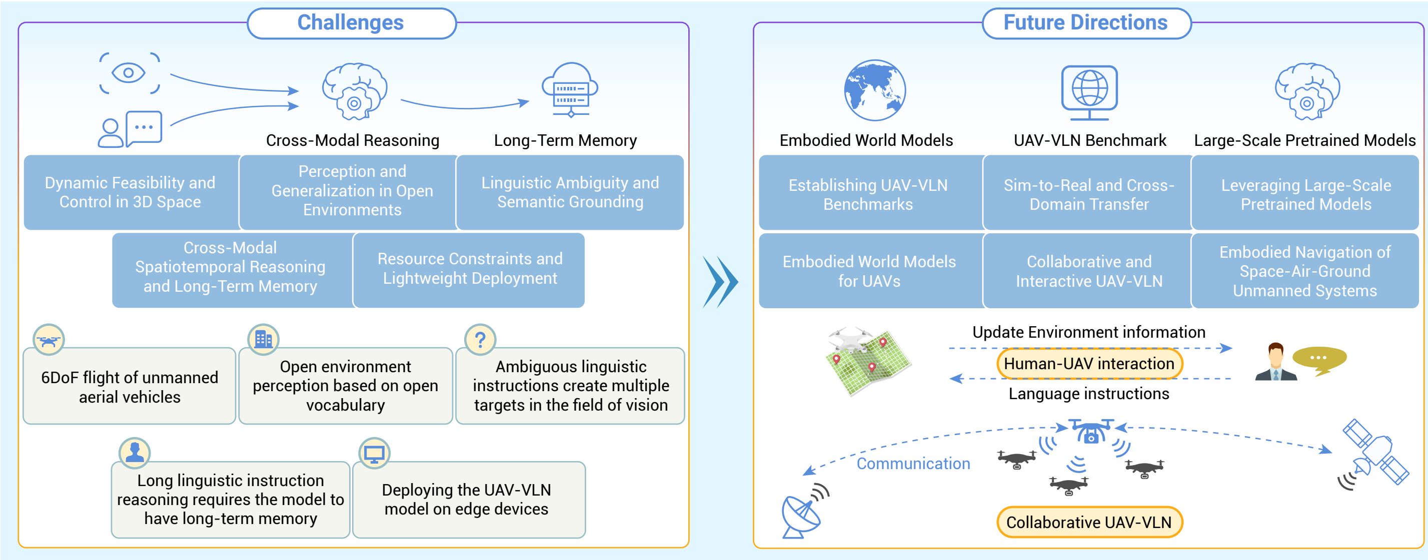

Figure 8. Challenge and future directions of UAV-VLN.

instructions to support navigation tasks for urban inspection and intelligent delivery. *AerialVLN*[80] introduces UAV-specific maneuver actions such as "ascend" and "dive," and designs long-horizon navigation tasks with an average path length exceeding 660 steps, greatly increasing the demands on agents' 3D spatial reasoning and decision-making capabilities. Meanwhile, annotation strategies have gradually evolved from manual collection to automated generation: for example, *AerialVLN*[80] relies on professional pilots to record trajectories, while *OpenFly*[31] employs semantic perception and language generation models to automatically synthesize instructions and plan trajectories, ensuring annotation quality while significantly improving efficiency.

Further enriching the diversity of 3D tasks, the *VDUAV* dataset[235] introduces a multi-turn dialogue setting for UAV navigation, where the agent must engage in an interactive conversation to clarify ambiguities or receive incremental instructions mid-flight. The *RefDrone* benchmark[236] shifts the focus to fine-grained spatial reasoning, requiring the UAV to navigate to a target specified by a complex referring expression within a cluttered 3D scene.[237] Lastly, the *UrbanVideo-Bench* combines navigation with video captioning challenges, providing dense temporal language annotations for long-horizon flight trajectories in urban environments, thereby supporting research in continuous perception and planning.

Evaluation metrics

In terms of evaluation metrics, the current mainstream VLN evaluation system focuses on navigation accuracy and task completion rate. Common evaluation metrics include Navigation Error (NE), Success Rate (SR), Oracle Success Rate (OSR), and Success Weighted by Path Length (SPL). Navigation Error measures the average Euclidean distance between the final position of the UAV and the target location. Success Rate refers to the proportion of tasks where the UAV reaches a point within a certain threshold (e.g., 3m) of the target, reflecting the accuracy of the navigation results. Oracle Success Rate is a more relaxed metric, where the task is considered successful as long as any point along the trajectory is within the success threshold of the target, used to assess potential reachability. Success Weighted by Path Length combines the efficiency and success of the navigation path by comparing the actual path length with the ideal path length, thereby weighting the success rate and encouraging shorter, more efficient path planning. These metrics complement each other and provide a multi-dimensional quantitative basis for evaluating the performance of the UAV-VLN task.

In addition to these navigation-focused metrics, some research has begun to address the quality of text generation, especially for complex tasks requiring language outputs like scene description and task planning. For instance, AeroVerse[1] introduced SkyAgent-Eval, an automated evaluation suite based on Large Language Models (LLMs). This method leverages the capabilities of GPT-4 to design specialized evaluation rubrics for different downstream tasks, including LLM-Judge-Scene for scene awareness, LLM-Judge-Reason&Nav for spatial reasoning and navigation, and LLM-Judge-Plan for task planning. These metrics aim to provide assessments that more closely align with human preferences by evaluating semantic consistency, instruction adherence, and logical soundness. This benchmark also incorporates traditional text-generation metrics like BLEU and SPICE to offer a more comprehensive evaluation of a model's overall language capabilities.

CHALLENGES AND FUTURE DIRECTIONS

Challenges

Dynamic feasibility and control in 3D space. Compared with ground robots, UAVs must manage far more complex motion dynamics in three-dimensional space, including multi-degree-of-freedom control (pitch, yaw, roll), nonlinear aerodynamic coupling effects, and external disturbances such as wind fields (Figure 8). Path planning and attitude control are thus no longer simple planar optimization problems, but joint optimizations involving time-varying state estimation and continuous high-dimensional control. When natural language commands specify fine-grained operations (e.g., "*fly around the tower and hover near the top*"), the system must simultaneously interpret semantic intent and ensure dynamically feasible trajectories. This tight coupling between control and semantics introduces challenges that go beyond existing VLN frameworks primarily designed for ground navigation.

Perception and generalization in open environments. UAV-VLN often takes place in unstructured and dynamic environments such as dense urban areas, forests, or post-disaster zones. UAVs must cope with illumination variations, weather changes, and sensor noise, while maintaining robust navigation without accurate maps or strong priors. Aerial perspectives further introduce large-scale variations and significant viewpoint shifts compared with ground robots. Although current models achieve strong performance in fixed or small-scale environments, their ability to generalize across diverse real-world scenarios remain limited, which restricts the reliability of UAV deployment in practice.

Linguistic ambiguity and semantic grounding. Natural language instructions frequently involve ambiguity and context-dependent expressions, such as "*descend behind the trees*" or "*fly near the red roof*". Such referents may be spatially uncertain, shift dramatically with viewpoint changes, or lack unique visual cues. UAVs, due to their aerial vantage points, are particularly prone to misalignment between linguistic descriptions and visual evidence. Building robust grounding mechanisms that connect ambiguous language to dynamic visual semantics remains a central challenge for UAV-VLN research.

Cross-modal spatiotemporal reasoning and long-term memory. UAV navigation tasks often require long-duration flights and multi-stage planning, where instructions may describe sequential goals (e.g., "*follow the river, cross* *the bridge, then land near the factory*"). This setting demands reasoning over both space and time, while maintaining a consistent task memory across long trajectories. However, most current methods still rely on short-term local perception, making it difficult to preserve global context, which leads to goal drifting or forgetting during execution. Developing memory-augmented models that can store, retrieve, and update multi-modal information over extended horizons is essential for reliable and coherent UAV navigation.

Resource constraints and lightweight deployment. In real-world deployment, UAVs face strict constraints on on-board computation, energy consumption, and communication bandwidth. Although multimodal large models show impressive navigation capabilities under laboratory conditions, their high computational and memory costs make direct deployment on UAV platforms impractical. Achieving efficient inference without sacrificing accuracy requires advances in architectural optimization and collaborative edge–cloud computing. Balancing accuracy and efficiency under constrained resources remains a key challenge for practical UAV-VLN systems.

Future directions

Establishing UAV-NLN benchmarks. Current research in UAV-VLN lacks unified benchmark tasks and large-scale standardized datasets. Existing datasets are often task-specific or environment-limited, hindering comprehensive evaluation of model generalization. Future efforts should aim to construct benchmarks covering diverse scenarios, multimodal inputs, and instruction variability. Integrating both large-scale virtual environments and field-collected real-world data would facilitate robust cross-domain evaluation, providing a standardized platform for algorithm comparison and community-wide progress.

Sim-to-real and cross-domain transfer. Simulation platforms offer convenient testbeds for UAV-VLN research, yet transferring models to real-world environments remains challenging due to perceptual, semantic, and dynamic discrepancies. Future research should explore domain adaptation,[238] adversarial training,[239] and synthetic data augmentation[240] to bridge this sim-to-real gap. Additionally, meta-learning[241] and self-supervised approaches could enable UAVs to rapidly adapt to new environments with limited real-world samples, improving robustness and reliability under operational conditions.

Leveraging pretrained large models. The advances in large language models (LLMs) and multimodal foundation models present promising opportunities for UAV-VLN. Future work may leverage these models to enhance instruction parsing, semantic alignment, and planning under complex natural language commands. Combining lightweight multimodal architectures with pretrained knowledge[242] can balance the trade-off between reasoning capability and computational efficiency, enabling real-time deployment on resource-constrained UAV platforms.

Embodied world models for UAVs. Beyond immediate perception and reactive planning, UAV-VLN systems would benefit from embodied world models,[243] which are continuously updated representations of the environment learned through interaction. These models enable predictive reasoning, long-horizon planning, and consistent cross-modal state maintenance, all of which are critical for large-scale, long-duration flights. Concrete implementations include graph-based semantic maps and learned neural scene representations, which have shown promise in capturing spatial and semantic structure. However, maintaining such models under dynamic conditions with environmental uncertainty remains an open challenge. Future research can focus on integrating embodied world models with multimodal inputs to enhance global navigation performance and task reliability.

Collaborative and interactive UAV-VLN. Fully autonomous operation is often insufficient for complex or high-risk tasks. Future UAV-VLN systems should emphasize collaboration, both with humans and among multiple UAVs. Human-UAV interaction can enable real-time adjustment of tasks via language, dialogue, or gestures, enhancing safety and reliability. Multi-UAV collaboration can support semantic sharing, dynamic task allocation, and cooperative path planning, extending navigation capabilities to large-scale and heterogeneous environments. Integrating these collaborative mechanisms will broaden UAV-VLN applicability and advance embodied intelligence research in practical scenarios.

Embodied navigation of space-air-ground unmanned systems. It combines space-based (satellites), air-based (drones), and ground-based (ground equipment) resources, through collaborative sensing, information fusion, and joint decision-making, achieves navigation capabilities far beyond those of a single platform. In environments where satellite signals are denied (e.g., tunnels, underground areas, dense urban regions) or ground visibility is limited (e.g., disaster sites), units within the system can complement each other's information, providing continuous and reliable navigation solutions; When a node in the space-based or air-based segment fails or is interfered with, other nodes can provide backup and support, ensuring the continuity of navigation.

CONCLUSION

This survey provides a comprehensive review of research progress in UAV-VLN, offering a structured summary across simulation platforms, task definitions, core methodologies, datasets and evaluation metrics, as well as application scenarios. Methodologically, we analyze rule-based, deep learning-driven, and multi-agent collaborative approaches, with particular emphasis on rule strategies, learning paradigms, graph- and grid- based spatial modeling, large model applications, and multi-UAV and satellite–UAV collaboration strategies. In terms of applications, UAV-VLN has demonstrated promising potential in disaster response, environmental monitoring, precision agriculture, and logistics. We further identify key technical challenges in complex three-dimensional dynamic environments, including high-degree-of-freedom control, perception and generalization in open environments, cross-modal language understanding, long-term spatiotemporal reasoning, and deployment under resource constraints. Based on these challenges, we outline several promising future research directions, encompassing standardized benchmark development, Sim-to-Real transfer, large model integration, embodied world modeling, collaborative human–UAV navigation strategies, and embodied navigation of space-air-ground unmanned systems. Overall, this survey provides a structured research framework and methodological reference for UAV-VLN, offering guidance for advancing both theoretical development and practical deployment of aerospace embodied intelligence.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

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The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

Not Applicable